WORD SENSE DISAMBIGUATION: SCALING UP, DOMAIN ADAPTATION, AND APPLICATION TO MACHINE TRANSLATION

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Summary

The process of identifying the correct meaning, or sense of a word in context, is known as word sense disambiguation (WSD). This thesis explores three important research issues for WSD.

Current WSD systems suffer from a lack of training examples. In our work, we describe an approach of gathering training examples for WSD from parallel texts. We show that incorporating parallel text examples improves performance over just using manually annotated examples. Using parallel text examples as part of our training data, we developed systems for the SemEval-2007 coarse-grained and fine-grained English all-words tasks, obtaining excellent results for both tasks.

In training and applying WSD systems on different domains, an issue that affects accuracy is that instances of a word drawn from different domains have different sense priors (the proportions of the different senses of a word). To address this issue, we estimate the sense priors of words drawn from a new domain using an algorithm based on expectation maximization (EM). We show that the estimated sense priors help to improve WSD accuracy. We also use this EM-based algorithm to detect a change in predominant sense between domains. Together with the use of count-merging and active learning, we are able to perform effective domain adaptation to port a WSD system to new domains.

Finally, recent research presents conflicting evidence on whether WSD systems can help to improve the performance of statistical machine translation (MT) systems. In our work, we show for the first time that integrating a WSD system achieves a statistically significant improvement on the translation performance of Hiero, a state-of-the-art statistical MT system.

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Chapter 1

Introduction

1.1 Word Sense Disambiguation

Many words have multiple meanings. For example, in the sentence "The institutions have already consulted the staff concerned through various *channels*, including discussion with the staff representatives", the word *channel* denotes a means of communication or access. However, in the sentence "A *channel* is typically what you rent from a telephone company", the word *channel* refers to a path over which electrical signals can pass. The process of identifying the correct meaning, or sense of a word in context, is known as word sense disambiguation (WSD) (Ng and Zelle, 1997). This is one of the fundamental problems in natural language processing (NLP).

In the typical setting, WSD is a classification problem where each ambiguous word is assigned a sense label, usually from a pre-defined sense inventory, during the disambiguation process. Being able to accurately disambiguate word sense is important for applications such as information retrieval, machine translation, etc.

In current WSD research, WordNet (Miller, 1990) is usually used as the sense

inventory. WordNet is a semantic lexicon for the English language, where words are organized into synonym sets (called synsets), with various semantic relations between these synonym sets. As an example, nouns are organized as a hierarchical structure based on hypernymy and hyponymy[1] relations. Thus, unlike a standard dictionary which merely lists word definitions in an alphabetical order, the conceptual organization of WordNet makes it a useful resource for NLP research.

1.2 SENSEVAL

Driven by a lack of standardized datasets and evaluation metics, a series of evaluation exercises called SENSEVAL were held. These exercises evaluated the strengths and weaknesses of WSD algorithms and participating systems created by research communities worldwide, with respect to different words and different languages.

SENSEVAL-1 (Kilgarriff, 1998), the first international workshop on evaluating WSD systems, was held in the summer of 1998, under the auspices of ACL SIGLEX (the Special Interest Group on the Lexicon of the Association for Computational Linguistics) and EURALEX (European Association for Lexicography). SENSEVAL-1 uses the HECTOR (Atkins, 1992) sense inventory.

SENSEVAL-2 (Edmonds and Cotton, 2001) took place in the summer of 2001. Two of the tasks in SENSEVAL-2 were the English all-words task (Palmer et al., 2001), and the English lexical sample task (Kilgarriff, 2001). In SENSEVAL-2, WordNet-1.7 was used as the sense inventory for these two tasks. A brief description of these two tasks follows.

- English all-words task: Systems must tag almost all of the content words (words

[1] Y is a hypernym of X if X is a (kind of) Y. X is a hyponym of Y if X is a (kind of) Y

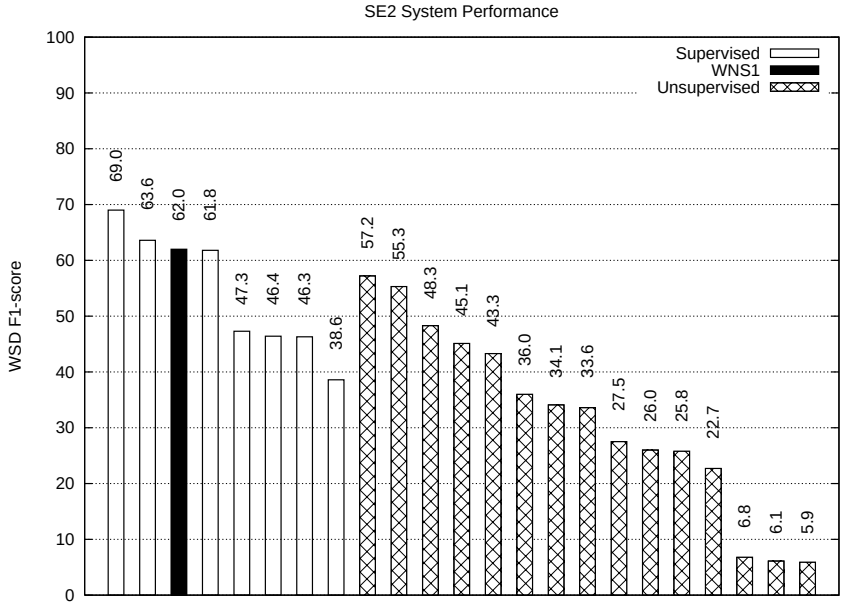


Figure 1.1: Performance of systems in the SENSEVAL-2 English all-words task. The single shaded bar represents the baseline strategy of using first WordNet sense, the empty white bars represent the supervised systems, and the pattern-filled bars represent the unsupervised systems.

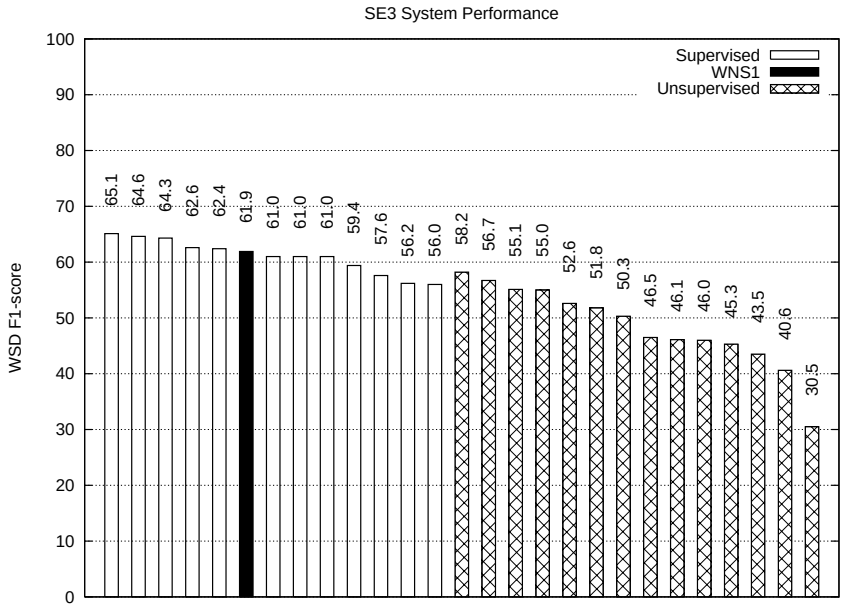


Figure 1.2: Performance of systems in the SENSEVAL-3 English all-words task.

having the part-of-speech noun, adjective, verb, or adverb) in a sample of running English text. No training data is provided for this task.

- English lexical sample task: Systems must tag instances of a selected sample of English words, where the instances are presented as short extracts of English text. A relatively large amount of annotated data, where the predetermined words are tagged in context, are provided as training data for this task.

Following the success of SENSEVAL-2, SENSEVAL-3 was held in the summer of 2004. Similar to SENSEVAL-2, two of the tasks for the English language are the English all-words task (Snyder and Palmer, 2004) and the English lexical sample task (Mihalcea, Chklovski, and Kilgarriff, 2004). The WordNet-1.7.1 sense inventory was used for these two tasks.

The SENSEVAL-2 and SENSEVAL-3 exercises show that among the various approaches to WSD, corpus-based supervised machine learning methods are the most successful. With this approach, one needs to obtain a corpus where each occurrence of an ambiguous word had been earlier manually annotated with the correct sense, according to some existing sense inventory, to serve as training data.

In WordNet, the senses of each word are ordered in terms of their frequency of occurrence in the English texts in the SemCor corpus (Miller et al., 1994), which is part of the Brown Corpus (BC) (Kucera and Francis, 1967). Since these texts are general in nature and do not belong to any specific domain, the first WordNet sense of each word is generally regarded as its most common sense. Hence, to gauge the performance of state-of-the-art supervised WSD systems, we investigate the performance of a baseline strategy which simply tags each word with its first WordNet sense. On the English all-words task of SENSEVAL-2, this strategy achieves an accuracy of 62.0%. As shown in Figure 1.1, only two participating systems achieve performance

better than this baseline accuracy. When applied on the English all-words task of SENSEVAL-3, the baseline strategy achieves an accuracy of 61.9%. As shown in Figure 1.2, only a few participating systems perform better than this baseline strategy and their accuracy improvements are marginal.

1.3 Research Problems in Word Sense Disambiguation

Results of SENSEVAL-2 and SENSEVAL-3 English all-words task show that supervised systems are more successful than unsupervised systems. The results also show, however, that current state-of-the-art supervised WSD systems still find it hard to outperform a simple WordNet first sense strategy on a consistent basis.

One problem the supervised systems currently face is a lack of a large amount of sense-tagged data for training. The sense annotation process is usually done by trained lexicographers and the obvious drawback here is the laborious manual sense-tagging involved. This problem is particularly severe for WSD, since sense-tagged data have to be collected for each ambiguous word of a language. Due to the laborious and expensive annotation process, as of today, only a handful of sense-tagged corpora are publicly available.

Another equally pressing problem that arises out of supervised learning is the issue of domain dependence. A WSD system trained on data from one domain, e.g., sports, will show a decrease in performance when applied on a different domain, e.g., economics. Tackling this problem is necessary for building scalable and wide-coverage WSD systems that are portable across different domains.

The third problem is the perceived lack of applications for WSD. Traditionally,

WSD is evaluated as an isolated task, without regard to any specific application. Hence, doubts have been expressed on the utility of WSD for actual NLP applications.

1.3.1 The Data Acquisition Bottleneck

Among the existing sense-tagged corpora, the SemCor corpus (Miller et al., 1994) is one of the most widely used. In SemCor, content words have been manually tagged with word senses from the WordNet sense inventory. Current supervised WSD systems (such as participants in the SENSEVAL English all-words task) usually rely on this relatively small manually annotated corpus for training examples. However, this has affected the scalability and performance of these systems. As we have shown in Figures 1.1 and 1.2, very few SENSEVAL participating systems perform better than the baseline WordNet first sense strategy.

In order to build wide-coverage and scalable WSD systems, tackling the data acquisition bottleneck for WSD is crucial. In an attempt to do this, the DSO corpus (Ng and Lee, 1996; Ng, 1997a) was manually annotated. It consists of 192,800 word occurrences of 121 nouns and 70 verbs. In another attempt to collect large amounts of sense-tagged data, Chklovski and Mihalcea initiated the Open Mind Word Expert (OMWE) project (Chklovski and Mihalcea, 2002) to collect sense-tagged data from Internet users. Data gathered through the OMWE project were used in the SENSEVAL-3 English lexical sample task. In that task, WordNet-1.7.1 was used as the sense inventory for nouns and adjectives, while Wordsmyth[2] was used as the sense inventory for verbs.

Although the DSO corpus and OMWE project are good initiatives, sense annotation is still done manually and this inherently limits the amount of data that can be

[2]http://www.wordsmyth.net

collected. As proposed by Resnik and Yarowsky, a source of potential training data is parallel texts (Resnik and Yarowsky, 1997), where translation distinctions in a target language can potentially serve as sense distinctions in the source language. In a later work (Resnik and Yarowsky, 2000), the authors investigated the probability that 12 different languages will differently lexicalize the senses of English words. They found that there appears to be a strong association with language distance from English, as non-Indo-European languages in general have a higher probability to differently lexicalize English senses, as compared to Indo-European languages. From their study, the Basque language has the highest probability of differently lexicalizing English senses, followed by Japanese, Korean, Chinese, Turkish, and so on.

To explore the potential of this approach, our prior work (Ng, Wang, and Chan, 2003) exploited English-Chinese parallel texts for WSD. For each noun of SENSEVAL-2 English lexical sample task, we provided some Chinese translations for each of the senses. Senses were lumped together if they were translated in the same way in Chinese. Given a word-aligned English-Chinese parallel corpus, these different Chinese translations then serve as the "sense-tags" of the corresponding English noun. Through this approach, we gathered training examples for WSD from parallel texts. Note that the examples are collected without manually annotating each individual ambiguous word occurrence, thus allowing us to gather the examples in a much shorter time. In (Ng, Wang, and Chan, 2003), we obtained encouraging results in our evaluation on the nouns of SENSEVAL-2 English lexical sample task.

1.3.2 Different Sense Priors Across Domains

The reliance of supervised WSD systems on annotated corpus raises the important issue of domain dependence. To investigate this, Escudero, Marquez, and Rigau

(2000) and Martinez and Agirre (2000) conducted experiments using the DSO corpus, which contains sentences from two different corpora, namely Brown Corpus (BC) and Wall Street Journal (WSJ). They found that training a WSD system on one part (BC or WSJ) of the DSO corpus, and applying it to the other can result in an accuracy drop of more than 10%. A reason given by the authors is that examples from different domains will exhibit greater differences such as variation in collocations, thus presenting different classification cues to the learning algorithm. Another reason pointed out in (Escudero, Marquez, and Rigau, 2000) is the difference in sense priors (i.e., the proportions of the different senses of a word) between BC and WSJ. For instance, the noun *interest* has these 6 senses in the DSO corpus: sense 1, 2, 3, 4, 5, and 8. In the BC part of the DSO corpus, these senses occur with the proportions: 34%, 9%, 16%, 14%, 12%, and 15%. However, in the WSJ part of the DSO corpus, the proportions are different: 13%, 4%, 3%, 56%, 22%, and 2%. When the authors assumed they knew the sense priors of each word in BC and WSJ, and adjusted these two datasets such that the proportions of the different senses of each word were the same between BC and WSJ, accuracy improved by 9%. In another work, Agirre and Martinez (2004) trained a WSD system on data which was automatically gathered from the Internet. The authors reported a 14% improvement in accuracy if they have an accurate estimate of the sense priors in the evaluation data and sampled their training data according to these sense priors. The work of these researchers showed that when the domain of the training data differs from the domain of the data on which the system is applied, there will be a decrease in WSD accuracy, with one major reason being the different sense priors across different domains. Hence, to build WSD systems that are portable across different domains, estimation of the sense priors (i.e., determining the proportions of the different senses of a word) occurring

in a text corpus drawn from a domain is important.

1.3.3 Perceived Lack of Applications for Word Sense Disambiguation

WSD is often regarded as an "intermediate task" that will ultimately contribute to some application tasks such as machine translation (MT) and information retrieval (IR). One is interested in the performance improvement of the particular application when WSD is incorporated.

Some prior research has tried to determine whether WSD is useful for IR. In (Krovets and Croft, 1992), the authors concluded that even with a simulated WSD program which gives perfect sense predictions for terms in the IR corpus, they obtained only a slight improvement in retrieval performance. Experiments in (Sanderson, 1994) indicate that retrieval performance degrades if the sense predictions are not at a sufficiently precise level. Also, WSD is probably only relevant to short queries as the words in a long query tend to be mutually disambiguating. On the other hand, experiments by Schütze and Pedersen (1995) where senses are automatically derived from the IR corpus, as opposed to adhering to a pre-existing sense inventory, show an improvement in retrieval performance. More recently, Agirre et al. (2007) organized a task as part of the SemEval-2007 (Agirre, Márquez, and Wicentowski, 2007) evaluation exercise, where the aim is to evaluate the usefulness of WSD for improving cross-lingual IR (CLIR) performance. The conclusion there is that WSD does not help CLIR. Given all these prior research efforts, it seems that more work still needs to be done to ascertain whether WSD helps IR.

In the area of machine translation, different senses of a word w in a source language may have different translations in a target language, depending on the particular

meaning of w in context. Hence, the assumption is that in resolving sense ambiguity, a WSD system will be able to help an MT system to determine the correct translation for an ambiguous word. Further, to determine the correct sense of a word, WSD systems typically use a wide array of features that are not limited to the local context of w, and some of these features may not be used by statistical MT systems. An early work to incorporate WSD in MT is reported in (Brown et al., 1991). In that work, the authors incorporated the predictions of their WSD system into a French-English MT system. They obtained the promising result of having an increased number of translations judged as acceptable after incorporating WSD. However, their evaluation was on a limited set of 100 sentence translations and their WSD system was only applied on a set of words with at most 2 senses.

To perform translation, state-of-the-art MT systems use a statistical phrase-based approach (Marcu and Wong, 2002; Koehn, 2003; Och and Ney, 2004) by treating phrases as the basic units of translation. In this approach, a phrase can be any sequence of consecutive words and is not necessarily linguistically meaningful. Capitalizing on the strength of the phrase-based approach, Chiang (2005) introduced a *hierarchical* phrase-based statistical MT system, Hiero, which achieves significantly better translation performance than Pharaoh (Koehn, 2004a), a state-of-the-art phrase-based statistical MT system.

Recently, some researchers investigated whether performing WSD will help to improve the performance of an MT system. For instance, Carpuat and Wu (2005) incorporated a Chinese WSD system into a Chinese-English MT system and reported the negative result that WSD degraded MT performance. On the other hand, experiments in (Vickrey et al., 2005) showed positive results when WSD was incorporated.

We note, however, that their experiments were not done using a full-fledged MT system and the evaluation was not on how well each source sentence was translated as a whole. In the same year, Cabezas and Resnik (2005) reported a relatively small improvement in Pharaoh's translation through the use of WSD. Without a statistical significance test, however, their work appears to be inconclusive. Considering the conflicting results reported by prior work, it is not clear whether a WSD system can help to improve the performance of a state-of-the-art statistical MT system.

1.4 Contributions of this Thesis

The contributions of this thesis lie in addressing the various issues described in Section 1.3. In the following sections, we describe our work and list the publications arising from our research.

1.4.1 Tackling the Data Acquisition Bottleneck

Our initial work (Ng, Wang, and Chan, 2003) shows that the approach of gathering training examples from parallel texts for WSD is promising. Motivated by this, in (Chan and Ng, 2005a), we evaluated the approach on a set of most frequently occurring nouns and investigated the performance in a fine-grained disambiguation setting, instead of using lumped senses as in (Ng, Wang, and Chan, 2003). When evaluated on a set of nouns in SENSEVAL-2 English all-words task using fine-grained scoring, classifiers trained on examples gathered from parallel texts achieve high accuracy, significantly outperforming the strategy of always tagging each word with its first WordNet sense. The performance of the approach is also comparable to training on manually sense annotated examples such as SemCor.

Further, we recently expanded the coverage to include collecting parallel text examples for a set of most frequently occurring adjectives and verbs. Using these examples gathered from parallel texts, together with examples from the SemCor and DSO corpus, we participated in the SemEval-2007 (Agirre, Márquez, and Wicentowski, 2007) (which is the most recent SENSEVAL evaluation) coarse-grained English all-words task and fine-grained English all-words task. Our system submitted to the coarse-grained English all-words task was ranked in first place out of 14 participants[3], while the system submitted to the fine-grained English all-words task was ranked in second place out of 13 participants (Chan, Ng, and Zhong, 2007). Also, as part of SemEval-2007, we organized an English lexical sample task using examples gathered from parallel texts (Ng and Chan, 2007).

1.4.2 Domain Adaptation for Word Sense Disambiguation

In the machine learning literature, algorithms to estimate class a priori probabilities (proportion of each class) have been developed, such as a confusion matrix algorithm (Vucetic and Obradovic, 2001) and an EM-based algorithm (Saerens, Latinne, and Decaestecker, 2002). In (Chan and Ng, 2005b), we applied these machine learning methods to automatically estimate the sense priors in the target domain. For instance, given the noun *interest* and the WSJ part of the DSO corpus, we will attempt to estimate the proportion of each sense of *interest* occurring in WSJ. We showed that these sense prior estimates help to improve WSD accuracy. In that work, we used naive Bayes as the training algorithm to provide posterior probabilities, or class membership estimates, for the instances in our target corpus, which is the test data of

[3]A system developed by one of the task organizers of the coarse-grained English all-words task gave the highest overall score for the coarse-grained English all-words task, but this score is not considered part of the official scores.

SENSEVAL-2 English lexical sample task. These probabilities were then used by the machine learning methods to estimate the sense priors of each word in the target corpus.

However, it is known that the posterior probabilities assigned by naive Bayes are not reliable, or not well calibrated (Domingos and Pazzani, 1996). These probabilities are typically too extreme, often being very near 0 or 1. Since these probabilities are used in estimating the sense priors, it is important that they are well calibrated. We addressed this in (Chan and Ng, 2006), exploring the estimation of sense priors by first calibrating the probabilities from naive Bayes. We also proposed using probabilities from logistic regression (which already gives well calibrated probabilities) to estimate the sense priors. We showed that by using well calibrated probabilities, we can estimate the sense priors more effectively. Using these estimates improves WSD accuracy and we achieved results that are better than using our earlier approach described in (Chan and Ng, 2005b).

In (Chan and Ng, 2007), we explored the issue of domain adaptation of WSD systems from another angle, by adding training examples from a new domain as additional training data to a WSD system. To reduce the effort required to adapt a WSD system to a new domain, we employed an active learning strategy (Lewis and Gale, 1994) to select examples to annotate from the new domain of interest. In that work, we performed domain adaptation for WSD of a set of nouns using *fine-grained* evaluation. The contribution of our work is not only in showing that active learning can be successfully employed to reduce the annotation effort required for domain adaptation in a *fine-grained* WSD setting. More importantly, our main focus and contribution is in showing how we can improve the effectiveness of a basic active learning approach when it is used for domain adaptation. In particular, we explored

the issue of different sense priors across different domains. Using the sense priors estimated by the EM-based algorithm, the predominant sense (the sense with the highest proportion) in the new domain is predicted. Using this predicted predominant sense and adopting a count-merging technique, we *improved* the effectiveness of the adaptation process.

1.4.3 Word Sense Disambiguation for Machine Translation

The Hiero MT system introduced in (Chiang, 2005) is currently one of the very best statistical MT system. In (Chan, Ng, and Chiang, 2007), we successfully integrate a state-of-the-art WSD system into this state-of-the-art hierarchical phrase-based MT system, Hiero. The integration is accomplished by introducing two additional features into the MT model which operate on the existing rules of the grammar, without introducing competing rules. These features are treated, both in feature-weight tuning and in decoding, on the same footing as the rest of the model, allowing it to weigh the WSD model predictions against other pieces of evidence so as to optimize translation accuracy (as measured by BLEU). The contribution of our work lies in showing for the first time that integrating a WSD system achieves statistically significant translation improvement for a state-of-the-art statistical MT system on an actual translation task.

1.4.4 Research Publications

Research carried out in this thesis has resulted in several publications. In the previous 3 sections, we described the contributions of these publications. In this section, we explicitly list the publications for each of the contribution areas.

Publications on *tackling the data acquisition bottleneck* are as follows. In addition,

we highlight that our WSD system submitted to the coarse-grained English all-words task was ranked in first place out of 14 participants, while the system submitted to the fine-grained English all-words task was ranked in second place out of 13 participants.

- **Yee Seng Chan**, Hwee Tou Ng and Zhi Zhong. 2007. NUS-PT: Exploiting Parallel Texts for Word Sense Disambiguation in the English All-Words Tasks. In *Proceedings of the* 4^{th} *International Workshop on Semantic Evaluations (SemEval-2007), pp. 253-256, Prague, Czech Republic.*

- Hwee Tou Ng and **Yee Seng Chan**. 2007. SemEval-2007 Task 11: English Lexical Sample Task via English-Chinese Parallel Text. In *Proceedings of the* 4^{th} *International Workshop on Semantic Evaluations (SemEval-2007), pp. 54-58, Prague, Czech Republic.*

- **Yee Seng Chan** and Hwee Tou Ng. 2005. Scaling up Word Sense Disambiguation via Parallel Texts. In *Proceedings of the Twentieth National Conference on Artificial Intelligence (AAAI-2005), pp. 1037-1042, Pittsburgh, USA.*

Publications on *domain adaptation for word sense disambiguation* are as follows:

- **Yee Seng Chan** and Hwee Tou Ng. 2007. Domain Adaptation with Active Learning for Word Sense Disambiguation. In *Proceedings of the* 45^{th} *Annual Meeting of the Association for Computational Linguistics (ACL-2007), pp. 49-56, Prague, Czech Republic.*

- **Yee Seng Chan** and Hwee Tou Ng. 2006. Estimating Class Priors in Domain Adaptation for Word Sense Disambiguation. In *Proceedings of the* 21^{st} *International Conference on Computational Linguistics and* 44^{th} *Annual Meeting of*

the Association for Computational Linguistics (COLING/ACL-2006), pp. 89-96, Sydney, Australia.

- **Yee Seng Chan** and Hwee Tou Ng. 2005. Word Sense Disambiguation with Distribution Estimation. In *Proceedings of the Nineteenth International Joint Conference on Artificial Intelligence (IJCAI-2005), pp. 1010-1015, Edinburgh, Scotland.*

The publication on exploring *word sense disambiguation for machine translation* is as follows:

- **Yee Seng Chan**, Hwee Tou Ng and David Chiang. 2007. Word Sense Disambiguation Improves Statistical Machine Translation. In *Proceedings of the* 45^{th} *Annual Meeting of the Association for Computational Linguistics (ACL-2007), pp. 33-40, Prague, Czech Republic.*

1.5 Outline of this Thesis

We have by now given an outline of the research issues in WSD that the work in this thesis seeks to address. In Chapter 2, we first describe various prior research related to the WSD problems highlighted in Section 1.3. In Chapter 3, we describe the knowledge sources and learning algorithms used for our supervised WSD system. In Chapter 4, we describe our approach of gathering training examples for WSD from parallel texts and evaluate the approach on the test data of SENSEVAL-2 and SENSEVAL-3 English all-words task. We also describe our participation in the recent SemEval-2007 evaluation exercise. In Chapter 5, we describe our work on estimation of the sense priors in a new text corpus. In Chapter 6, we look at another facet

of domain adaptation for WSD systems by adding training examples from the new domain, as additional training data to a WSD system. We use active learning as a basis for reducing the annotation effort and several other techniques to further improve the effectiveness of the adaptation process. In Chapter 7, we describe in detail our work done in exploring the question of whether WSD is useful for machine translation. Finally in Chapter 8, we conclude this thesis and describe some potential future work.

Chapter 2

Related Work

As mentioned in Chapter 1, corpus-based supervised learning is the most successful approach to WSD. An early work using supervised learning is that of (Black, 1988), which developed decision tree models from manually sense annotated examples for five test words. Some of the features used in that work, such as collocations and single words occurring in the surrounding context of the ambiguous word, are still frequently found in current WSD systems. This notion of using words in the surrounding context, or words on either side of an ambiguous word w, as clues for disambiguation, is first outlined in (Weaver, 1955). In that work, Weaver discussed the need for WSD in machine translation and asked the question of what is the minimum size of the context, or minimum number of words on either side of w, that one needs to consider for a reliable prediction of the correct meaning of w.

In the next chapter, we describe the WSD system we use for our experiments, which is based on supervised learning with machine learning algorithms such as naive Bayes or support vector machines. We note, though, that there are many different supervised methods developed, such as the k nearest neighbors (kNN), based on

memory-based learning (Daelemans, van den Bosch, and Zavrel, 1999). Several WSD systems that report good results in previous research use memory-based learning (Ng and Lee, 1996; Hoste et al., 2002; Hoste, Kool, and Daelemans, 2001)

In the following sections, we first describe related work aimed at tackling the lack of a large amount of training data for WSD. We then describe work related to domain adaptation of WSD systems. Then, we discuss the utility of WSD for application tasks such as machine translation (MT) and information retrieval (IR).

2.1 Acquiring Training Data for Word Sense Disambiguation

Early efforts made to overcome a lack of sense annotated data for WSD exploit a bootstrapping approach. In bootstrapping, an initial set of examples for each sense of an ambiguous word w is first manually annotated. Training statistics gathered from these examples are then used to disambiguate additional occurrences of w and those occurrences which are disambiguated with a high level of confidence are added as additional training examples. This approach was used in (Hearst, 1991) for performing WSD on a set of nouns. However, the results indicate that an initial set of at least 10 manually annotated examples of each sense is necessary, and that 20 to 30 examples are necessary for high precision. In another work (Yarowsky, 1995), Yarowsky noted that word collocations provide reliable clues to differentiate between the senses of w and introduced an unsupervised algorithm to disambiguate senses in an untagged corpus. Beginning with a small number of seed collocations representative of each sense of w, all occurrences of w containing the seed collocates are

annotated with the collocation's corresponding sense label. Using these initial annotations, the algorithm then incrementally identify more collocations for the different senses. These additional collocations are then used to gather more sense annotated examples. Although results indicate that this algorithm achieves a high accuracy of above 90%, the evaluation was limited to a set of words having only 2 senses each.

In (Dagan and Itai, 1994), the authors cast the traditional problem of disambiguating between senses into one of target word selection for machine translation. In their work, the different "senses" of a source word are defined to be all its possible translations in the target language, as listed in a bilingual lexicon. To guide the target lexical choice, they consider the frequency of word combinations in a monolingual corpus of the target language. The use of different target translations as sense distinctions of an ambiguous source word bears some similarity to our approach of using parallel texts for acquiring training examples. However, unlike our approach of using *parallel* texts where the focus is on gathering sense annotated examples for WSD, the work of (Dagan and Itai, 1994) is on performing WSD using independent monolingual corpora of the source and target languages.

Due to the lack of a large sense annotated training corpus for WSD, early research efforts such as (Black, 1988; Leacock, Towell, and Voorhees, 1993; Bruce and Wiebe, 1994; Gale, Church, and Yarowsky, 1992) tend to be evaluated only on a small set of words. A notable exception is the work of (Ng and Lee, 1996; Ng, 1997a) where they introduced and evaluated on the DSO corpus, which consists of manually sense annotated examples for 121 nouns and 70 verbs. In the previous chapter, we mentioned that there was a project called Open Mind Word Expert (OMWE), which was initiated by Chklovski and Mihalcea (2002). The project enlists the help of web users to manually sense annotate examples for WSD and uses active learning to select the

particular examples to present to the web users for sense annotation. In another work (Mihalcea, 2002a), Mihalcea generated a sense-tagged corpus known as GenCor. The corpus was generated from a set of initial seeds gathered from sense-tagged examples of SemCor, examples extracted from WordNet, etc. Incorporating GenCor as part of the training data of their WSD system achieves good results on the test data of SENSEVAL-2 English all-words task (Mihalcea, 2002b). More recently, the OntoNotes project (Hovy et al., 2006) was initiated to manually sense annotate the texts from the Wall Street Journal portion of the Penn Treebank (Marcus, Santorini, and Marcinkiewicz, 1993). Till date, the project had gathered manual sense annotations for a large set of nouns and verbs, according to a coarse-grained sense inventory.

Recently, there has also been work on combining training examples from different words (Kohomban and Lee, 2005). In that work, Kohomban and Lee merged examples of words in the same semantic class, and perform an initial classification of target word occurrences based on those semantic classes. Then, simple heuristics (such as choosing the least ordered sense of WordNet) were used to obtain the fine-grained classifications. Their resulting system shows good results when evaluated on the test data of SENSEVAL-3 English all-words task.

In work related to our approach of gathering examples from parallel texts, Li and Li (2002) investigated a bilingual bootstrapping technique to predict the correct translation of a source word which has many possible target translations. The research of Chugur, Gonzalo, and Verdejo (2002) dealt with sense distinctions across multiple languages. In their work, they are interested in measuring quantities such as sense relatedness between two meanings of an ambiguous word, based on the probability that the two meanings, or senses, having the same translation across a set of instances

in multiple languages. Ide, Erjavec, and Tufis (2002) investigated word sense distinctions using parallel corpora. Resnik and Yarowsky (2000) considered word sense disambiguation using multiple languages. Our present work can be similarly extended beyond bilingual corpora to multilingual corpora.

The research most similar to ours is the work of Diab and Resnik (2002), where training examples are gathered from machine translated parallel corpora through an unsupervised method of noun group disambiguation. They evaluated several variants of their system on the nouns of SENSEVAL-2 English all-words task, achieving a best performance of 56.8%. In contrast, as we will show in Table 4.4 of Chapter 4, we achieved an accuracy of 76.2% using our approach of gathering examples from parallel texts. This surpasses the performance of the baseline WordNet first sense strategy, which gives 70.6% accuracy. We note, however, that the approach in (Diab and Resnik, 2002) is unsupervised and uses machine translated parallel corpora, whereas our approach relies on manually translated parallel corpora. In more recent work (Diab, 2004), a supervised WSD system was bootstrapped using annotated data produced by the unsupervised approach described in (Diab and Resnik, 2002), and evaluated on SENSEVAL-2 English lexical sample task. Building on the work of Diab and Resnik (Diab and Resnik, 2002), some researchers (Bhattacharya, Getoor, and Bengio, 2004) built probabilistic models using parallel corpus with an unsupervised approach. Performance on a selected subset of nouns in SENSEVAL-2 English all-words task is promising, but still lags behind the top 3 systems of SENSEVAL-2 English all-words task.

2.2 Domain Adaptation for Word Sense Disambiguation

We have highlighted that it is important to perform domain adaptation of WSD systems, in order to build systems that are applicable across different domains. One of the issues with domain adaptation for WSD is to estimate the sense priors in a new corpus. McCarthy et al. (2004b) provided a partial solution by describing a method to predict the predominant sense, or the most frequent sense, of a word in a corpus. Using the noun *interest* as an example (which occurs in the Brown corpus (BC) part of the DSO corpus with the proportions of 34%, 9%, 16%, 14%, 12%, and 15% for its senses 1, 2, 3, 4, 5, and 8, while the proportions in the Wall Street Journal (WSJ) part of the DSO corpus are 13%, 4%, 3%, 56%, 22%, and 2%), their method will try to predict that sense 1 is the predominant sense in the BC part of the DSO corpus, while sense 4 is the predominant sense in the WSJ part of the corpus. The same method is used in a related work (McCarthy et al., 2004a) to identify infrequently occurring word senses.

Besides the issue of different sense priors across different domains, researchers have also noted that examples from different domains present different classification cues to the learning algorithm. There are various related research efforts in applying active learning for domain adaptation. Zhang, Damerau, and Johnson (2003) presented work on sentence boundary detection using generalized Winnow, while Hakkani-Tür et al. (2004) performed language model adaptation of automatic speech recognition systems. In both papers, out-of-domain and in-domain data were simply mixed together without maximum a posteriori estimation such as count-merging. In the area

of WSD, Ng (1997b) is the first to suggest using intelligent example selection techniques such as active learning to reduce the annotation effort for WSD. Following that, several work investigated using active learning for WSD. Fujii et al. (1998) used selective sampling for a Japanese language WSD system, Chen et al. (2006) used active learning for 5 verbs using coarse-grained evaluation, and Dang (2004) employed active learning for another set of 5 verbs. In a recent work, Zhu and Hovy (2007) explored several resampling techniques (e.g. over-sampling) to improve the effectiveness of active learning for WSD, for a set of words having very skewed or highly imbalanced sense priors. In their work, they experimented on the OntoNotes examples for a set of 38 nouns. We note that all these research efforts only investigated the use of active learning to reduce the annotation effort necessary for WSD, but did not deal with the porting of a WSD system to a different domain. Escudero, Marquez, and Rigau (2000) used the DSO corpus to highlight the importance of the issue of domain dependence of WSD systems, but did not propose methods such as active learning or count-merging to address the specific problem of how to perform domain adaptation for WSD.

2.3 Word Sense Disambiguation for Machine Translation

In Chapter 1, we had briefly described several recent research efforts on investigating the usefulness of WSD for MT. We now describe them in more details. Carpuat and Wu (2005) integrated the translation predictions from a Chinese WSD system (Carpuat, Su, and Wu, 2004) into a Chinese-English word-based statistical MT system using the ISI ReWrite decoder (Germann, 2003). Though they acknowledged

that directly using English translations as word senses would be ideal, they instead predicted the HowNet (Dong, 2000) sense of a word and then used the English gloss of the HowNet sense as the WSD model's predicted translation. They did not incorporate their WSD model or its predictions into their translation model; rather, they used the WSD predictions either to constrain the options available to their decoder, or to postedit the output of their decoder. They reported the negative result that WSD decreased the performance of MT based on their experiments. Also, their experiments were conducted with a word-based MT system, whereas state-of-the-art MT systems use a phrase-based model.

In another work (Vickrey et al., 2005), the WSD problem was recast as a *word translation* task. The translation choices for a word w were defined as the set of words or phrases aligned to w, as gathered from a word-aligned parallel corpus. The authors showed that they were able to improve their model's accuracy on two simplified translation tasks: word translation and blank-filling.

Recently, Cabezas and Resnik (2005) experimented with incorporating WSD translations into Pharaoh, a state-of-the-art phrase-based MT system (Koehn, Och, and Marcu, 2003). Their WSD system provided additional translations to the phrase table of Pharaoh, which fired a new model feature, so that the decoder could weigh the additional alternative translations against its own. However, they could not automatically tune the weight of this feature in the same way as the others. They obtained a relatively small improvement, and no statistical significance test was reported to determine if the improvement was statistically significant.

More recently, Carpuat and Wu (2007) incorporated WSD into Pharaoh, by dynamically changing Pharaoh's phrase translation table given each source sentence to be translated. Since in translating each source sentence, a different phrase table

is loaded into the MT model of Pharaoh, this simulated context dependent phrase translation probabilities. They report that WSD improves translation performance, which is consistent with our observation in (Chan, Ng, and Chiang, 2007).

Chapter 3

Our Word Sense Disambiguation System

For our experiments, we followed the supervised learning approach of (Lee and Ng, 2002; Lee, Ng, and Chia, 2004), by training an individual classifier for each word.

3.1 Knowledge Sources

Following (Lee and Ng, 2002; Lee, Ng, and Chia, 2004), we use the 3 knowledge sources of local collocations, part-of-speech (POS) of neighboring words, and single words in the surrounding context. We omit the syntactic relation features for efficiency reasons, since according to results reported in (Lee and Ng, 2002), using the 3 knowledge sources without the syntactic relation features affects WSD accuracy by less than 1%. Before extracting the knowledge sources, we use a sentence segmentation program (Reynar and Ratnaparkhi, 1997) to segment the words surrounding the ambiguous word w into individual sentences.

3.1.1 Local Collocations

For each occurrence of an ambiguous word w in a particular sentence, we note the tokens appearing on the left and right of w in the sentence to extract 11 features based on them: $C_{-1,-1}$, $C_{+1,+1}$, $C_{-2,-2}$, $C_{+2,+2}$, $C_{-2,-1}$, $C_{-1,+1}$, $C_{+1,+2}$, $C_{-3,-1}$, $C_{-2,+1}$, $C_{-1,+2}$, and $C_{+1,+3}$. Here, $C_{i,j}$ refers to a sequence of tokens around w, where subscripts i and j denote the position (relative to w) of the first and last token of the sequence respectively. For instance, $C_{+1,+1}$ refers to just the single token on the immediate right of w. Also, $C_{-1,+2}$ refers to a sequence of 3 tokens which consists of the token on the immediate left of w, followed by the two tokens on the immediately right of w. Similar to (Lee and Ng, 2002), we employ the feature selection parameter M_2, where a feature t is selected if t occurs in some sense of w M_2 or more times in the training data.

3.1.2 Part-of-Speech (POS) of Neighboring Words

Based on the POS tags of tokens in the same sentence as w, we extracted these 7 features: P_{-3}, P_{-2}, P_{-1}, P_0, P_{+1}, P_{+2}, P_{+3}. Here, the subscript refers to the position of the token relative to w. For instance, P_0 denotes the POS tag of w, P_{-1} denotes the POS tag of the token on the immediate left of w, P_{+1} denotes the POS tag of the token on the immediate right of w, etc. To assign POS tags to the tokens, we use the POS tagger of (Ratnaparkhi, 1996).

3.1.3 Surrounding Words

A context of a few sentences around an occurrence of w is usually given as an example of w (typically consisting of the sentence before w, the sentence containing w, and

the sentence after w). For the knowledge source of surrounding words, we consider all unigrams (single words) in these sentences as features. Note that unlike the other two knowledge sources mentioned earlier (local collocations and POS of neighboring words), the unigrams we consider here can be in a different sentence from w. Following (Lee and Ng, 2002), feature selection using the parameter M_2 can be optionally applied for this knowledge source.

3.2 Learning Algorithms and Feature Selection

Here we describe the learning algorithms used to perform our WSD experiments.

3.2.1 Performing English Word Sense Disambiguation

Except for our work in Chapter 7 which performs Chinese WSD to investigate whether WSD helps to improve the quality of Chinese-English machine translation, all remaining experiments in this thesis perform WSD on English words.

For those experiments on English WSD, we use the 3 knowledge sources of local collocations, POS of neighboring words, and surrounding words, as described above. As learning algorithm, we use either naive Bayes (NB) (Duda and Hart, 1973) or support vector machines (SVM) (Vapnik, 1995). For our experiments, we use the implementations of NB and SVM in WEKA (Witten and Frank, 2000) with default parameters. Using NB as a learning algorithm is appropriate for the experiments on domain adaptation (Chapters 5, 6) where the focus is on comparing between the various domain adaptation methods. Since NB is relatively fast operationally, this also helps to speed up the experiments on active learning (Chapter 6) where classifications are performed during each adaptation iteration. On experiments in Chapter 4 where

we built WSD systems to participate in the SemEval-2007 evaluation exercise, we use SVM as the learning algorithm as experiments in (Lee and Ng, 2002) show that SVM gives better WSD accuracy than NB.

When using NB as our learning algorithm, we followed the approach in (Lee and Ng, 2002) of performing feature selection for the local collocations and surrounding words knowledge sources by setting $M_2 = 3$. When using SVM as our learning algorithm, we followed (Lee and Ng, 2002; Lee, Ng, and Chia, 2004) by not performing feature selection (i.e., $M_2 = 0$).

3.2.2 Performing Chinese Word Sense Disambiguation

In Chapter 7 when we perform Chinese WSD, we similarly use the knowledge sources of local collocations, POS of neighboring words, and surrounding words. For local collocations, however, we use 3 features only: $C_{-1,+1}$, $C_{-1,-1}$, and $C_{+1,+1}$, without feature selection (i.e., $M_2 = 0$). For the POS knowledge source, we similarly use 3 features: P_{-1}, P_0, and P_{+1}. For the surrounding words knowledge source, we use feature selection which includes a unigram only if it occurs $M_2 = 3$ or more times in some sense of a Chinese ambiguous word in the training data. For our experiments here, we are trying to improve machine translation performance via integrating our WSD system. Hence, it is important to build a high accuracy WSD system. Thus, as learning algorithm, we use the LIBSVM (Chang and Lin, 2001) implementation of SVM with default parameters, except that we use a polynomial kernel with parameters -d (degree) set to 1, and -g (gamma) set to 1. In classifying, we output the classification probability of each class. To measure the accuracy of our Chinese WSD classifier according to this setup, we evaluate it on the test data of SENSEVAL-3 Chinese lexical sample task. We obtain accuracy that compares favorably to the best

participating system (Carpuat, Su, and Wu, 2004) in the task.

Chapter 4

Tackling the Data Acquisition Bottleneck

Currently, supervised learning is the best performing approach to WSD. These supervised WSD systems, however, face the critical problem of a lack of a large amount of training data. In this chapter, we first describe our approach of gathering training examples for WSD from parallel texts. We then evaluate our approach on the test data of SENSEVAL-2 and SENSEVAL-3 English all-words task. We also present the evaluation results of our systems, which made use of examples gathered from parallel texts, developed for the coarse-grained English all-words task and fine-grained English all-words task of the recent SemEval-2007 evaluation exercise. In both tasks, we obtained good results. Our systems were ranked in first place for the coarse-grained English all-words task, and second place for the fine-grained English all-words task. All the experiments in this chapter are performed with SVM as the learning algorithm. Finally, we also discuss and analyze the annotation accuracy of examples gathered from parallel texts.

4.1 Gathering Training Data from Parallel Texts

In this section, we describe the parallel texts used in our experiments and the process of gathering training data from them. Before describing in detail the steps involved, we briefly summarize them here:

- After ensuring that the parallel texts are sentence-aligned, we tokenize the English texts and perform word segmentation on the Chinese texts.
- Perform word alignment between the tokenized English texts and word-segmented Chinese texts.
- Based on the word alignment output, manually assign suitable Chinese translations to the WordNet senses of an English word.
- From the English side of the parallel texts, select those occurrences of the English word which have been aligned to one of the Chinese translations chosen. Record each English word occurrence as an example of the particular WordNet sense which the Chinese translation is assigned to.

4.1.1 The Parallel Corpora

We list in Table 4.1 the six English-Chinese parallel corpora (available from Linguistic Data Consortium (LDC)) from which we gather examples for experiments described in this thesis. Briefly, the six parallel corpora are:

- Hong Kong Hansards: Excerpts from the official record of the proceedings of the legislative council of the Hong Kong Special Administrative Region (HKSAR).
- Hong Kong News: Press releases from the information services department of the HKSAR.

Parallel corpora	Size of texts in million words (MB)	
	English texts	Chinese texts
Hong Kong Hansards	39.4 (216.6)	34.9 (143.2)
Hong Kong News	16.1 (90.3)	14.8 (63.6)
Hong Kong Laws	9.9 (49.8)	10.1 (37.4)
Sinorama	10.0 (53.5)	10.1 (40.5)
Xinhua News	2.1 (11.6)	2.0 (8.9)
English translation of Chinese Treebank	0.1 (0.7)	0.1 (0.4)
Total	77.6 (422.5)	72.0 (294.0)

Table 4.1: Size of English-Chinese parallel corpora

- Hong Kong Laws: Law codes acquired from the department of justice of the HKSAR.
- Sinorama: Chinese news stories and their English translations collected via the Sinorama magazine of Taiwan.
- Xinhua News: News articles from the Xinhua news agency.
- English translations of Chinese treebank: Chinese treebank corpus aligned with the English translations provided by LDC.

To make use of the parallel corpora, they have to be sentence and word aligned. The sentences of the six corpora were already pre-aligned, either manually or automatically, when they were prepared. After ensuring the corpora were sentence aligned, we tokenized the English texts[1], and performed word segmentation on the Chinese texts using the segmenter described in (Low, Ng, and Guo, 2005). We then made use of the GIZA++ software (Och and Ney, 2000) to perform word alignment on the parallel corpora. Due to the size of the parallel corpora, we were not able to align all six parallel corpora in one alignment run of GIZA++. We split the Hong Kong Hansards corpus into two separate alignment runs, the Sinorama and Hong Kong

[1] http://www.cis.upenn.edu/∼treebank/tokenizer.sed

Laws corpora were lumped into one alignment run, and the remaining three corpora (Hong Kong News, Xinhua News, and English translation of Chinese Treebank) were lumped as the last of the four alignment runs.

4.1.2 Selection of Target Translations

We took the same approach as described in (Ng, Wang, and Chan, 2003) to select some possible Chinese translations for each sense of an English word *w*. Following (Ng, Wang, and Chan, 2003), we will illustrate the approach with the noun *channel*.

WordNet 1.7 lists 7 senses for the noun *channel*, as shown in Table 4.2. From the word alignment output of GIZA++, we will select some appropriate Chinese words aligned to the noun *channel* as Chinese translations for its various senses.

After assigning Chinese translations to the various senses, from the word alignment output of GIZA++, we select those occurrences of the noun *channel* which have been aligned to one of the Chinese translations chosen. The English side of these occurrences will then serve as training data for the noun *channel*, as they are considered to have been disambiguated and "sense-tagged" by the appropriate Chinese translations. As an illustration, Figure 4.1 shows that an occurrence of the noun *channel* has been aligned to a selected Chinese translation "途径" (tu jing). Since "途径" was selected as a translation for sense 5 of *channel* according to Table 4.2, the English side of this occurrence is gathered as a training example for sense 5 of *channel*.

In (Ng, Wang, and Chan, 2003), two senses will be lumped together if they are translated in the same way in Chinese. However, in our current work, we evaluate the approach of gathering examples for WSD from parallel texts using fine-grained disambiguation. To do this, we assign the Chinese translation to the most suitable sense. For instance, as shown in Table 4.2, the same Chinese translation "频道" (pin

WordNet sense id	WordNet English sense description	Chinese translations
1	A path over which electrical signals can pass	频道
2	A passage for water	水道, 水渠, 排水渠
3	A long narrow furrow	沟
4	A relatively narrow body of water	海峡
5	A means of communication or access	途径
6	A bodily passage or tube	导管
7	A television station and its programs	频道

Table 4.2: WordNet sense descriptions and assigned Chinese translations of the noun *channel*

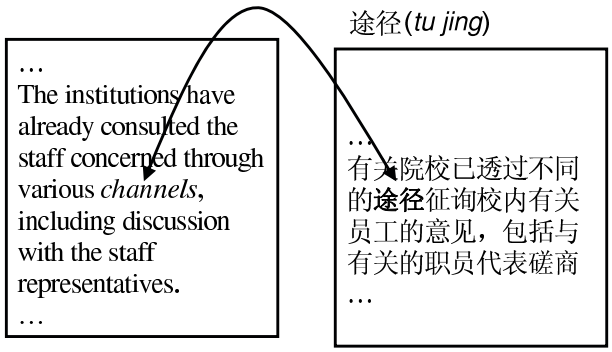


Figure 4.1: An occurrence of *channel* aligned to a selected Chinese translation.

dao) can be assigned to senses 1 and 7 of the noun *channel*. To decide whether it is more suitable as a translation for sense 1 or sense 7, we inspect a few (typically 10) occurrences of *channel* which are aligned to "频道". Assuming the majority of examples that are inspected are used as sense 1 of *channel*, then from the word alignment output of GIZA++, all occurrences of the noun *channel* which have been aligned to "频道" will be gathered as training examples for sense 1 of *channel*. Consequently, there will be no parallel text examples gathered for sense 7 of *channel*.

An additional complementary approach will be to use longer Chinese translations to tease apart the senses represented by the original ambiguous Chinese translation. For instance, one of the nouns in the SENSEVAL-3 English all-words task is *record*, and the Chinese word "纪录" (ji lu) is an appropriate translation for several of its

senses. Sense 3 of *record* has the meaning "an extreme attainment, the best (or worst) performance ever attested", and the meaning of sense 6 is "a list of crimes for which an accused person has been previously convicted". Although "纪录" is an appropriate translation for both senses, we can expand it to obtain translations that are specific to each sense. For the noun *record*, "最高纪录", "世界纪录" and "全国纪录" will be specific to sense 3, while "刑事纪录" and "犯罪纪录" will be specific to sense 6. To obtain these expanded translations, we simply observe in the Chinese portion of the parallel texts the set of Chinese words on the immediate left, and immediate right of the original translation "纪录". To make use of these expanded translations, we will as before first select those occurrences of the noun *record* aligned to "纪录". Each occurrence will then be matched against the various expanded translations, in order to decide which sense of *record* to assign the occurrence to. In our current work, we use this approach whenever appropriate longer translations are available.

In this work, we manually assign Chinese translations for a set of nouns, adjectives, and verbs using the process described above. The average time needed to assign target Chinese translations for one noun, adjective, and verb is 20, 25 and 40 minutes respectively. This is a relatively short time, compared to the effort otherwise needed to manually sense annotate training examples. Once the Chinese translations are assigned, the number of examples gathered will depend only on the size of the parallel texts. More examples can be automatically gathered as more parallel texts become available.

4.2 Evaluation on English All-words Task

The evaluation results of the earlier work of (Ng, Wang, and Chan, 2003) on the nouns of SENSEVAL-2 English lexical sample task show that parallel text provides a viable source of training examples for WSD. However, since our aim is to alleviate the problem of a general lack of training data faced by current supervised WSD systems, we need to expand the coverage to a larger set of words and also provide parallel text examples for words belonging to other POS categories besides noun.

In the rest of this chapter, we describe our work of gathering parallel text examples for a set of frequently occurring nouns, adjectives, and verbs. After gathering these examples, suitable evaluation datasets include the test data of SENSEVAL-2 and SENSEVAL-3 English all-words task. Unlike the experiments in (Ng, Wang, and Chan, 2003) which focus on exploring the viability of gathering WSD training examples from parallel texts, our aim in expanding the approach to a larger set of words in various POS categories is to build a high performance and wide coverage supervised WSD system. For the experiments reported in the rest of this chapter, we use SVM as our learning algorithm.

We first discuss the set of words for which we provide Chinese translations, before presenting the evaluation results on the SENSEVAL-2 and SENSEVAL-3 English all-words task.

4.2.1 Selection of Words Based on Brown Corpus

One of the widely used corpora in NLP research is the Brown corpus (BC). As the BC is built as a balanced corpus containing texts in various genres, it is representative of a general text article.

To gauge the coverage of the BC corpus on the test examples of the SENSEVAL-2 and SENSEVAL-3 English all-words task, we first tabulate the set of polysemous nouns, adjectives, and verbs of the SENSEVAL-2 English all-words task which does not occur in the BC. Then, we calculate the number of SENSEVAL-2 English all-words task test examples belonging to these polysemous words. For the SENSEVAL-2 English all-words task, we obtained a total of 81 such test examples. Of these, using the strategy of tagging each example with its first sense in WordNet would have provided the correct sense label for 52 of these test examples. The remaining 29 polysemous test examples which do not have the first sense in WordNet as their correct sense represent a mere 1.4% of the total number of test examples for the nouns, adjectives and verbs of SENSEVAL-2 English all-words task. The corresponding figure for SENSEVAL-3 English all-words task is 1.2%.

We note that frequently occurring words are usually highly polysemous and hard to disambiguate. To maximize the benefits of using parallel texts, we gathered training data from parallel texts for the set of most frequently occurring noun, adjective, and verb types in the BC. These word types (730 nouns, 326 adjectives, and 190 verbs) represent 60% of the noun, adjective, and verb tokens in BC. To gather examples from parallel texts for these words, we assigned appropriate Chinese translations to each sense of a word using the approach described in Section 4.1. Also, similar to the test data of SENSEVAL-3 English all-words task, we used WordNet-1.7.1 as our sense inventory.

4.2.2 Manually Sense-Annotated Corpora

As mentioned, the SemCor corpus (Miller et al., 1994) is one of the few currently available, manually sense-annotated corpora for WSD. It is widely used by various systems which participated in the English all-words task of SENSEVAL-2 and SENSEVAL-3, including one of the top performing teams (Hoste, Kool, and Daelemans, 2001; Decadt, Hoste, and Daelemans, 2004) which performed consistently well in both SENSEVAL all-words tasks. Besides SemCor, the DSO corpus (Ng and Lee, 1996) also contains manually annotated examples for WSD.

Hence, to build a high performance WSD system, we also gathered examples from SemCor and DSO corpus as part of our training data. For SemCor, we obtained a copy of the corpus based on WordNet-1.7.1 sense inventory from the website of Dr. Mihalcea[2]. For the DSO corpus which is based on WordNet-1.5 sense inventory, we manually mapped each of the 70 verb types present in the corpus to WordNet-1.7.1, to be consistent with the rest of our training data.[3]

4.2.3 Evaluations on SENSEVAL-2 and SENSEVAL-3 English all-words Task

In this section, we describe our evaluation results on the test data of SENSEVAL-2 and SENSEVAL-3 English all-words task. Both tasks require systems to provide the sense labels for almost all the nouns, adjectives, verbs, and adverbs in a sample of running texts. Although the test data of SENSEVAL-3 English all-words task is based on WordNet-1.7.1 senses which is consistent with our training data, the test data of

[2]http://lit.csci.unt.edu/∼rada/downloads/semcor/semcor1.7.1.tar.gz

[3]We did not use the examples for nouns in the DSO corpus because adding them provided negligible differences to the classification accuracies.

System	Prediction accuracy	
	SE-2	SE-3
Our predictions	94.1	96.8
S1	93.9	97.0
S2	92.8	96.7
S3	94.1	97.4

Table 4.3: POS tag and lemma prediction accuracies for SENSEVAL-2 (SE-2) and SENSEVAL-3 (SE-3) English all-words task.

Dataset	No. of test examples	WNS1	SC	Top systems			PT	SC+ DSO	SC+DSO +PT
				S1	S2	S3			
Noun	1067	70.6	75.0	78.0	74.5	70.0	76.2	75.0	77.6
Adjective	465	61.9	64.1	70.1	62.4	63.9	64.3	64.1	66.7
Verb	550	44.2	48.7	53.3	48.4	45.3	48.6	50.6	50.4
All	2473	62.0	65.5	69.0	63.6	61.8	65.9	65.9	67.4

Table 4.4: SENSEVAL-2 English all-words task evaluation results.

Dataset	No. of test examples	WNS1	SC	Top systems			PT	SC+ DSO	SC+DSO +PT
				S1	S2	S3			
Noun	895	70.6	74.0	71.2	70.6	71.6	72.8	74.0	74.5
Adjective	351	65.2	68.1	67.2	71.2	71.5	71.4	68.1	72.3
Verb	731	52.5	57.7	59.4	56.5	54.4	53.2	57.2	58.0
All	2041	61.9	65.9	65.2	64.6	64.1	64.4	65.7	67.0

Table 4.5: SENSEVAL-3 English all-words task evaluation results.

SENSEVAL-2 English all-words task is based on WordNet-1.7 senses. Hence, to evaluate on the SENSEVAL-2 test data, we automatically mapped it from WordNet-1.7 to WordNet-1.7.1 using the sense mappings publicly provided by Dr. Mihalcea[4]. Hence, all our evaluations on the SENSEVAL-2 and SENSEVAL-3 English all-words task are based on WordNet-1.7.1 sense inventory.

For the SENSEVAL-2 and SENSEVAL-3 English all-words tasks, the correct POS tag and lemma of each test example are not given by the task organizers. Hence, we used the POS tag from the mrg parse files released as part of the test data and

[4]http://lit.csci.unt.edu/∼rada/downloads/wordnet.mappings/synset.mapping.wn1.7.wn1.7.1.gz

performed lemmatization using WordNet, to automatically predict the POS tag and lemma of each test example. When compared against the answer key of SENSEVAL-2 English all-words task, we note that we correctly predicted 94.1% of the POS tag and lemma pair, as shown in the row *Our predictions* of Table 4.3. The corresponding prediction accuracy for SENSEVAL-3 English all-words task is 96.8%. These figures meant that our WSD system will definitely give the wrong sense prediction for 5.9% and 3.2% of the test examples of SENSEVAL-2 and SENSEVAL-3, respectively. The POS tag and lemma prediction accuracies of the top 3 systems in both tasks are also shown in the same table. Note that our prediction accuracies are comparable to those of the top 3 systems of each task. This means that we do not derive any additional advantage in subsequent WSD classification by performing better POS tag and lemma predictions.

As shown in Table 4.4 and 4.5, there are a total of 2473 and 2041 test examples in SENSEVAL-2 and SENSEVAL-3 English all-words task, respectively. The 2 tables also show the breakdown of test examples into the POS categories of noun, adjective, and verb. For instance, our SENSEVAL-2 English all-words task test data, based on the WordNet-1.7.1 sense inventory, has a total of 1067, 465 and 550 test examples for noun, adjective, and verb, respectively. The rest of the test examples are either for adverbs or labelled with a 'U' tag by the organizers of the task, representing an untaggable test example. Similarly for SENSEVAL-3 English all-words task, we have a total of 895, 351, and 731 test examples for noun, adjective, and verb, respectively. The rest of the test examples either belong to adverbs, are labelled as untaggable, or have multiple answer senses belonging to multiple POS categories (there are 17 such test examples belonging to multiple POS categories).

As a comparison, we also tabulate the accuracy figures for the top 3 participating

systems in the SENSEVAL-2 and SENSEVAL-3 English all-words task, from the publicly available set of answers for SENSEVAL-2 and SENSEVAL-3 participants. The accuracies of the top 3 SENSEVAL-2 systems are listed in Table 4.4 as S1 (Mihalcea and Moldovan, 2001), S2 (Hoste, Kool, and Daelemans, 2001), and S3 (Crestan, El-Beze, and Loupy, 2001), arranged in order of performance over all the evaluation examples in the SENSEVAL-2 English all-words task. Similarly, the accuracies of the top 3 SENSEVAL-3 systems are listed in Table 4.5 as S1 (Decadt, Hoste, and Daelemans, 2004), S2 (Mihalcea and Faruque, 2004), and S3 (Yuret, 2004).

As mentioned in Chapter 1, a simple baseline strategy which previous participating systems in SENSEVAL-2 and SENSEVAL-3 English all-words task find hard to surpass is to simply tag each test example with its first WordNet sense (we will subsequently refer to this strategy as WNS1). As shown under the column *WNS1* in Table 4.4, this strategy achieves a WSD accuracy of 62.0% on the SENSEVAL-2 English all-words test data. On the SENSEVAL-3 English all-words test data, this strategy achieves a similar accuracy of 61.9%, as shown in Table 4.5.

As another basis for comparison, we would like to measure the accuracy of a WSD system relying on training examples drawn from SemCor. As shown under the column *SC* in Table 4.4, a WSD system trained on examples gathered from SemCor and evaluated on the SENSEVAL-2 English all-words task test data achieved an accuracy of 65.5%. The classification accuracies of the WSD system over the nouns, adjectives, and verbs of the test data are shown in the rows *Noun*, *Adjective*, and *Verb* of the table. Table 4.5 shows the corresponding accuracies when evaluated over the test data of SENSEVAL-3 English all-words task.

Next, we want to measure the accuracy of a WSD system trained on examples gathered from parallel texts. We note that the parallel texts from which we are

drawing examples are a mixture of various genres, containing articles from legislative proceedings, press releases, etc. In contrast, the test data of SENSEVAL-2 and SENSEVAL-3 English all-words task is mainly drawn from the Wall Street Journal, which covers business and financial news. Research in (Agirre and Martinez, 2004; Escudero, Marquez, and Rigau, 2000) has shown that when the training and test data are gathered from different domains, the different sense priors (proportion of each sense) between the domains affect the classification accuracy. Since we are using the SemCor corpus as part of our training data, a simple heuristic would be to simply adhere to the sense priors (proportion of each sense) in the SemCor corpus when gathering examples from parallel texts.

In gathering examples from parallel texts, a maximum of 1,000 examples were gathered for each of the frequently occurring noun and adjective types, while a maximum of 500 examples were gathered for each of the frequently occurring verb types. For each word, the examples from the parallel corpora were randomly chosen but adhered to the sense priors of that word in the SemCor corpus. Results given under the column *PT* in Table 4.4 and 4.5 show that a WSD system trained *only* on such examples gathered from parallel texts achieved an accuracy of 65.9% and 64.4% on the test data of SENSEVAL-2 and SENSEVAL-3 English all-words task, respectively. We note that these overall accuracies, as well as the accuracies over the individual categories of noun, adjective, and verb, are always significantly higher than the baseline WNS1 accuracies. Also, the WSD accuracies obtained by training on examples gathered from parallel texts are comparable to accuracies of a WSD system trained on the manually annotated examples of SemCor.

Since our aim is to build a high performance WSD system, we are also using examples available from the DSO corpus as part of our training data. For this, a

System	WNS1	S1	PT	SC	SC+DSO	SC+DSO+PT
WNS1	*	$\ll$	$\ll$	$\ll$	$\ll$	$\ll$
S1		*	$\gg$	$\gg$	$\gg$	$>$
PT			*	$\sim$	$\sim$	$\ll$
SC				*	$<$	$\ll$
SC+DSO					*	$\ll$
SC+DSO+PT						*

Table 4.6: Paired t-test between the various results over all the test examples of SENSEVAL-2 English all-words task. "$\sim$", ("$>$" and "$<$"), and ("$\gg$" and "$\ll$") correspond to the p-value > 0.05, $(0.01, 0.05]$, and ≤ 0.01 respectively. For instance, the $\ll$ between WNS1 and PT means that PT is significantly better than WNS1 at a p-value of ≤ 0.01.

System	WNS1	S1	PT	SC	SC+DSO	SC+DSO+PT
WNS1	*	$\ll$	$\ll$	$\ll$	$\ll$	$\ll$
S1		*	$\sim$	$\sim$	$\sim$	$<$
PT			*	$<$	$<$	$\ll$
SC				*	$\sim$	$<$
SC+DSO					*	$\ll$
SC+DSO+PT						*

Table 4.7: Paired t-test between the various results over all the test examples of SENSEVAL-3 English all-words task.

maximum of 500 examples were randomly chosen for each of the verb types present in the DSO corpus. In gathering the examples for each verb, we similarly adhere to the sense priors of that verb in the SemCor corpus. These examples gathered from DSO were combined with the examples from SemCor to form an aggregate set of manually annotated examples. As shown under the column *SC+DSO* of Table 4.4, a WSD system trained on this aggregate set of examples and evaluated over the test data of SENSEVAL-2 English all-words task achieved an accuracy of 65.9%. The corresponding accuracy on the SENSEVAL-3 English all-words task is 65.7%, as shown in Table 4.5.

Finally, we added the parallel text examples gathered earlier, to this aggregate

set of SemCor and DSO examples. As shown under the column *SC+DSO+PT* of Table 4.4 and 4.5, adding these parallel text examples improved the WSD accuracies to 67.4% and 67.0% when evaluated on the test data of SENSEVAL-2 and SENSEVAL-3, respectively. These results show that although using examples gathered from parallel texts alone as training data does not achieve accuracies that are significantly better than training on the manually annotated examples of SemCor and DSO, they nevertheless are able to help to further improve WSD accuracy over the strong baseline of using the examples of SemCor and DSO.

Paired t-tests were conducted to see if one system is significantly better than another. The t statistic of the difference between each test instance pair is computed, giving rise to a p-value. The results of significance tests for the various experiments on the SENSEVAL-2 English all-words task are given in Table 4.6, while those for SENSEVAL-3 are given in Table 4.7.

The significance test results show that for both SENSEVAL-2 and SENSEVAL-3 English all-words tasks, the parallel text system *PT*, which was trained only on examples gathered from parallel texts, always significantly outperforms the baseline *WNS1* of choosing the first sense of WordNet. Also, the $SC + DSO + PT$ system which has parallel text examples added always performs significantly better than the $SC + DSO$ system trained on the manually annotated examples of SemCor and DSO.

4.3 Evaluation on SemEval-2007

SemEval-2007 is the most recent SENSEVAL evaluation exercise. Using training examples gathered from parallel texts, SemCor, and DSO corpus, we participated

in the coarse-grained English all-words task (Navigli, Litkowski, and Hargraves, 2007) and fine-grained English all-words task (Pradhan et al., 2007) of SemEval-2007. In this section, we describe the systems we developed for these two tasks and our official evaluation results.

In the coarse-grained English all-words task, systems have to perform WSD of all content words (noun, adjective, verb, and adverb) occurring in five documents, using a coarse-grained version of the WordNet sense inventory. In the fine-grained English all-words task, systems have to predict the correct sense of verbs and head nouns of the verb arguments occurring in three documents, according to the fine-grained sense inventory of WordNet.

We developed 2 separate systems; one for each task. Our system employed for the coarse-grained English all-words task was trained with the coarse-grained sense inventory released by the task organizers, while our system employed for the fine-grained English all-words task was trained with the fine-grained sense inventory of WordNet.

4.3.1 Sense Inventory

The test data of the two SemEval-2007 tasks we participated in are based on the WordNet-2.1 sense inventory. The examples we gathered from the parallel texts and the SemCor corpus are, however, based on the WordNet-1.7.1 sense inventory. Hence, there is a need to map these examples from WordNet-1.7.1 to WordNet-2.1 sense inventory. For this, we rely primarily on the WordNet sense mappings automatically generated by (Daude, Padro, and Rigau, 2000). To ensure good accuracy of the mappings, we performed some manual corrections of our own, focusing on the set of most frequently occurring nouns, adjectives, and verbs. For the verb examples

System	Accuracy (%)
SC+DSO+PT	58.7
SC+DSO+PTnoun	58.1
SC+DSO+PTverb	58.5
SC+DSO	57.8
PT	55.5
WNS1	53.5

Table 4.8: Scores for the SemEval-2007 fine-grained English all-words task, using different sets of training data. SC+DSO refers to using examples gathered from SemCor and DSO corpus. Similarly, SC+DSO+PT refers to using examples gathered from SemCor, DSO corpus, and parallel texts. SC+DSO+PTnoun is similar to SC+DSO+PT, except that parallel text examples are only gathered for nouns. Similarly, PTverb means that parallel text examples are only gathered for verbs.

from the DSO corpus, we manually mapped them from their original WordNet-1.5 senses to WordNet-2.1 senses.

4.3.2 Fine-Grained English All-words Task

Our system employed for the fine-grained English all-words task was trained on examples tagged with fine-grained WordNet-2.1 senses (mapped from WordNet-1.7.1 senses and WordNet-1.5 senses as described earlier). Unlike the coarse-grained English all-words task, the correct POS tag and lemma of each test example are not given in the fine-grained task. Hence, we used the POS tag from the mrg parse files released as part of the test data and performed lemmatization using WordNet. We obtained a score of 58.7% in this task, as shown in the row $SC + DSO + PT$ of Table 4.8. This puts our system in second position among the 13 participants of this task. If we exclude parallel text examples and train only on examples gathered from the SemCor and DSO corpus, we obtain a score of 57.8%, as shown in the row $SC + DSO$. We note that although there is a modest improvement in accuracy when parallel text examples are added, this increase is not statistically significant. We note

System	Accuracy (%)
SC+DSO+PT	82.5
SC+DSO+PTnoun	82.3
SC+DSO+PTadj	81.8
SC+DSO+PTverb	81.8
SC+DSO	81.7
PT	80.0
WNS1	78.9

Table 4.9: Scores for the SemEval-2007 coarse-grained English all-words task, using different sets of training data.

Doc-ID	No. of test examples	Accuracy (%)	
		Our system	Task organizers
d001	368	88.3	86.1
d002	379	88.1	85.5
d003	500	83.4	79.6
d004	677	76.1	86.9
d005	345	81.4	75.7
Overall	2269	82.5	83.2

Table 4.10: Score of each individual test document, for the SemEval-2007 coarse-grained English all-words task.

that there are only 465 test examples for this fine-grained task (much fewer than the coarse-grained task), so this test data set may be too small to serve as an effective evaluation data set.

4.3.3 Coarse-Grained English All-words Task

Our system employed for the coarse-grained English all-words task was trained with the coarse-grained WordNet-2.1 sense inventory released by the task organizers. For this task, the POS tag and lemma of each test example are explicitly given by the task organizers. Our system developed for this task obtained a score of 82.5% in this task, as shown in the row $SC + DSO + PT$ of Table 4.9. For comparison, the WordNet first sense baseline score as calculated by the task organizers is 78.9%.

It turns out that among the 14 participating systems in this task, the UOR-SSI system developed by one of the task organizers returned the best score of 83.2%. This system is based on the Structural Semantics Interconnections algorithm (Navigli and Velardi, 2005). To disambiguate word senses, it uses semantic relations in WordNet, semantic relations extracted from annotated corpora, and dictionaries of collocations. Since the score of this system is not considered part of the official scores, our score puts our system in the *first* position among the participants of this task. Further, the task description paper (Navigli, Litkowski, and Hargraves, 2007) reveals that our system out performed the UOR-SSI system on all test documents except the fourth document d004. We will describe some investigations into our system's relatively poor performance on this document shortly.

To gauge the contribution of parallel text examples, we retrained our system using only examples gathered from the SemCor and DSO corpus. As shown in the row $SC + DSO$ of Table 4.9, this gives a score of 81.7% when scored against the answer keys released by the task organizers. Although adding examples from parallel texts gives only a modest improvement in score, this improvement is statistically significant at a p-value ≤ 0.01. Also, we are improving over the very strong baseline of training on manually annotated examples of the SemCor and DSO corpus. Moreover, we note that this improvement is achieved from a relatively small set of word types which are found to be frequently occurring in BC. Future work can explore expanding the set of word types by automating the process of assigning Chinese translations to each sense of an English word, with the use of suitable bilingual lexicons. Finally, we also calculated the contribution of parallel text examples for each individual POS category of noun ($SC + DSO + PTnoun$), adjective ($SC + DSO + PTadj$), and verb ($SC + DSO + PTverb$). As shown in Table 4.9, parallel text examples gathered for

each POS category provided improvement in score.

As part of the evaluation results, the task organizers also released the scores of our system on each of the 5 test documents. We show in Table 4.10 the total number of test examples in each document, along with the score we obtained for each document under the column *Our system*. We note that our system obtained a relatively low score on the fourth document, which is a Wikipedia entry on computer programming. To determine the reason for the low score, we looked through the list of test words in that document. We noticed that the noun *program* has 20 test examples occurring in that fourth document. From the answer keys released by the task organizers, all 20 test examples belong to the sense of "a sequence of instructions that a computer can interpret and execute", for which our WSD system does not have any training examples. Similarly, we noticed that another noun *programming* has 27 test examples occurring in the fourth document which belong to the sense of "creating a sequence of instructions to enable the computer to do something", for which our WSD system does not have any training examples. Thus, these two words alone account for 47 of the errors made by our system in this task, representing 2.1% of the 2,269 test examples of this task. In Table 4.10 under the column *Task organizers*, we show the scores obtained by the system developed by the task organizers. This was the best performing system we had mentioned earlier, but where its score was not considered part of the official scores. Interestingly, we note that the performance of our WSD system is better across all test documents, except the fourth one.

Error type	No. of error occurrences
Wrong sentence alignment	3
Wrong word alignment	11
Ambiguous Chinese translation	103
Wrong POS tag	11
Inappropriate translation in text	9
Ambiguous context	16
Total	153

Table 4.11: Sense-tag analysis over 1000 examples

4.4 Sense-tag Accuracy of Parallel Text Examples

As part of the SemEval-2007 evaluation exercise, we organized an English lexical sample task for WSD (Ng and Chan, 2007), where the sense-annotated examples were gathered from parallel texts. Two tracks were organized for the task, with each track using a different corpus. For one of the tracks, we used the Sinorama parallel corpus and measured the annotation accuracy of examples gathered from the corpus. In this section, we will discuss the different types of annotation errors found in these examples.

The word alignment output of GIZA++ contains much noise in general (especially for the low frequency words). However, note that in our approach, we only select the English word occurrences that align to the selected Chinese translations. Hence, while the complete set of word alignment output contains much noise, the subset of word occurrences chosen may still have high quality sense tags.

To investigate the sense-tag accuracy of the training examples gathered from parallel texts, we manually inspected a random selection of 100 examples each from 5 nouns and 5 adjectives. These 10 words have an average of 8.6 senses per word in the WordNet-1.7.1 sense inventory. Our manual inspection reveals the following main types of sense annotation errors.

Wrong sentence alignment Due to erroneous sentence segmentation or sentence alignment, the correct Chinese word that an English word w should align to is not present in its Chinese sentence counterpart. In this case, word alignment will align the wrong Chinese word to w.

Wrong word alignment Sometimes, GIZA++ will align an incorrect Chinese word to an English occurrence. For instance, for the English-Chinese phrase pair "...smile on his face ..." and "面 带 笑容", the English word "face" which has the meaning of "the front of the human head from the forehead to the chin", should be aligned to the Chinese word "面" but is instead wrongly aligned to the Chinese word "笑容". Since the Chinese word "笑容" was assigned as a translation for sense 2 of the noun "face" which has the meaning "the expression on a person's face", this particular occurrence of "face" is wrongly gathered as an example for sense 2. Another situation of wrong word alignment occurs when the English word occurrence has no translation in the corresponding Chinese sentence. GIZA++ might then align the English word w to some Chinese word. If that aligned Chinese word happens to be one of the assigned translations for w (but belonging to a different sense), then this will constitute an incorrect example. Wrong word alignment can also occur when the sentence is too long. GIZA++ imposes a limit on the maximum sentence length. Sentences longer than this limit will have the corresponding portion pruned off. Sometimes, the correct Chinese word that an English word w should align to is in the portion of the sentence that was pruned off. Thus, word alignment will align the wrong Chinese word to w.

Ambiguous Chinese translation Some Chinese translations assigned are actually appropriate across multiple senses of a word. For instance, the translation "简单" is assigned to sense 1 of the adjective *simple*, which has the meaning "having

few parts; not complex or complicated or involved". Examples for the sense as given by WordNet includes "a simple problem", "simple mechanisms", "a simple design", etc. However, "简单" is also appropriate for sense 2 of *simple*, which has the meaning "easy and not involved or complicated". Hence, some examples gathered via the Chinese translation "简单" for sense 1 of the adjective *simple* actually has the *easy* meaning of sense 2. Note that this also highlights the fact that WordNet senses are sometimes too fine-grained, with several senses sharing very similar meaning.

Wrong POS tag We might be wrongly gathering some examples due to POS tagging errors made by the POS tagger. For instance, some words such as "face" and "work" can either be a noun or a verb. When a POS tagger wrongly assigns a verb occurrence of "face" as having a POS tag of noun, and that particular occurrence of "face" happens to be aligned to a Chinese word which has been chosen as a translation for one of the senses of the noun "face", we would wrongly gather that occurrence of "face" as a training example.

Inappropriate translation in text In the English-Chinese parallel texts that we are using, we find that some English words are inappropriately translated. For instance, in the English sentences "At present, he is an assistant professor of architecture at Chung Yuan Christian University. His experience in the field is rich.", the English noun "field" should have the sense 4 meaning of "a branch of knowledge". However, the noun "field" is inappropriately translated as "田野" in the Chinese text. Since the occurrence of "field" was aligned to "田野" by GIZA++ and "田野" was chosen as a translation for another sense of the noun "field", an incorrect example was gathered.

Ambiguous context We are sometimes unable to clearly distinguish the correct sense of an example. In these situations, we regard the example as wrongly tagged

to avoid inflating the sense-tag accuracy.

The result of the analysis is shown in Table 4.11. We note that the main source of errors is the inherent ambiguity of some Chinese translations. The row *Wrong word alignment* summarizes the errors incurred due to GIZA++. From these 1,000 examples, we measure a sense annotation accuracy of 84.7%, which compares favorably with the quality of manually sense tagged corpus prepared in SENSEVAL-2 (Kilgarriff, 2001).

4.5 Summary

In order to build a wide-coverage WSD system, tackling the data acquisition bottleneck for WSD is crucial. In this chapter, we showed that the approach of gathering training examples from parallel texts is promising. With manually assigned Chinese translations, we gathered examples from parallel texts for a set of frequently occurring nouns, adjectives, and verbs. When evaluated on the SENSEVAL-2 and SENSEVAL-3 English all-words task using fine-grained scoring, classifiers trained on parallel text examples always significantly outperformed the strategy of choosing the first sense of WordNet. For both SENSEVAL-2 and SENSEVAL-3, we showed that parallel text examples can help to further improve the performance of classifiers trained on the manually annotated examples of SemCor and DSO.

We also participated in the coarse-grained English all-words task and fine-grained English all-words task of SemEval-2007. Using training examples gathered from parallel texts, SemCor, and the DSO corpus, we trained supervised WSD systems. Evaluation results showed that this approach achieved good performance in both tasks.

Chapter 5

Word Sense Disambiguation with Sense Prior Estimation

Supervised WSD systems that are trained on one domain but applied to another domain show a decrease in performance, with one major reason being that different domains have different sense priors. Hence, estimation of sense priors is important for building widely applicable WSD systems. In (Chan and Ng, 2005b) and (Chan and Ng, 2006), we used various algorithms to estimate the sense priors in a new text corpus and showed that they are effective in improving WSD accuracies.

In this chapter, we first describe the various algorithms to estimate the sense priors. Then, in Section 5.3, we describe the notion of being well calibrated and discuss why using well calibrated probabilities helps in estimating the sense priors. We also describe an algorithm to calibrate the probability estimates from naive Bayes. Then in Section 5.4, we discuss the corpora and the set of words we use for our experiments. In Section 5.5, we present our experimental results over all the words in our dataset. In Section 5.6, we describe experiments with using the well calibrated probabilities

of logistic regression to estimate the sense priors. We note that estimation of sense priors is important when there is a change in domain, usually being reflected by a change in predominant senses of words. In Section 5.7, we assume we know the true predominant sense of each word in the training and target domains, and present our evaluation results over those words having different predominant senses between the two domains. In a practical setting, however, we do not know the true predominant sense of each word in a particular domain. In Section 5.8, we predict the predominant sense of each word and evaluate on those words where the predicted predominant senses differ between the training and test data. In Section 5.9, we conclude this chapter. Finally, note that for the experiments performed in this chapter, we use the naive Bayes and logistic regression implementation in WEKA with default parameters.

5.1 Estimation of Priors

To estimate the sense priors, or a priori probabilities of the different senses in a new data set, we make use of a confusion matrix algorithm (Vucetic and Obradovic, 2001) or an EM-based algorithm (Saerens, Latinne, and Decaestecker, 2002). In this section, we describe these two algorithms and the predominant sense method introduced by McCarthy et al. (2004b).

5.1.1 Confusion Matrix

Let us assume that from a set of labeled data D_L, a classifier is used to compute the conditional probability $\widehat{p}_L(\omega_j|\omega_i)$, which is an estimate of the probability of classifying an instance as class ω_j , when in fact it belongs to class ω_i . Then, one can apply this classifier with known conditional probabilities $\widehat{p}_L(\omega_j|\omega_i)$ to a set of unlabeled data D_U

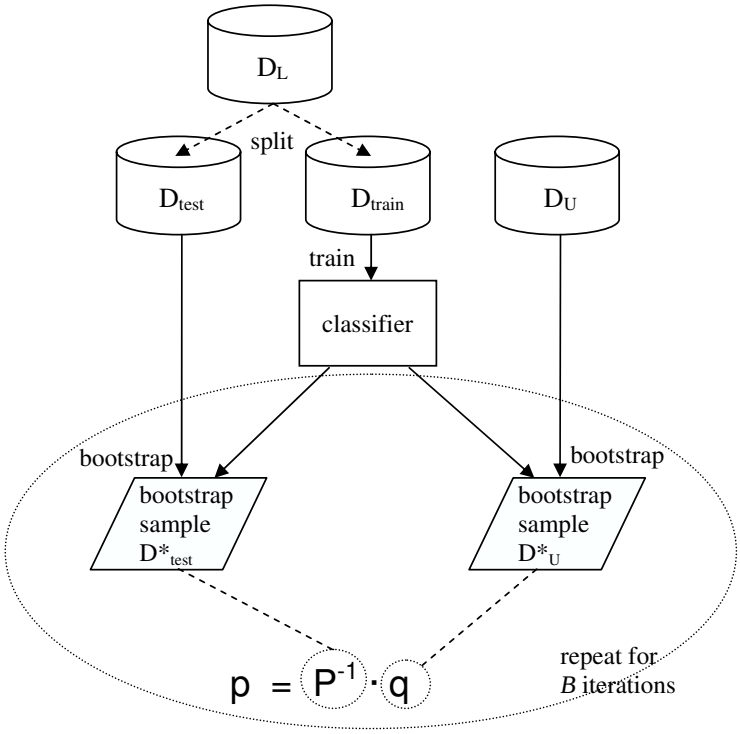


Figure 5.1: Sense priors estimation using the confusion matrix algorithm.

to obtain its predictions. From these predictions, one can estimate the probability of predicting class ω_j on D_U, which we will denote as $\widehat{q}(\omega_j)$. The a priori probabilities $\widehat{p}(\omega_i)$ on D_U (which in our context are the sense priors we want to estimate) are then estimated by solving the following equation:

$$\widehat{q}(\omega_j) = \sum_{i=1}^{n} \widehat{p}_L(\omega_j|\omega_i)\widehat{p}(\omega_i), \qquad j = 1, \ldots, n \tag{5.1}$$

where n represents the number of classes. Equation (5.1) can be represented in matrix form as $\mathbf{q} = \mathbf{P} \cdot \mathbf{p}$, from which the a priori probabilities on D_U, represented by $\mathbf{p}$, can be estimated by solving:

$$\mathbf{p} = \mathbf{P}^{-1} \cdot \mathbf{q} \tag{5.2}$$

To obtain estimates of $\mathbf{P}$ and $\mathbf{q}$, bootstrap sampling (Efron and Tibshirani, 1993) is employed. In bootstrap sampling, given an original sample X with n examples, bootstrap sample X^* is obtained by randomly sampling n examples from X with replacement. To estimate the conditional probabilities $\widehat{p}_L(\omega_j|\omega_i)$, we need to split our labeled data D_L into D_{train} and D_{test}. We will first use Figure 5.1 to provide an overview of the confusion matrix algorithm before giving the algorithmic details.

As shown in Figure 5.1, we first split D_L into D_{train} and D_{test}. Then, we generate a bootstrap sample D^*_{test} from D_{test} and apply the classifier trained on D_{train} on D^*_{test}. This gives us the conditional probabilities $\widehat{p}_L(\omega_j|\omega_i)$, or the $\mathbf{P}$ matrix. We similarly generate a bootstrap sample D^*_U from D_U and apply the same classifier on D^*_U. Using this classification result, we calculate $\widehat{q}(\omega_j)$, which is the vector $\mathbf{q}$. Using Equation 5.2, we then solve for $\mathbf{p}$. We repeat this process of obtaining bootstrap samples D^*_{test} and D^*_U, then calculating the vector $\mathbf{p}$ of a priori probabilities, for a total of B iterations. We then average the vectors $\mathbf{p}$ over the B iterations to obtain our final estimate of the a priori probabilities, or the sense priors of the different senses in the unlabeled data D_U.

Now, we will give the confusion matrix algorithm. We first define $n^*_{test}(\omega_j, \omega_i)$ as the number of examples in a bootstrap sample D^*_{test} predicted to be of class ω_j when the true class is ω_i. Also, we define $n^*_U(\omega_j)$ as the number of examples in a bootstrap sample D^*_U predicted to be of class ω_j. Then, given D_{test}, D_U, and a classifier, repeat the following for B iterations (in our experiments, we set B to 200):

- Generate a bootstrap sample from n_{test} examples of D_{test} and calculate:
  $\widehat{p}^*_L(\omega_j|\omega_i) = \frac{n^*_{test}(\omega_j,\omega_i)}{\sum_j n^*_{test}(\omega_j,\omega_i)} \qquad \text{for } i,j = 1,\ldots,n$
- Generate a bootstrap sample from n_U examples of D_U and calculate:
  $\widehat{q}^*(\omega_j) = \frac{n^*_U(\omega_j)}{n_U} \qquad \text{for } j = 1,\ldots,n$

- Use Equation (5.2) to calculate $\widehat{p}^*(\omega_i)^{(b)}$for $i = 1, \ldots, n$

After B iterations, estimate the a priori probabilities $\widehat{p}(\omega_i) = \frac{1}{B}\sum_{b=1}^{B}\widehat{p}^*(\omega_i)^{(b)}$

5.1.2 EM-Based Algorithm

Most of this section is based on (Saerens, Latinne, and Decaestecker, 2002), which introduced the EM-based algorithm[1] to estimate the a priori probabilities in a new corpus. Assume we have a set of labeled data D_L with n classes and a set of N independent instances $(\mathbf{x}_1, \ldots, \mathbf{x}_N)$ from a new data set. The likelihood of these N instances can be defined as:

$$\begin{aligned} L(\mathbf{x}_1, \ldots, \mathbf{x}_N) &= \prod_{k=1}^{N} p(\mathbf{x}_k) \\ &= \prod_{k=1}^{N}\left[\sum_{i=1}^{n} p(\mathbf{x}_k, \omega_i)\right] \\ &= \prod_{k=1}^{N}\left[\sum_{i=1}^{n} p(\mathbf{x}_k|\omega_i)p(\omega_i)\right] \end{aligned} \tag{5.3}$$

Assuming the within-class densities $p(\mathbf{x}_k|\omega_i)$, i.e., the probabilities of observing $\mathbf{x}_k$ given the class ω_i, do not change from the training set D_L to the new data set, we can define: $p(\mathbf{x}_k|\omega_i) = p_L(\mathbf{x}_k|\omega_i)$. To determine the a priori probability estimates $\widehat{p}(\omega_i)$ of the new data set that will maximize the likelihood of (5.3) with respect to $p(\omega_i)$, we can apply the iterative procedure of the EM algorithm. In effect, through maximizing the likelihood of (5.3), we obtain the a priori probability estimates as a by-product.

[1] A derivation of this algorithm is available in the Appendix section of (Saerens, Latinne, and Decaestecker, 2002).

Let us now define some notations. When we apply a classifier trained on D_L on an instance $\mathbf{x}_k$ drawn from the new data set D_U, we get $\widehat{p}_L(\omega_i|\mathbf{x}_k)$, which we define as the probability of instance $\mathbf{x}_k$ being classified as class ω_i by the classifier trained on D_L. Further, let us define $\widehat{p}_L(\omega_i)$ as the a priori probabilities of class ω_i in D_L. This can be estimated by the class frequency of ω_i in D_L. We also define $\widehat{p}^{(s)}(\omega_i)$ and $\widehat{p}^{(s)}(\omega_i|\mathbf{x}_k)$ as estimates of the new a priori and a posteriori probabilities at step s of the iterative EM procedure. Assuming we initialize $\widehat{p}^{(0)}(\omega_i) = \widehat{p}_L(\omega_i)$, then for each instance $\mathbf{x}_k$ in D_U and each class ω_i, the EM algorithm provides the following iterative steps:

$$\widehat{p}^{(s)}(\omega_i|\mathbf{x}_k) = \frac{\widehat{p}_L(\omega_i|\mathbf{x}_k)\frac{\widehat{p}^{(s)}(\omega_i)}{\widehat{p}_L(\omega_i)}}{\sum_{j=1}^{n}\widehat{p}_L(\omega_j|\mathbf{x}_k)\frac{\widehat{p}^{(s)}(\omega_j)}{\widehat{p}_L(\omega_j)}} \tag{5.4}$$

$$\widehat{p}^{(s+1)}(\omega_i) = \frac{1}{N}\sum_{k=1}^{N}\widehat{p}^{(s)}(\omega_i|\mathbf{x}_k) \tag{5.5}$$

where Equation (5.4) represents the expectation E-step, Equation (5.5) represents the maximization M-step, and N represents the number of instances in D_U. Note that the probabilities $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ and $\widehat{p}_L(\omega_i)$ in Equation (5.4) will stay the same throughout the iterations for each particular instance $\mathbf{x}_k$ and class ω_i. The new a posteriori probabilities $\widehat{p}^{(s)}(\omega_i|\mathbf{x}_k)$ at step s in Equation (5.4) are simply the a posteriori probabilities in the conditions of the labeled data, $\widehat{p}_L(\omega_i|\mathbf{x}_k)$, weighted by the ratio of the new priors $\widehat{p}^{(s)}(\omega_i)$ to the old priors $\widehat{p}_L(\omega_i)$. The denominator in Equation (5.4) is simply a normalizing factor.

The a posteriori $\widehat{p}^{(s)}(\omega_i|\mathbf{x}_k)$ and a priori probabilities $\widehat{p}^{(s)}(\omega_i)$ are re-estimated sequentially during each iteration s for each new instance $\mathbf{x}_k$ and each class ω_i, until the convergence of the estimated probabilities $\widehat{p}^{(s)}(\omega_i)$. In the context of our work, these are the sense priors that we want to estimate. This iterative procedure will

increase the likelihood of (5.3) at each step.

5.1.3 Predominant Sense

A method of automatically ranking WordNet senses to determine the predominant, or most frequent sense, of a noun in the BNC corpus is presented in (McCarthy et al., 2004b). Using the method of (Lin, 1998), a thesaurus is first acquired from the parsed 90 million words of written English from the BNC corpus to provide the k nearest neighbors to each target noun, along with the distributional similarity score (*dss*) between the target noun and its neighbor. The WordNet similarity package (Pedersen, Patwardhan, and Michelizzi, 2004) is then used to give a WordNet similarity measure (*wnss*), which is used to weigh the contribution that each neighbor makes to the various senses of the target noun. Through a combination of *dss* and *wnss*, a prevalence score for each sense of the target noun is calculated, from which the predominant sense of the noun in BNC is determined.

Though the focus of the method is to determine the predominant sense, we could obtain sense priors estimates by normalizing the prevalence score of each sense. We implemented this method in order to evaluate its effectiveness in improving WSD accuracy. Our implementation achieved accuracies close to those reported by McCarthy et al. (2004b). In that work, the authors reported a *jcn measure* predominant sense accuracy of 54.0% on the SemCor corpus, while we measured 53.3% using our implementation. On the SENSEVAL-2 English all-words task, 64.0% precision and 63.0% recall were reported. Our implementation gave 66.2% precision and 63.4% recall. The differences could be due to some minor processing steps which were not described in detail in (McCarthy et al., 2004b). Finally, note that this predominant sense method is only effective on a *very large* text corpus, as the thesaurus can only

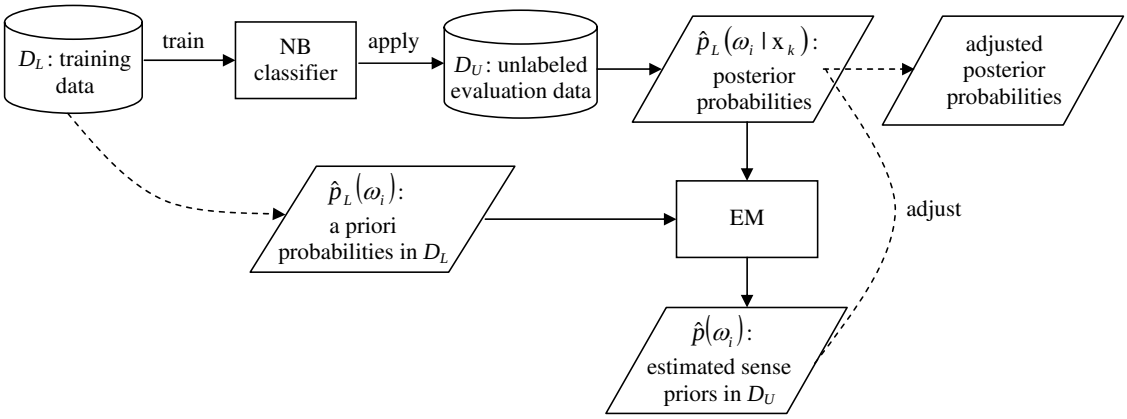


Figure 5.2: Sense priors estimation using the EM algorithm.

be effectively generated from a very large corpus.

5.2 Using A Priori Estimates

If a classifier estimates posterior class probabilities $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ when presented with a new instance $\mathbf{x}_k$ from D_U, the $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ probabilities can be directly adjusted according to the estimated a priori probabilities $\widehat{p}(\omega_i)$ on D_U, thus giving a new set of class membership predictions.

Denoting predictions of the classifier as $\widehat{p}_L(\omega_i|\mathbf{x}_k)$, a priori probability of class ω_i from D_L as $\widehat{p}_L(\omega_i)$, and estimated a priori probability of class ω_i from D_U as $\widehat{p}(\omega_i)$, adjusted predictions $\widehat{p}_{adjust}(\omega_i|\mathbf{x}_k)$ can be calculated as:

$$\widehat{p}_{adjust}(\omega_i|\mathbf{x}_k) = \frac{\widehat{p}_L(\omega_i|\mathbf{x}_k)\frac{\widehat{p}(\omega_i)}{\widehat{p}_L(\omega_i)}}{\sum_j \widehat{p}_L(\omega_j|\mathbf{x}_k)\frac{\widehat{p}(\omega_j)}{\widehat{p}_L(\omega_j)}} \tag{5.6}$$

Figure 5.2 shows the process of estimating and using the sense priors with the EM-based algorithm. As shown, we first train, for instance a naive Bayes classifier, on the labeled training data D_L. The classifier is then applied on the unlabeled evaluation

data D_U to obtain a set of posterior probability estimates $\widehat{p}_L(\omega_i|\mathbf{x}_k)$, which are our initial class membership predictions. Using $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ and the a priori probabilities $\widehat{p}_L(\omega_i)$, or proportion of each class in D_L, we estimate the sense priors $\widehat{p}(\omega_i)$ in D_U with the EM-based algorithm using Equation 5.4 and 5.5. These estimated sense priors $\widehat{p}(\omega_i)$ can then be used to adjust the initial predictions $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ using Equation 5.6, to obtain a new set of class membership predictions $\widehat{p}_{adjust}(\omega_i|\mathbf{x}_k)$. We will show in the experimental section later that $\widehat{p}_{adjust}(\omega_i|\mathbf{x}_k)$ are more accurate than the initial $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ predictions.

5.3 Calibration of Probabilities

In our eariler work (Chan and Ng, 2005b), the posterior probabilities assigned by a naive Bayes classifier are used by the EM procedure described in Section 5.1.2 to estimate the sense priors $\widehat{p}(\omega_i)$ in a new dataset. However, it is known that the posterior probabilities assigned by naive Bayes are not well calibrated (Domingos and Pazzani, 1996).

It is important to use an algorithm which gives well calibrated probabilities, if we are to use the probabilities in estimating the sense priors. In this section, we will first describe the notion of being well calibrated before discussing why having well calibrated probabilities helps in estimating the sense priors. Finally, we will introduce a method used to calibrate the probabilities.

5.3.1 Well Calibrated Probabilities

Assume for each instance $\mathbf{x}$, a classifier outputs a probability $S_{\omega_i}(\mathbf{x})$ between 0 and 1, of $\mathbf{x}$ belonging to class ω_i. The classifier is well-calibrated if the empirical class

membership probability $p(\omega_i|S_{\omega_i}(\mathbf{x}) = t)$ converges to the probability value $S_{\omega_i}(\mathbf{x}) = t$ as the number of examples classified goes to infinity (Zadrozny and Elkan, 2002). Intuitively, if we consider all the instances to which the classifier assigns a probability $S_{\omega_i}(\mathbf{x})$ of say 0.6, then 60% of these instances should be members of class ω_i.

5.3.2 Being Well Calibrated Helps Estimation

To see why using an algorithm which gives well calibrated probabilities helps in estimating the sense priors, let us rewrite Equation (5.5), the M-step of the EM procedure, as the following:

$$\widehat{p}^{(s+1)}(\omega_i) = \frac{1}{N} \sum_{t \in S_{w_i}} \sum_{k \in \{q: S_{\omega_i}(\mathbf{x}_q) = t\}} \widehat{p}^{(s)}(\omega_i|\mathbf{x}_k) \tag{5.7}$$

where $S_{\omega_i} = \{t_1, \ldots, t_m\}$ denotes the set of posterior probability values for class ω_i, and $S_{\omega_i}(\mathbf{x}_q)$ denotes the posterior probability of class ω_i assigned by the classifier for instance $\mathbf{x}_q$.

Based on $t_1, \ldots, t_m$, we can imagine that we have m bins, where each bin is associated with a specific t value. Now, distribute all the instances in the new dataset D_U into the m bins according to their posterior probabilities $S_{\omega_i}(\mathbf{x})$. Let B_l, for $l = 1, \ldots, m$, denote the set of instances in bin l.

Note that $|B_1| + \cdots + |B_l| + \cdots + |B_m| = N$. Now, let p_l denote the proportion of instances with true class label ω_i in B_l. Given a well calibrated algorithm, $p_l = t_l$

by definition and Equation (5.7) can be rewritten as:

$$\begin{aligned} \widehat{p}^{(s+1)}(\omega_i) &= \frac{1}{N}\left(t_1|B_1| + \cdots + t_m|B_m|\right) \\ &= \frac{1}{N}\left(p_1|B_1| + \cdots + p_m|B_m|\right) \\ &= \frac{N_{\omega_i}}{N} \end{aligned} \tag{5.8}$$

where N_{ω_i} denotes the number of instances in D_U with true class label ω_i. Therefore, $\widehat{p}^{(s+1)}(\omega_i)$ reflects the proportion of instances in D_U with true class label ω_i. Hence, using an algorithm which gives well calibrated probabilities helps in the estimation of sense priors.

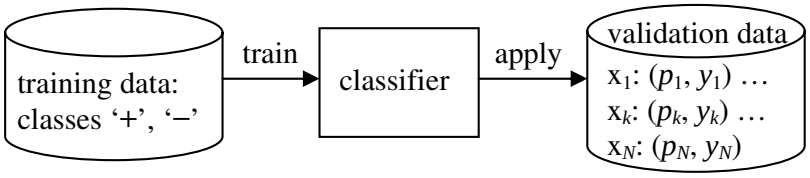
5.3.3 Isotonic Regression

Zadrozny and Elkan (2002) successfully used a method based on isotonic regression (Robertson, Wright, and Dykstra, 1988) to calibrate the probability estimates from naive Bayes. To compute the isotonic regression, they used the pair-adjacent violators (PAV) (Ayer et al., 1955) algorithm, which we show in Figure 5.3. Briefly, what PAV does is to initially view each data value as a level set. While there are two adjacent sets that are out of order (i.e., the left level set is above the right one) then the sets are combined and the mean of the data values becomes the value of the new level set.

PAV works on binary class problems. In a binary class problem, we have a positive class and a negative class. Now, let $D = (p_k, \mathbf{x}_k), 1 \leq k \leq N$, where $\mathbf{x}_1, \ldots, \mathbf{x}_N$ represent N examples and p_k is the probability of $\mathbf{x}_k$ belonging to the positive class, as predicted by a classifier. Further, let y_k represent the true label of $\mathbf{x}_k$. For a binary class problem, we let $y_k = 1$ if $\mathbf{x}_k$ is a positive example and $y_k = 0$ if $\mathbf{x}_k$ is a negative example. The PAV algorithm takes in a set of (p_k, y_k), sorted in ascending order of p_k

Input: training set (p_k, y_k) sorted in ascending order of p_k
Initialize $g_k = y_k$
While $\exists$ k such that $g_j, \ldots, g_{k-1} > g_k, \ldots, g_l$, where $g_j = \cdots = g_{k-1}$ and $g_k = \cdots = g_l$ $(j < k \leq l)$
  Set $m = \frac{\sum_{q=j}^{l} g_q}{l-j+1}$
  Replace $g_j, \ldots, g_l$ with m

Figure 5.3: PAV algorithm.



Sort the set of (p_k, y_k) in increasing order of p_k :

Sorted p values:

0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0

Corresponding y values:

0	0	1	0	1	0	0	1	1	1
0	0	0.5	0.5	1	0	0	1	1	1
0	0	0.5	0.5	0.33	0.33	0.33	1	1	1
0	0	0.4	0.4	0.4	0.4	0.4	1	1	1

Calibration mapping:

0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
0	0	0.4	0.4	0.4	0.4	0.4	1	1	1

Figure 5.4: PAV illustration.

and returns a series of increasing step-values, where each step-value $g_{j,l}$ (denoted by m in Figure 5.3) is associated with a lowest boundary value p_j and a highest boundary value p_l. We performed 10-fold cross-validation on the training data to assign values to p_k. We then applied the PAV algorithm to obtain values for g_k. To obtain the calibrated probability estimate for a test instance $\mathbf{x}$, we find the boundary values p_j and p_l where $p_j \leq S_{\omega_i}(\mathbf{x}) \leq p_l$ and assign $g_{j,l}$ as the calibrated probability estimate.

As an illustration of the PAV algorithm, let us refer to Figure 5.4. After training our classifier on the binary class training data, we apply it on our validation data to obtain a set $D = (p_k, \mathbf{x}_k), 1 \leq k \leq N$. Similarly, we let y_k represent the true label of $\mathbf{x}_k$ and sort the set of (p_k, y_k) in ascending order of p_k. Assume we have N=10 validation instances, their sorted p values are 0.1, 0.2, ..., 1.0; and their corresponding y values are as shown in the figure: 0 0 1 0 1 0 0 1 1 1. Note that if the prediction probabilities p_k had ranked the instances perfectly, all the 0's will come before all the 1's and we would have "0 0 0 0 0 1 1 1 1 1". Starting from the first, or leftmost y value, the PAV algorithm searches for any occurrence where a y value is greater than the value on its right. In essence, the PAV algorithm will try to *smooth out* the series of y values. In our example given in Figure 5.4, the PAV algorithm detects that y_3 (with a value of 1) is greater than y_4 (with a value of 0). The average of these 2 numbers is computed, resulting in the second series of values: 0 0 0.5 0.5 1 0 0 1 1 1. The PAV algorithm now detects that the 3 underlined numbers (1 0 0) are "out of order". Their average value is computed and we have the third series of numbers: 0 0 0.5 0.5 0.33 0.33 0.33 1 1 1. Finally, the algorithm detects that the 5 underlined numbers (0.5 0.5 0.33 0.33 0.33) are "out of order" and averages them, resulting in the last series of numbers: 0 0 0.4 0.4 0.4 0.4 0.4 1 1 1. Since all numbers are now in increasing order, the PAV algorithm ends its execution and we have obtained the calibration mapping, which is

just a mapping between numbers. For this example, our mapping indicates that if our original probability estimate p_k of belonging to the positive class is $0 \leq p_k \leq 0.2$, the new estimate is 0; if $0.3 \leq p_k \leq 0.7$, the new estimate is 0.4, etc. If p_k falls between two boundary values, such as if $0.2 < p_k < 0.3$, we average the associated calibrated probabilities to obtain $(0 + 0.4)/2 = 0.2$.

To apply PAV on a multiclass problem, we first reduce the problem into a number of binary class problems. For reducing a multiclass problem into a set of binary class problems, experiments in (Zadrozny and Elkan, 2002) suggest that the one-against-all approach works well. In one-against-all, a separate classifier is trained for each class ω_i, where examples belonging to class ω_i are treated as positive examples and all other examples are treated as negative examples. A separate classifier is then learnt for each binary class problem and the probability estimates from each classifier are calibrated. Finally, the calibrated binary-class probability estimates are combined to obtain multiclass probabilities, computed by a simple normalization of the calibrated estimates from the binary classifiers, as suggested by Zadrozny and Elkan (2002). For instance, assume a particular problem consists of 4 classes and their calibrated binary-class probabilities are 0.2, 0.3, 0.3, and 0.5. To normalize these probabilities, we first compute their total $(0.2 + 0.3 + 0.3 + 0.5) = 1.3$ and then divide each probability by the total. This gives the normalized calibrated probabilities $0.2/1.3 = 0.15$, $0.3/1.3 = 0.23$, etc.

5.4 Selection of Dataset

In this section, we discuss the motivations in choosing the particular corpora and the set of words used in our experiments.

5.4.1 DSO Corpus

The DSO corpus is made up of texts drawn from Brown corpus (BC) and Wall Street Journal (WSJ). BC is a balanced corpus and contains texts in various categories such as religion, fiction, etc. In contrast, the focus of the WSJ corpus is on financial and business news. Escudero, Marquez, and Rigau (2000) exploited the difference in coverage between these two corpora to separate the DSO corpus into its BC and WSJ parts for investigating the domain dependence of several WSD algorithms. Following their setup, we also use the DSO corpus in our experiments. Since BC is a balanced corpus, and training a classifier on a general corpus before applying it to a more specific corpus is a natural scenario, we use examples from the BC portion of DSO as training data, and examples from the WSJ portion of DSO as evaluation data, or the target dataset.

5.4.2 Parallel Texts

To build a wide-coverage WSD system, we require a large amount of training examples. In Chapter 4, we have shown that parallel texts provide an effective source for gathering these examples. However, note that the parallel texts we use (as given in Table 4.1) are gathered from different sources such as legislative proceedings, magazine articles, etc. Hence, examples gathered from parallel texts typically present a natural domain difference from the target data on which we apply the WSD system. In particular, we note that since the test data of the English lexical sample task in SENSEVAL-2 and SENSEVAL-3 is largely drawn from the British National corpus (BNC), this represents a domain difference from the parallel text examples. Hence, we include a set of experiments where we train on parallel text examples and evaluate on the nouns of SENSEVAL-2 and SENSEVAL-3 English lexical sample task.

Dataset	Total no. of words	No. different PS	No. same PS
DSO nouns	119	37	82
DSO verbs	66	28	38
SE2 nouns	15	6	9
SE3 nouns	17	9	8

Table 5.1: Number of words with different or the same predominant sense (PS) between the training and test data.

Following (Ng, Wang, and Chan, 2003), in gathering examples from parallel texts, senses will be lumped together if they are translated in the same way in Chinese.

5.5 Results Over All Words

We first present our experimental results over all the words of our test data, no matter whether they have different or the same predominant sense between the training and test data.

As mentioned earlier, the DSO corpus contains annotated examples for 121 nouns and 70 verbs. After leaving out the few nouns and verbs which have only BC examples and no WSJ examples in the DSO corpus, we are left with a set of 119 nouns and 66 verbs, as shown in Table 5.1. Among these words, 37 nouns and 28 verbs have different predominant senses between the training data (BC portion of DSO) and test data (WSJ portion of DSO). For the remaining 82 nouns and 38 verbs as shown under the column *No. same PS* of Table 5.1, their respective predominant sense remains unchanged between the BC and WSJ portion of the DSO corpus.

For the nouns of SENSEVAL-2 and SENSEVAL-3 English lexical sample tasks, we do not perform WSD on 7 SENSEVAL-2 nouns that are lumped into one sense (i.e., all the senses of each of these nouns were translated into the same Chinese

Classifier	NB				
Method	L	True	CM_{NB}	EM_{NB}	EM_{LogR}
DSO nouns	64.0	67.9	64.5	64.7	64.6
DSO verbs	58.1	62.3	58.8	58.9	59.0
SE2 nouns	70.5	72.2	70.8	70.8	71.3
SE3 nouns	62.1	63.6	63.0	62.8	63.0

Table 5.2: Micro-averaged WSD accuracies over all the words, using the various methods. The naive Bayes here are multiclass naive Bayes (NB).

Classifier	NB			
Method	True − L	CM_{NB} − L	EM_{NB} − L	EM_{LogR} − L
DSO nouns	3.9	0.5 (12.8%)	0.7 (17.9%)	0.6 (15.4%)
DSO verbs	4.2	0.7 (16.7%)	0.8 (19.0%)	0.9 (21.4%)
SE2 nouns	1.7	0.3 (17.6%)	0.3 (17.6%)	0.8 (47.1%)
SE3 nouns	1.5	0.9 (60.0%)	0.7 (46.7%)	0.9 (60.0%)

Table 5.3: Relative accuracy improvement based on non-calibrated probabilities.

word). In (Saerens, Latinne, and Decaestecker, 2002) which introduced the EM-based algorithm, experiments were conducted using a minimum of 50 training examples for each class. In our current work, we use a similar but less restrictive criterion of omitting those words with less than 50 examples. This omitted 7 SENSEVAL-2 nouns and 3 SENSEVAL-3 nouns as they have less than 50 parallel text examples available. Thus, we are left with a set of 15 SENSEVAL-2 nouns and 17 SENSEVAL-3 nouns, as shown under the column *Total no. of words* in Table 5.1. For each noun, we gathered a maximum of 500 parallel text examples as training data, similar to what we had done in (Chan and Ng, 2005b).

5.5.1 Experimental Results

We now present experimental results on the set of words listed under the column *Total no. of words* in Table 5.1. We used the supervised WSD system described in Chapter 3 with naive Bayes as our learning algorithm. All accuracies reported in our experiments are micro-averages over the test examples.

We record the WSD accuracies achieved by a multiclass naive Bayes classifier (without any adjustment), in the column L under *NB* in Table 5.2. For the *EM-based algorithm*, the predictions $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ of these naive Bayes classifiers are then used in Equation (5.4) and (5.5) to estimate the sense priors $\widehat{p}(\omega_i)$, before being adjusted by these estimated sense priors based on Equation (5.6). The resulting WSD accuracies after this adjustment are listed in the column EM_{NB} in Table 5.2. For instance, in Table 5.2 we see that for the set of DSO verbs, we obtained a WSD accuracy of 58.1% using the original predictions of the naive Bayes classifier. If we adjust these predictions by the sense priors estimated via the EM-based algorithm, performance improves to 58.9%.

Corresponding WSD accuracies achieved from adjusting the original predictions $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ by the sense priors estimated by the *confusion matrix* algorithm are listed under the column CM_{NB}. To provide a basis for comparison, we also adjusted the predictions $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ by the *true* sense priors $p(\omega_i)$ of the test data. The accuracies thus obtained are shown under the column *True* in Table 5.2.

The increases in WSD accuracies obtained through using the estimated sense priors are given in Table 5.3 (the numbers in this table are derived from Table 5.2). The column $True - L$ in the table shows the increase in WSD accuracy obtained by using the true sense priors of the test data. Note that this represents the maximum possible increase in accuracy achievable provided we know these *true* sense priors

$p(\omega_i)$. In the column $EM_{NB} - L$ in Table 5.3, we list the increase in WSD accuracy when the naive Bayes predictions are adjusted by the sense priors $\widehat{p}(\omega_i)$ which are *automatically* estimated using the EM procedure. The relative improvements obtained with using the *estimated* sense priors $\widehat{p}(\omega_i)$, as compared against using the *true* sense priors $p(\omega_i)$, are given as percentages in brackets. For instance, for the set of DSO verbs, adjusting the original predictions by the sense priors estimated via the EM algorithm gives an improvement of 0.8% in accuracy, against an improvement of 4.2% if we were to use the true sense priors. Thus, the relative improvement is $0.8/4.2 = 19\%$. Corresponding figures of relative improvements based on using sense priors estimated by the confusion matrix algorithm are given under the column $CM_{NB} - L$.

In Section 5.1.3, we mentioned that we could normalize the prevalence score of each sense to obtain estimated sense priors via the predominant sense method. We note that the thesaurus used as part of the predominant sense method is acquired from the BNC corpus, from which the majority of the SENSEVAL-2 and SENSEVAL-3 English lexical sample task test data are drawn. Hence, we applied the sense priors estimated via the predominant sense method on our test data of SENSEVAL-2 and SENSEVAL-3 nouns, obtaining an accuracy of 70.6% and 62.6%, respectively. Note that these are lower than the scores obtained via the confusion matrix algorithm and EM-based algorithm, consistent with the findings in (Chan and Ng, 2005b). This suggests that in a supervised setting where training data is available, the confusion matrix and EM-based algorithms estimate the sense priors more effectively than the unsupervised predominant sense method. The predominant sense method also has the drawback that it is only able to estimate the sense priors, or predominant sense, in a very large text corpus, which is needed to construct the thesaurus. In contrast, the confusion matrix algorithm is applicable on texts of any size. For the EM-based

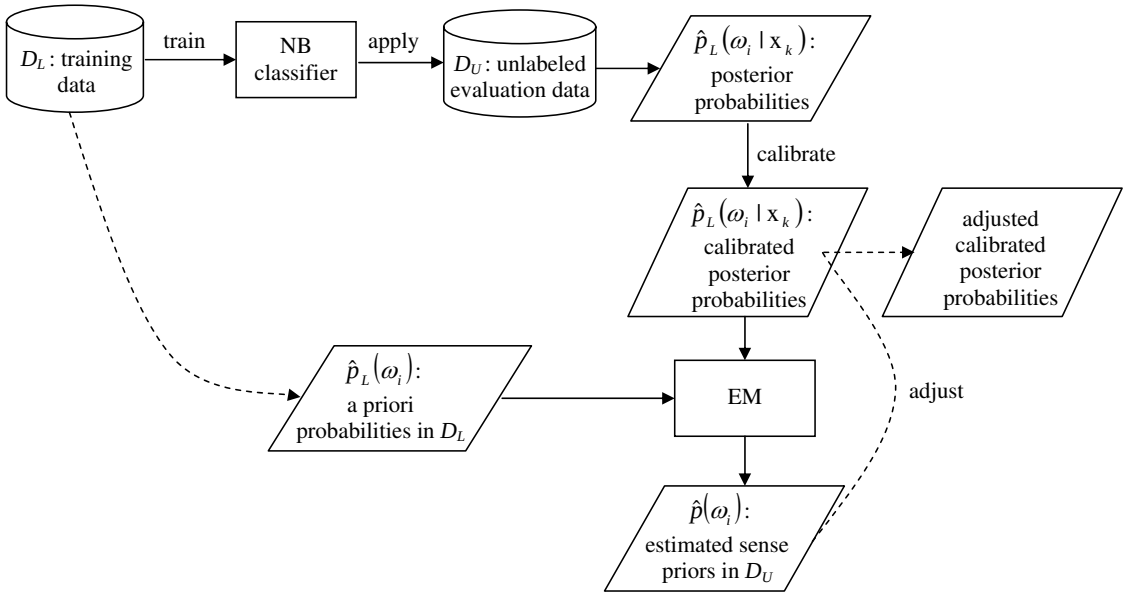


Figure 5.5: Sense priors estimation using the EM algorithm with calibration.

algorithm, experiments in (Saerens, Latinne, and Decaestecker, 2002) show that the size of the target corpus has little effect on its effectiveness.

Next, we used the one-against-all approach to reduce each multiclass problem into a set of binary class problems. We trained a naive Bayes classifier for each binary class problem and calibrated the probabilities from these binary classifiers. The WSD accuracies of these calibrated naive Bayes classifiers (denoted by *NBcal*) are given in the column L under *NBcal* of Table 5.4. The predictions of these classifiers are then used to estimate the sense priors $\widehat{p}(\omega_i)$, before being adjusted by these estimates based on Equation (5.6). Figure 5.5 gives an overview of the process when using the calibrated probabilities to estimate the sense priors via the EM-based algorithm. Note the similarity with Figure 5.2. The difference is that we calibrate the probabilities before providing them to the EM algorithm and that these are in turn adjusted by the estimated sense priors. The resulting WSD accuracies after adjustment are listed

Classifier	NBcal				
Method	L	True	CM_{NBcal}	EM_{NBcal}	EM_{LogR}
DSO nouns	65.8	70.8	66.0	66.1	67.4
DSO verbs	58.9	64.7	59.1	59.8	60.7
SE2 nouns	70.7	72.4	70.8	71.0	71.3
SE3 nouns	62.1	64.6	63.2	63.7	63.5

Table 5.4: Micro-averaged WSD accuracies over all the words, using the various methods. The naive Bayes classifiers here are with calibrated probabilities (NBcal).

Classifier	NBcal			
Method	True − L	CM_{NBcal} − L	EM_{NBcal} − L	EM_{LogR} − L
DSO nouns	5.0	0.2 (4.0%)	0.3 (6.0%)	1.6 (32.0%)
DSO verbs	5.8	0.2 (3.4%)	0.9 (15.5%)	1.8 (31.0%)
SE2 nouns	1.7	0.1 (5.9%)	0.3 (17.6%)	0.6 (35.3%)
SE3 nouns	2.5	1.1 (44.0%)	1.6 (64.0%)	1.4 (56.0%)

Table 5.5: Relative accuracy improvement based on calibrated probabilities.

in column EM_{NBcal} in Table 5.4. Corresponding accuracies when adjusted by the sense priors predicted by the confusion matrix algorithm are given under the column CM_{NBcal}. Similarly, we also adjust the calibrated prediction probabilities by the *true* sense priors $p(\omega_i)$ of the test data and show the accuracies obtained under the column *True* in Table 5.4. Similar to Table 5.3, Table 5.5 gives the increase in WSD accuracies obtained through adjusting the calibrated predictions by the various sense priors.

The results show that calibrating the probabilities improves WSD accuracy. In particular, EM_{NBcal}, where the sense priors are estimated via the EM-based algorithm achieves the highest accuracy among the methods described so far (with the natural exclusion of adjusting by the true sense priors, of course). Also, note that the confusion matrix algorithm has the rather strong assumption that the conditional

probabilities $\widehat{p}_L(\omega_j|\omega_i)$ stay the same from the training or labeled data D_L, to the test or unlabeled data D_U on which we want to estimate the sense priors. Furthermore, the method also involves the time consuming process of performing many additional classification runs, such as multiple bootstrap samplings and cross-validations to calculate matrices $\mathbf{P}$ and vectors $\mathbf{q}$. In contrast, the EM-based method does not require any additional experimental runs. To estimate the sense priors using the EM-based method, we only need to iteratively perform the two EM steps of Equation (5.4) and (5.5). In view of these considerations, we focus on using the EM-based algorithm to estimate the sense priors for the rest of our experiments in this chapter.

5.6 Sense Priors Estimation with Logistic Regression

The experimental results show that the sense priors estimated using the calibrated probabilities of naive Bayes are effective in increasing the WSD accuracy. However, using a learning algorithm which already gives well calibrated posterior probabilities may be more effective in estimating the sense priors. One possible algorithm is logistic regression, which directly optimizes for getting approximations of the posterior probabilities. Hence, its probability estimates are already well calibrated (Zhang and Yang, 2004; Niculescu-Mizil and Caruana, 2005).

We trained logistic regression classifiers and evaluated them on the set of words of the four datasets. However, the WSD accuracies of these unadjusted logistic regression classifiers are on average lower than those of the unadjusted naive Bayes classifiers. One possible reason is that being a discriminative learner, logistic regression requires more training examples for its performance to catch up to, and possibly

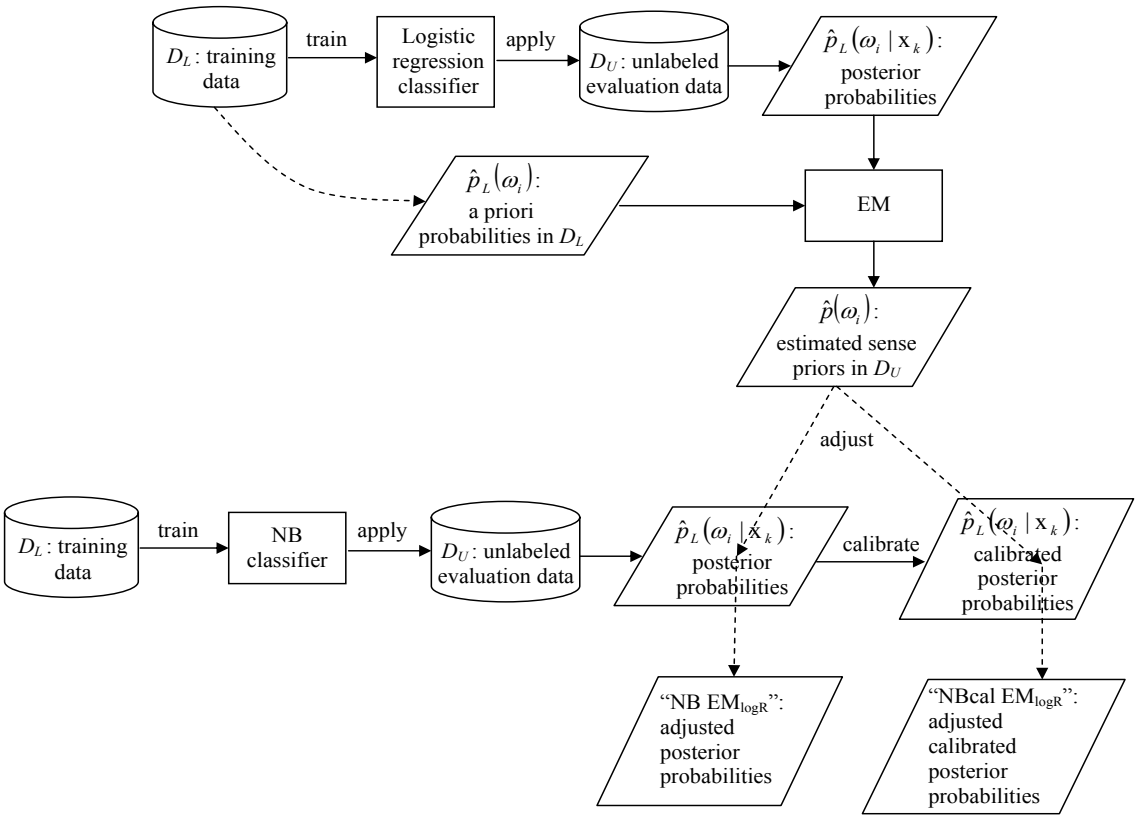


Figure 5.6: Sense priors estimation with logistic regression.

even overtake, the generative naive Bayes learner (Ng and Jordan, 2001).

Although the accuracy of logistic regression as a basic classifier is lower than that of naive Bayes, its predictions may still be suitable for estimating sense priors. These sense priors could then be used to adjust the prediction probabilities of the naive Bayes classifiers. Figure 5.6 gives an overview of the process. Notice that the top half of the figure is very similar to Figure 5.2, except that the naive Bayes classifier is replaced by the logistic regression classifier.

To elaborate on Figure 5.6, we first train a logistic regression classifier on the labeled training data D_L. The classifier is then applied on the unlabeled evaluation data D_U to obtain a set of posterior probability estimates $\widehat{p}_L(\omega_i|\mathbf{x}_k)$, which are our

initial class membership predictions. Using $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ and the a priori probabilities $\widehat{p}_L(\omega_i)$, or proportion of each class in D_L, we estimate the sense priors $\widehat{p}(\omega_i)$ in D_U with the EM-based algorithm using Equation 5.4 and 5.5. The steps described up till now are exactly the same as those in Figure 5.2, except that the naive Bayes classifier is replaced by the logistic regression classifier. As a result, we have computed the sense priors estimated by logistic regression.

As shown in the lower half of Figure 5.6, we now train naive Bayes classifers on D_L and apply them on D_U, to obtain an initial set of naive Bayes predictions $\widehat{p}_L(\omega_i|\mathbf{x}_k)$. We then either apply (using Equation (5.6)) the sense priors estimated earlier by logistic regression on these naive Bayes prediction probabilities to obtain a set of adjusted predictions "$NB\ EM_{logR}$", or we can calibrate the original naive Bayes predictions before applying the sense priors to obtain "$NBcal\ EM_{logR}$".

The WSD accuracy of "$NB\ EM_{logR}$" (the predictions $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ of the *uncalibrated* naive Bayes adjusted by the sense priors estimated with logistic regression) is given in the column EM_{LogR} under *NB* of Table 5.2. Corresponding WSD accuracies of "$NBcal\ EM_{logR}$" (the predictions $\widehat{p}_L(\omega_i|\mathbf{x}_k)$ of the *calibrated* naive Bayes adjusted by the sense priors estimated with logistic regression) is given in the column EM_{LogR} under *NBcal* of Table 5.4. The relative improvements over using the true sense priors, based on the uncalibrated and calibrated probabilities, are given in the column $EM_{LogR} - L$ of Table 5.3 and Table 5.5, respectively. The results show that the sense priors estimated with logistic regression are in general effective in further improving the WSD accuracies.

5.7 Experiments Using True Predominant Sense Information

Research by (McCarthy et al., 2004b) highlighted that the sense priors of a word in a corpus depend on the domain from which the corpus is drawn. A change of predominant sense is often indicative of a change in domain, as different corpora drawn from different domains usually give different predominant senses. For example, the predominant sense of the noun *interest* in the Brown corpus (BC) part of the DSO corpus has the meaning "a sense of concern with and curiosity about someone or something". In the Wall Street Journal (WSJ) part of the DSO corpus, the noun *interest* has a different predominant sense with the meaning "a fixed charge for borrowing money", reflecting the business and finance focus of the WSJ corpus.

Estimation of sense priors is important when there is a significant change in sense priors between the training and target dataset, such as when there is a change in domain between the datasets. In this section, we focus on experiments involving words having *different* predominant senses between the training and test data. In our experiments involving the DSO corpus, we focus on the set of nouns and verbs which have different predominant senses between the BC and WSJ parts of the corpus. This gives us a set of 37 nouns and 28 verbs, as tabulated in Table 5.1. For experiments involving the nouns of SENSEVAL-2 and SENSEVAL-3 English lexical sample task, we focus on the set of nouns having different predominant senses between the examples gathered from parallel texts and the evaluation data for the two SENSEVAL tasks. This gives a set of 6 nouns for SENSEVAL-2 and 9 nouns for SENSEVAL-3, as tabulated in Table 5.1.

Classifier	NB				NBcal			
Method	L	True	EM_{NB}	EM_{LogR}	L	True	EM_{NBcal}	EM_{LogR}
DSO nouns	44.5	51.9	46.1	46.6	45.8	57.4	47.0	51.1
DSO verbs	46.7	53.9	48.3	48.7	46.9	57.2	49.5	50.8
SE2 nouns	61.7	64.4	62.4	63.0	62.3	65.3	63.2	63.5
SE3 nouns	53.9	56.6	54.9	55.7	55.4	59.1	58.8	58.4

Table 5.6: Micro-averaged WSD accuracies using the various methods, for the set of words having *different* predominant senses between the training and test data. The different naive Bayes classifiers are: multiclass naive Bayes (NB) and naive Bayes with calibrated probabilities (NBcal).

Dataset	True − L	EM_{NB} − L	EM_{LogR} − L
DSO nouns	7.4	1.6 (21.6%)	2.1 (28.4%)
DSO verbs	7.2	1.6 (22.2%)	2.0 (27.8%)
SE2 nouns	2.7	0.7 (25.9%)	1.3 (48.1%)
SE3 nouns	2.7	1.0 (37.0%)	1.8 (66.7%)

Table 5.7: Relative accuracy improvement based on uncalibrated probabilities.

Dataset	True − L	EM_{NBcal} − L	EM_{LogR} − L
DSO nouns	11.6	1.2 (10.3%)	5.3 (45.7%)
DSO verbs	10.3	2.6 (25.2%)	3.9 (37.9%)
SE2 nouns	3.0	0.9 (30.0%)	1.2 (40.0%)
SE3 nouns	3.7	3.4 (91.9%)	3.0 (81.1%)

Table 5.8: Relative accuracy improvement based on calibrated probabilities.

Method comparison			DSO nouns	DSO verbs	SE2 nouns	SE3 nouns
NB_EM_{LogR}	vs. NB_EM_{NB}	(add logR)	$\gg$	$\gg$	$\gg$	$\gg$
NBcal_EM_{NBcal}	vs. NB_EM_{NB}	(add cal)	$\sim$	$\gg$	$>$	$\gg$
NBcal_EM_{NBcal}	vs. NB_EM_{LogR}	(cal vs. logR)	$\sim$	$\gg$	$\sim$	$\gg$
NBcal_EM_{LogR}	vs. NB_EM_{NB}	(add logR and cal)	$\gg$	$\gg$	$\gg$	$\gg$
NBcal_EM_{LogR}	vs. NB_EM_{LogR}	(add cal)	$\gg$	$\gg$	$\sim$	$\gg$
NBcal_EM_{LogR}	vs. NBcal_EM_{NBcal}	(add logR)	$\gg$	$\gg$	$\sim$	$\sim$

Table 5.9: Paired t-tests between the various methods for the four datasets. Here, logistic regression is abbreviated as logR and calibration as cal.

From the results given in Table 5.6, we see that calibrating the probabilities improves WSD accuracy and using the sense priors estimated by logistic regression is effective in improving the results. In the case of DSO nouns, the improvement due to the use of logistic regression is especially significant; from 45.8% to 51.1%. Similar to the previous section, we show in Table 5.7 and 5.8 the increase in WSD accuracy from using the automatically estimated sense priors $\hat{p}(w_i)$, as compared to using the true sense priors $p(w_i)$.

Paired t-tests were conducted to see if one method is significantly better than another. The t statistic of the difference between each test instance pair is computed, giving rise to a p value. The results of significance tests for the various methods on the four datasets are given in Table 5.9, where the symbols "$\sim$", "$>$", and "$\gg$" correspond to p-value > 0.05, (0.01, 0.05], and ≤ 0.01 respectively.

The methods in Table 5.9 are represented in the form *a1_a2*, where *a1* denotes adjusting the predictions of which classifier, and *a2* denotes how the sense priors are estimated. As an example, NBcal_EM_{LogR} specifies that the sense priors estimated by logistic regression are used to adjust the predictions of the calibrated naive Bayes classifier, and corresponds to accuracies in column EM_{LogR} under *NBcal* in Table 5.6.

NB_EM_{NB} represents our earlier approach in (Chan and Ng, 2005b). The significance tests show that the approach of using calibrated naive Bayes probabilities to estimate sense priors, and then adjusting the calibrated probabilities by these sense priors estimates (NBcal_EM_{NBcal}) is more effective than NB_EM_{NB} (refer to row 2 of Table 5.9). For DSO nouns, though the results are similar, the p value is a relatively low 0.06.

Using sense priors estimated by logistic regression further improves performance. For example, row 1 of Table 5.9 shows that adjusting the predictions of multiclass

naive Bayes classifiers by sense priors estimated by logistic regression (NB_EM_{LogR}) performs significantly better than using sense priors estimated by multiclass naive Bayes (NB_EM_{NB}). Finally, using sense priors estimated by logistic regression to adjust the predictions of calibrated naive Bayes (NBcal_EM_{LogR}) in general performs significantly better than most other methods, achieving the best overall performance.

5.8 Experiments Using Predicted Predominant Sense Information

Results from the previous section show that it is critical and effective to adjust the predictions of words having different predominant senses between the training and test data. However, in a practical setting, we do not know the true predominant sense of each word in a particular domain or dataset. In this section, we use the EM-based algorithm to estimate the sense priors in the test data. The sense with the highest estimated sense prior is taken as the predominant sense of the word.

Similar to Table 5.1, we show in Table 5.10 the number of words having different, or the same predominant sense, for the four datasets. In addition, each number in brackets gives the number of words where the EM-based algorithm predicts that there is a change in predominant sense. For instance, for the 37 DSO nouns having different predominant senses between the training and test data, the EM-based algorithm is able to correctly predict that the predominant sense changes for 25 of the nouns. Similarly for the 82 DSO nouns where their predominant sense remains unchanged between the training and test data, the EM-based algorithm is able to correctly predict that there is no change in predominant sense for 81 of the nouns (i.e., it incorrectly predicts that one noun has its predominant sense changed). This means

Dataset	Total no. of words	No. different PS	No. same PS
DSO nouns	119 (26)	37 (25)	82 (1)
DSO verbs	66 (20)	28 (19)	38 (1)
SE2 nouns	15 (6)	6 (4)	9 (2)
SE3 nouns	17 (6)	9 (5)	8 (1)
Total	217 (58)	80 (53)	137 (5)

Table 5.10: Number of words with different or the same predominant sense (PS) between the training and test data. Numbers in brackets give the number of words where the EM-based algorithm predicts a change in predominant sense.

Classifier	NB				NBcal			
Method	L	True	EM_{NB}	EM_{LogR}	L	True	EM_{NBcal}	EM_{LogR}
DSO nouns	47.5	55.4	49.6	50.0	48.5	60.1	48.9	54.0
DSO verbs	49.8	58.1	51.7	52.4	50.9	60.2	53.6	55.9
SE2 nouns	67.5	69.8	67.9	68.8	67.4	70.0	67.9	68.7
SE3 nouns	55.8	61.5	58.4	59.2	57.2	64.6	64.2	62.9

Table 5.11: Micro-averaged WSD accuracies over the words with predicted different predominant senses between the training and test data.

Dataset	True − L	EM_{NB} − L	EM_{LogR} − L
DSO nouns	7.9	2.1 (26.6%)	2.5 (31.6%)
DSO verbs	8.3	1.9 (22.9%)	2.6 (31.3%)
SE2 nouns	2.3	0.4 (17.4%)	1.3 (56.5%)
SE3 nouns	5.7	2.6 (45.6%)	3.4 (59.6%)

Table 5.12: Relative accuracy improvement based on uncalibrated probabilities.

Dataset	True − L	EM_{NBcal} − L	EM_{LogR} − L
DSO nouns	11.6	0.4 (3.4%)	5.5 (47.4%)
DSO verbs	9.3	2.7 (29.0%)	5.0 (53.8%)
SE2 nouns	2.6	0.5 (19.2%)	1.3 (50.0%)
SE3 nouns	7.4	7.0 (94.6%)	5.7 (77.0%)

Table 5.13: Relative accuracy improvement based on calibrated probabilities.

that the algorithm predicts that 26 (25+1) DSO nouns have different predominant senses between the training and test data.

We then evaluate over the set of 58 words where the EM-based algorithm predicts a change in predominant sense between the training and test data. The improvements in WSD accuracy from adjusting the predictions using the estimated sense priors for these words are shown in Table 5.11. The relative improvements based on uncalibrated and calibrated probabilities are shown in Tables 5.12 and 5.13, respectively. The results show that in a practical setting where one does not know whether predominant senses of words changes between the training and test data, one can still estimate and use the sense priors to improve WSD accuracy. Finally, we note that the best results are obtained using the sense priors estimated by logistic regression.

5.9 Summary

Differences in sense priors between training and target domain datasets will result in a loss of WSD accuracy. In this chapter, we show that using well calibrated probabilities to estimate sense priors is important. By calibrating the probabilities of the naive Bayes algorithm, and using the probabilities given by logistic regression (which are already well calibrated), we achieve improvements in WSD accuracy. We also highlight the importance of estimating the sense priors when there is a change in domain, which could be reflected by a change in predominant sense. We show that the EM-based algorithm is effective in predicting a change in predominant sense. Evaluation over the set of words where the predominant senses between the training and test data are predicted to be different shows that the EM-based algorithm is able to predict the sense priors effectively to improve WSD accuracy. Finally, using logistic

regression to estimate the sense priors via the EM-based algorithm gives consistently good improvements to WSD accuracy.

Chapter 6

Domain Adaptation with Active Learning for Word Sense Disambiguation

We have already highlighted the importance of performing domain adaptation for WSD. In this chapter, we explore domain adaptation of WSD systems by adding training examples from the new domain, as additional training data to a WSD system. To reduce the effort required to adapt a WSD system to a new domain, we employ an active learning strategy (Lewis and Gale, 1994) to select examples to annotate from the new domain of interest. To our knowledge, our work is the first to use active learning for domain adaptation for WSD. A similar work is the recent research by Chen et al. (2006), where active learning was used successfully to reduce the annotation effort for WSD of 5 English verbs using *coarse-grained* evaluation. In that work, the authors only used active learning to reduce the annotation effort and did not deal with the porting of a WSD system to a new domain.

Domain adaptation is necessary when the training and target domains are different. In our work, we perform domain adaptation for WSD of a set of nouns using *fine-grained* evaluation. The contribution of our work is not only in showing that active learning can be successfully employed to reduce the annotation effort required for domain adaptation in a *fine-grained* WSD setting. More importantly, our main focus and contribution is in showing how we can improve the effectiveness of a basic active learning approach when it is used for domain adaptation. In particular, we explore the issue of different sense priors across different domains. Using the sense priors estimated by expectation-maximization (EM), the predominant sense in the new domain is predicted. Using this predicted predominant sense and adopting a count-merging technique, we *improve* the effectiveness of the adaptation process.

In the next section, we discuss the choice of corpus and nouns used in our experiments. We then introduce active learning for domain adaptation, followed by count-merging. Performance of domain adaptation using active learning and count-merging is then presented. Next, we show that by using the predominant sense of the target domain as predicted by the EM-based algorithm, we improve the effectiveness of the adaptation process. Our empirical results show that for the set of nouns which have different predominant senses between the training and target domains, we are able to reduce the annotation effort by 71%.

6.1 Experimental Setting

For the experiments performed in this chapter, we use the naive Bayes implementation in WEKA as our learning algorithm. In this section, we discuss the motivations for choosing the particular corpus and the set of nouns to conduct our domain adaptation

experiments.

6.1.1 Choice of Corpus

Similar to the last chapter, we made use of the DSO corpus to perform our experiments on domain adaptation. The DSO corpus has two parts: Brown corpus (BC) and the Wall Street Journal (WSJ). Since BC is a balanced corpus, and since performing adaptation from a general corpus to a more specific corpus is a natural scenario, we focus on adapting a WSD system trained on BC to WSJ. Henceforth, out-of-domain data will refer to BC examples, and in-domain data will refer to WSJ examples.

6.1.2 Choice of Nouns

The WordNet Domains resource (Magnini and Cavaglià, 2000) assigns domain labels to synsets in WordNet. Since the focus of the WSJ corpus is on business and financial news, we can make use of WordNet Domains to select the set of nouns having at least one synset labeled with a business or finance related domain label. This is similar to the approach taken in (Koeling, McCarthy, and Carroll, 2005) where they focus on determining the predominant sense of words in corpora drawn from finance versus sports domains.[1] Hence, we select the subset of DSO nouns that have at least one synset labeled with any of these domain labels: *commerce*, *enterprise*, *money*, *finance*, *banking*, and *economy*. This gives a set of 21 nouns: *book*, *business*, *center*, *community*, *condition*, *field*, *figure*, *house*, *interest*, *land*, *line*, *money*, *need*, *number*, *order*, *part*, *power*, *society*, *term*, *use*, *value*.[2]

[1]Note however that the coverage of the WordNet Domains resource is not comprehensive, as about 31% of the synsets are simply labeled with "factotum", indicating that the synset does not belong to a specific domain.

[2]25 nouns have at least one synset labeled with the listed domain labels. In our experiments, 4 out of these 25 nouns have an accuracy of more than 90% before adaptation (i.e., training on just

Dataset	No. of senses		MFS accuracy (%)	No. of training examples	No. of adaptation examples
	BC	WSJ			
21 nouns	6.7	6.8	61.1	310	406
9 nouns	7.9	8.6	65.8	276	416

Table 6.1: The average number of senses in BC and WSJ, average MFS accuracy, average number of BC training, and WSJ adaptation examples per noun.

For each noun, all the BC examples are used as out-of-domain training data. One-third of the WSJ examples for each noun are set aside as evaluation data, and the rest of the WSJ examples are designated as in-domain adaptation data. The row *21 nouns* in Table 6.1 shows some information about these 21 nouns. For instance, these nouns have an average of 6.7 senses in BC and 6.8 senses in WSJ. This is slightly higher than the 5.8 senses per verb in (Chen et al., 2006), where the experiments were conducted using coarse-grained evaluation. Assuming we had access to an "oracle" which determines the predominant sense, or the most frequent sense (MFS), of each noun in our WSJ test data perfectly, and we assign this most frequent sense to each noun in the test data, we would have achieved an accuracy of 61.1% as shown in the column *MFS accuracy* of Table 6.1. Finally, we note that we have an average of 310 BC training examples and 406 WSJ adaptation examples per noun.

6.2 Active Learning

For our experiments, we use the WSD system described in Chapter 3 with naive Bayes as the learning algorithm. In our domain adaptation study, we start with a WSD system built using training examples drawn from BC. We then investigate

the BC examples) and accuracy improvement is less than 1% after all the available WSJ adaptation examples are added as additional training data. To obtain a clearer picture of the adaptation process, we discard these 4 nouns, leaving a set of 21 nouns.

```
D_T ← the set of BC training examples
D_A ← the set of untagged WSJ adaptation examples
Γ ← WSD system trained on D_T
repeat
   p_min ← ∞
   for each d ∈ D_A do
      ŝ ← word sense prediction for d using Γ
      p ← confidence of prediction ŝ
      if p < p_min then
         p_min ← p, d_min ← d
      end
   end
   D_A ← D_A − d_min
   provide correct sense s for d_min and add d_min to D_T
   Γ ← WSD system trained on new D_T
end
```

Figure 6.1: Active learning

the utility of adding additional in-domain training data from WSJ. In the baseline approach, the additional WSJ examples are randomly selected. With active learning (Lewis and Gale, 1994), we use *uncertainty sampling* as shown in Figure 6.1. In each iteration, we train a WSD system on the available training data and apply it on the WSJ adaptation examples. Among these WSJ examples, the example predicted with the lowest confidence is selected and removed from the adaptation data. The correct label is then supplied for this example and it is added to the training data.

Note that in the experiments reported in this chapter, all the adaptation examples are already pre-annotated before the experiments start, since all the WSJ adaptation examples come from the DSO corpus which have already been sense-annotated. Hence, the annotation of an example needed during each adaptation iteration is simulated by performing a lookup without any manual annotation.

6.3 Count-merging

We also employ a technique known as *count-merging* in our domain adaptation study. Count-merging assigns different weights to different examples to better reflect their relative importance. Roark and Bacchiani (2003) showed that weighted count-merging is a special case of maximum a posteriori (MAP) estimation, and successfully used it for probabilistic context-free grammar domain adaptation (Roark and Bacchiani, 2003) and language model adaptation (Bacchiani and Roark, 2003).

Count-merging can be regarded as scaling of counts obtained from different data sets. We let $\widetilde{c}$ denote the counts from out-of-domain training data, $\bar{c}$ denote the counts from in-domain adaptation data, and $\widehat{p}$ denote the probability estimate by count-merging. We can scale the out-of-domain and in-domain counts with different factors, or just use a single weight parameter β:

$$\widehat{p}(f_j|s_i) = \frac{\widetilde{c}(f_j, s_i) + \beta\bar{c}(f_j, s_i)}{\widetilde{c}(s_i) + \beta\bar{c}(s_i)} \tag{6.1}$$

Similarly,

$$\widehat{p}(s_i) = \frac{\widetilde{c}(s_i) + \beta\bar{c}(s_i)}{\widetilde{c} + \beta\bar{c}} \tag{6.2}$$

Obtaining an optimum value for β is not the focus of this work. Instead, we are interested to see if assigning a higher weight to the in-domain WSJ adaptation examples, as compared to the out-of-domain BC examples, will improve the adaptation process. Hence, we just use a β value of 3 in our experiments involving count-merging.

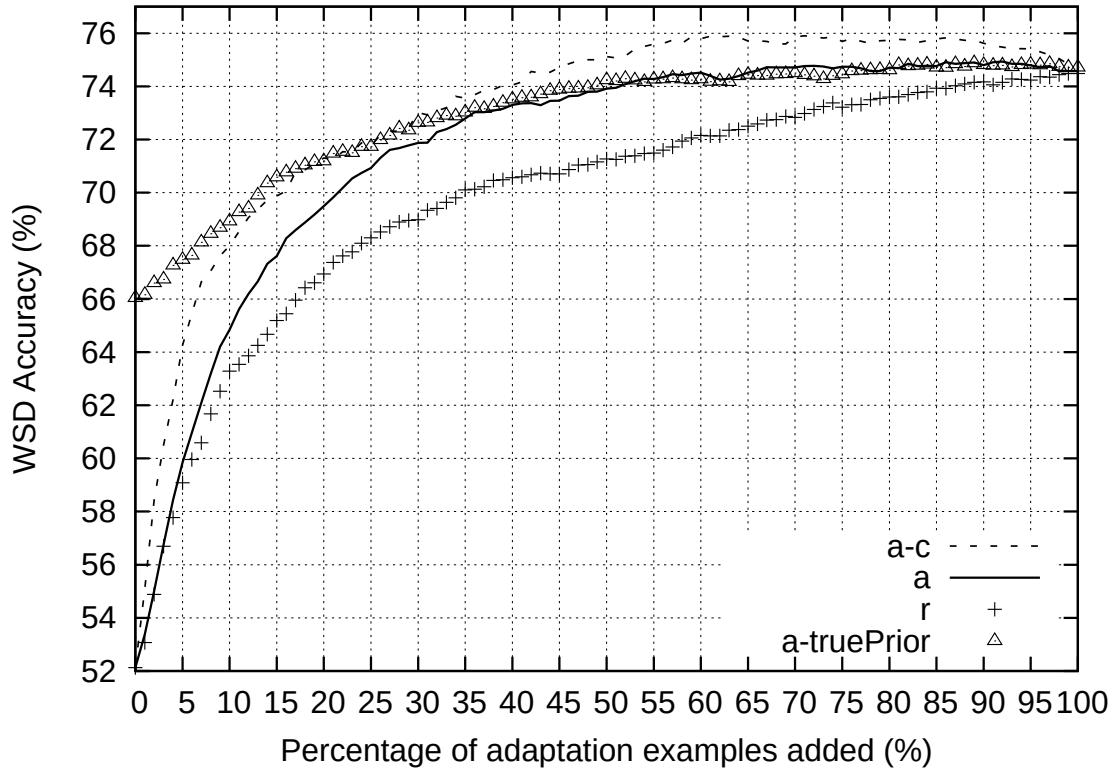


Figure 6.2: Adaptation process for all 21 nouns. In the graph, the curves are: r (random selection), a (active learning), a-c (active learning with count-merging), a-truePrior (active learning, with BC examples gathered to adhere to true sense priors in WSJ).

6.4 Experimental Results

For each adaptation experiment, we start off with a classifier built from an initial training set consisting of the BC training examples. At each adaptation iteration, WSJ adaptation examples are selected *one at a time* and added to the training set. The adaptation process continues until all the adaptation examples are added. Classification accuracies averaged over 3 random trials on the WSJ test examples at each iteration are calculated. Since the number of WSJ adaptation examples differs for

each of the 21 nouns, the learning curves we will show in the various figures are plotted in terms of different percentage of adaptation examples added, varying from 0 to 100 percent in steps of 1 percent. To obtain these curves, we first calculate for each noun, the WSD accuracy when different percentages of adaptation examples are added. Then, for each percentage, we calculate the macro-average WSD accuracy over all the nouns to obtain a single learning curve representing all the nouns.

6.4.1 Utility of Active Learning and Count-merging

In Figure 6.2, the curve *r* represents the adaptation process of the baseline approach, where additional WSJ examples are randomly selected during each adaptation iteration. The adaptation process using active learning is represented by the curve *a*, while applying count-merging with active learning is represented by the curve *a-c*. Note that random selection *r* achieves its highest WSD accuracy after *all* the adaptation examples are added. To reach the same accuracy, the *a* approach requires the addition of only 57% of adaptation examples. The *a-c* approach is even more effective and requires only 42% of adaptation examples. This demonstrates the effectiveness of count-merging in further reducing the annotation effort, when compared to using only active learning. To reach the MFS accuracy of 61.1% as shown earlier in Table 6.1, *a-c* requires just 4% of the adaptation examples.

6.4.2 Using Sense Priors Information

As mentioned previously, research in (Escudero, Marquez, and Rigau, 2000) noted an improvement in accuracy when they adjusted the BC and WSJ datasets such that the proportions of the different senses of each word were the same between BC and WSJ. We can similarly choose BC examples such that the sense priors in the BC

training data adhere to the sense priors in the WSJ evaluation data. To gauge the effectiveness of this approach, we first assume that we know the *true* sense priors of each noun in the WSJ evaluation data. We then gather BC training examples for a noun to adhere as much as possible to the sense priors in WSJ. Assume sense s_i is the predominant sense in the WSJ evaluation data, and s_i has a sense prior of p_i in the WSJ data and has n_i BC training examples. Taking n_i examples to represent a sense prior of p_i, we proportionally determine the number of BC examples to gather for the other senses according to their respective sense priors in WSJ. If there are insufficient training examples in BC for some sense s, whatever available examples of s are used.

This approach gives an average of 195 BC training examples for the 21 nouns. With this new set of training examples, we perform adaptation using active learning and obtain the *a-truePrior* curve in Figure 6.2. The *a-truePrior* curve shows that by ensuring that the sense priors in the BC training data adhere as much as possible to the sense priors in the WSJ data, we start off with a higher WSD accuracy. However, the performance is no different from the *a* curve after 35% of adaptation examples are added. A possible reason might be that by strictly adhering to the sense priors in the WSJ data, we have removed too many BC training examples, from an average of 310 examples per noun as shown in Table 6.1 to an average of 195 examples.

6.4.3 Using Predominant Sense Information

Research by McCarthy et al. (2004b) and Koeling, McCarthy, and Carroll (2005) pointed out that a change of predominant sense is often indicative of a change in domain. For example, the predominant sense of the noun *interest* in the BC part of the DSO corpus has the meaning "a sense of concern with and curiosity about

someone or something". In the WSJ part of the DSO corpus, the noun *interest* has a different predominant sense with the meaning "a fixed charge for borrowing money", which is reflective of the business and finance focus of the WSJ corpus.

Instead of restricting the BC training data to adhere strictly to the sense priors in WSJ, another alternative is just to ensure that the predominant sense in BC is the same as that of WSJ. Out of the 21 nouns, 12 nouns have the same predominant sense in both BC and WSJ. The remaining 9 nouns that have different predominant senses in the BC and WSJ data are: *center*, *field*, *figure*, *interest*, *line*, *need*, *order*, *term*, *value*. The row *9 nouns* in Table 6.1 gives some information for this set of 9 nouns. To gauge the utility of this approach, we conduct experiments on these nouns by first assuming that we know the *true* predominant sense in the WSJ data. Assume that the WSJ predominant sense of a noun is s_i and s_i has n_i examples in the BC data. We then gather BC examples for a noun to adhere to this WSJ predominant sense, by gathering only up to n_i BC examples for each sense of this noun. This approach gives an average of 190 BC examples for the 9 nouns. This is higher than an average of 83 BC examples for these 9 nouns if BC examples are selected to follow the sense priors of WSJ evaluation data as described in the last subsection 6.4.2.

For these 9 nouns, the average KL-divergence between the sense priors of the original BC data and WSJ evaluation data is 0.81. This drops to 0.51 after ensuring that the predominant sense in BC is the same as that of WSJ, confirming that the sense priors in the newly gathered BC data more closely follow the sense priors in WSJ. Using this new set of training examples, we perform domain adaptation using active learning to obtain the curve *a-truePred* in Figure 6.3. For comparison, we also plot the curves *a* and *a-truePrior* for this set of 9 nouns in Figure 6.3. Results in Figure 6.3 show that *a-truePred* starts off at a higher accuracy and performs consistently

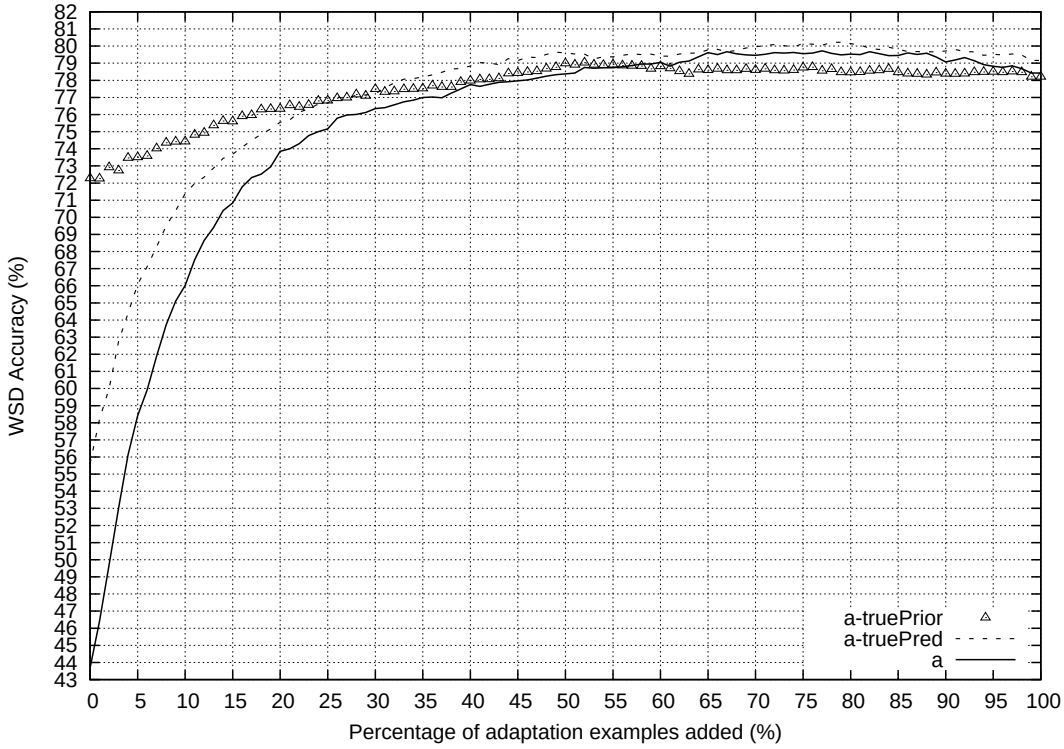


Figure 6.3: Using true predominant sense for the 9 nouns. The curves are: a (active learning), a-truePrior (active learning, with BC examples gathered to adhere to true sense priors in WSJ), a-truePred (active learning, with BC examples gathered such that its predominant sense is the same as the *true* predominant sense in WSJ).

better than the *a* curve. In contrast, though *a-truePrior* starts at a high accuracy, its performance is lower than *a-truePred* and *a* after 50% of adaptation examples have been added. The approach represented by *a-truePred* is a compromise between ensuring that the sense priors in the training data follow as closely as possible the sense priors in the evaluation data, while retaining enough training examples. These results highlight the importance of striking a balance between these two goals.

In Section 5.1.3, we described the method presented in (McCarthy et al., 2004b), where the aim is to determine the predominant sense of a word in a corpus. We have

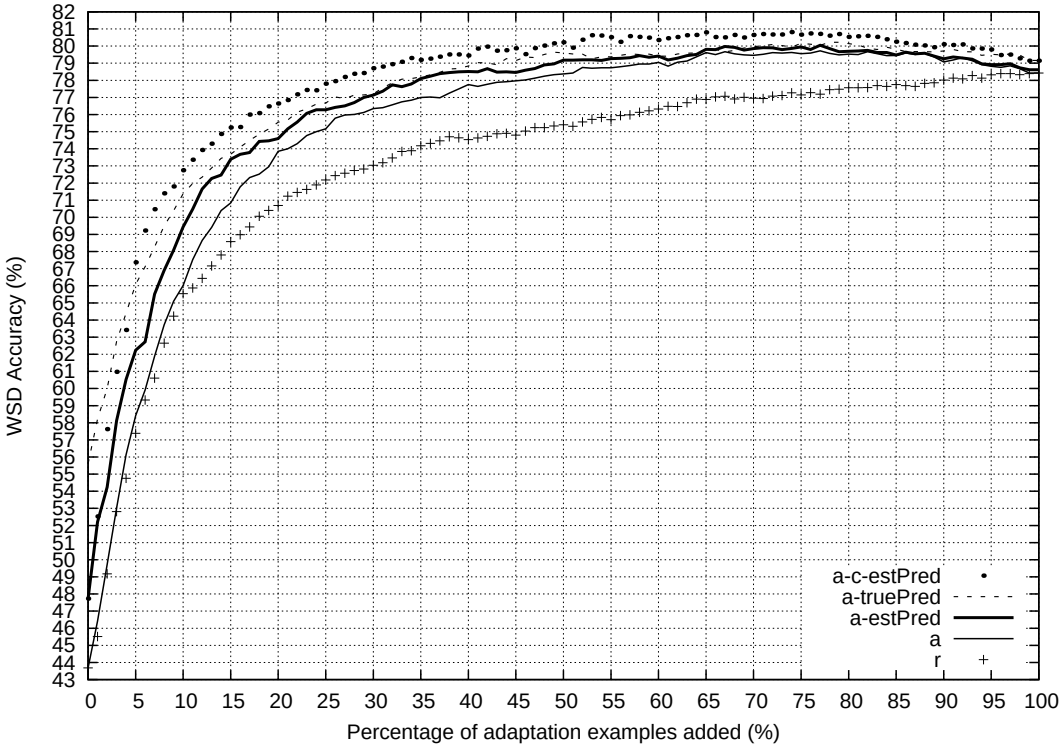


Figure 6.4: Using estimated predominant sense for the 9 nouns. The curves are: r (random selection), a (active learning), a-truePred (active learning, with BC examples gathered such that its predominant sense is the same as the *true* predominant sense in WSJ), a-estPred (similar to a-truePred, except that the predominant sense in WSJ is *estimated* by the EM-based algorithm), a-c-estPred (employing count-merging with a-estPred).

shown, however that in a supervised setting where one has access to some annotated training data, the EM-based algorithm described in the previous chapter estimates the sense priors more effectively than the method described in (McCarthy et al., 2004b). Hence, we use the EM-based algorithm to estimate the sense priors in the WSJ evaluation data for each of the 21 nouns. The sense with the highest estimated sense prior is taken as the predominant sense of the noun.

For the set of 12 nouns where the predominant sense remains unchanged between

Accuracy	% adaptation examples needed			
	r	a	a-estPred	a-c-estPred
50%: 61.1	8	7 (0.88)	5 (0.63)	4 (0.50)
60%: 64.5	10	9 (0.90)	7 (0.70)	5 (0.50)
70%: 68.0	15	12 (0.80)	9 (0.60)	6 (0.40)
80%: 71.5	23	16 (0.70)	12 (0.52)	9 (0.39)
90%: 74.9	46	24 (0.52)	21 (0.46)	15 (0.33)
100%: 78.4	100	51 (0.51)	38 (0.38)	29 (0.29)

Table 6.2: Annotation savings and percentage of adaptation examples needed to reach various accuracies.

BC and WSJ, the EM-based algorithm is able to predict that the predominant sense remains unchanged for *all* 12 nouns. Hence, we will focus on the 9 nouns which have different predominant senses between BC and WSJ for our remaining adaptation experiments. For these 9 nouns, the EM-based algorithm correctly predicts the WSJ predominant sense for 6 nouns. Hence, the algorithm is able to predict the correct predominant sense for 18 out of 21 nouns overall, representing an accuracy of 86%.

Figure 6.4 plots the curve *a-estPred*, which is similar to *a-truePred*, except that the predominant sense is now estimated by the EM-based algorithm. Employing count-merging with *a-estPred* produces the curve *a-c-estPred*. For comparison, the curves *r*, *a*, and *a-truePred* are also plotted. The results show that *a-estPred* performs consistently better than *a*, and *a-c-estPred* in turn performs better than *a-estPred*. Hence, employing the predicted predominant sense and count-merging, we further improve the effectiveness of the active learning-based adaptation process.

With reference to Figure 6.4, the WSD accuracies of the *r* and *a* curves before and after adaptation are 43.7% and 78.4% respectively. Starting from the mid-point 61.1% accuracy, which represents a 50% accuracy increase from 43.7%, we show in Table 6.2 the percentage of adaptation examples required by the various approaches to reach certain levels of WSD accuracies. For instance, to reach the final accuracy

of 78.4%, *r*, *a*, *a-estPred*, and *a-c-estPred* require the addition of 100%, 51%, 38%, and 29% adaptation examples respectively. The numbers in brackets give the ratio of adaptation examples needed by *a*, *a-estPred*, and *a-c-estPred* versus random selection *r*. For instance, to reach a WSD accuracy of 78.4%, *a-c-estPred* needs only 29% adaptation examples, representing a ratio of 0.29 and an annotation saving of 71%. Note that this represents a more effective adaptation process than the basic active learning *a* approach, which requires 51% adaptation examples. Hence, besides showing that active learning can be used to reduce the annotation effort required for domain adaptation, we have further improved the effectiveness of the adaptation process by using the predicted predominant sense of the new domain and adopting the count-merging technique.

6.5 Summary

Domain adaptation is important to ensure the general applicability of WSD systems across different domains. In this chapter, we have shown that active learning is effective in reducing the annotation effort required in porting a WSD system to a new domain. Also, we have successfully used an EM-based algorithm to detect a change in predominant sense between the training and new domain. With this information on the predominant sense of the new domain and incorporating count-merging, we have shown that we are able to improve the effectiveness of the original adaptation process achieved by the basic active learning approach.

Chapter 7

Word Sense Disambiguation for Machine Translation

Recent research presents conflicting evidence on whether WSD systems can help to improve the performance of statistical machine translation (MT) systems. In this chapter, we show how we successfully integrate a state-of-the-art WSD system into the state-of-the-art hierarchical phrase-based MT system, Hiero. We show for the first time that integrating a WSD system improves the performance of a state-of-the-art statistical MT system on an actual translation task. Furthermore, the improvement is statistically significant.

We start the chapter by describing the Hiero MT system and introducing the two new features used to integrate the WSD system into Hiero. We then describe the training data used by the WSD system. Following that, we describe how the WSD translations provided are used by the decoder of the Hiero MT system. Then, we present and analyze our experimental results, before concluding the chapter.

7.1 Hiero

Hiero (Chiang, 2005) is a hierarchical phrase-based model for statistical machine translation, based on weighted synchronous context-free grammar (CFG) (Lewis and Stearns, 1968). A synchronous CFG consists of rewrite rules such as the following:

$$\mathrm{X} \rightarrow \langle \gamma, \alpha \rangle \tag{7.1}$$

where X is a non-terminal symbol, and each of γ and α is a string of terminal and non-terminal symbols in the source and target language, respectively. There is a one-to-one correspondence between the non-terminals in γ and α indicated by co-indexation. Hence, γ and α always have the same number of non-terminal symbols. For instance, we could have the following grammar rule:

$$\mathrm{X} \rightarrow \langle \text{每 月 到 } \mathrm{X}_{\boxed{1}}, \text{go to } \mathrm{X}_{\boxed{1}} \text{ every month to} \rangle \tag{7.2}$$

where boxed indices represent the correspondences between non-terminal symbols.

Hiero extracts the synchronous CFG rules automatically from a word-aligned parallel corpus. One can treat a rule as a mapping, or as a translation. For instance, the above rule indicates that we will translate the phrase "每 月 到 $\mathrm{X}_{\boxed{1}}$" as "go to $\mathrm{X}_{\boxed{1}}$ every month to".

To translate a source sentence, the goal is to find its most probable derivation using the extracted grammar rules. For instance, assume that *c1 ... c9* in Figure 7.1 represents a Chinese source sentence with 9 words. To translate this source sentence, Hiero attempts to use the extracted grammar rules to find a suitable derivation that spans the sentence.

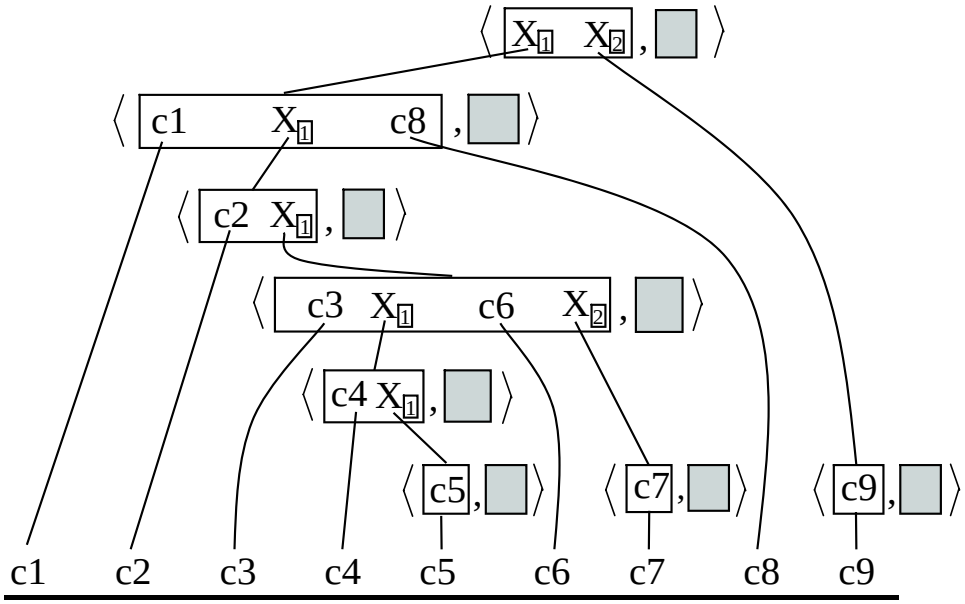


Figure 7.1: An example derivation which consists of 8 grammar rules. The source string of each rule is represented by the box before the comma, while the shaded boxes represent the target strings of the rules.

Hiero uses a general log-linear model (Och and Ney, 2002) where the weight of a derivation D for a particular source sentence and its translation is

$$w(D) = \prod_i \phi_i(D)^{\lambda_i} \tag{7.3}$$

where ϕ_i is a feature function and λ_i is the weight for feature ϕ_i. To ensure efficient decoding, the ϕ_i are subject to certain locality restrictions. Essentially, they should be defined as products of functions defined on isolated synchronous CFG rules. However, it is possible to extend the domain of locality of the features somewhat. For instance, an n-gram language model adds a dependence on $(n-1)$ neighboring target-side words (Wu, 1996; Chiang, 2007), making decoding much more difficult but still polynomial. In our work, we add features that depend on the neighboring *source-side* words,

which does not affect decoding complexity at all because the source string is fixed. In principle we could add features that depend on arbitrary source-side context.

7.1.1 New Features in Hiero for WSD

To incorporate WSD into Hiero, we use the translations proposed by the WSD system to help Hiero obtain a better or more probable derivation during the translation of each source sentence. To achieve this, when a grammar rule R is considered during decoding, and we recognize that some of the terminal symbols (words) in α are also chosen by the WSD system as translations for some terminal symbols (words) in γ, we compute the following features:

- $P_{wsd}(t \mid s)$ gives the contextual probability of the WSD classifier choosing t as a translation for s, where t (s) is some substring of terminal symbols in α (γ). Because this probability only applies to some rules, and we don't want to penalize those rules, we must add another feature,

- $Pty_{wsd} = \exp(-|t|)$, where t is the translation chosen by the WSD system. This feature, with a negative weight, rewards rules that use translations suggested by the WSD module.

Note that we can take the negative logarithm of the rule/derivation weights and think of them as costs rather than probabilities. If we do this, then to translate a source sentence, our goal will be to find the derivation with the least cost. To illustrate, consider Figure 7.1. The cost of a derivation depends on the rules that make up the derivation. The cost of a rule, in turn, consists of the costs contributed by features defined on the rule. Hence to translate a source sentence, Hiero tries different rules to find the derivation with the least cost. Now, assume that Hiero

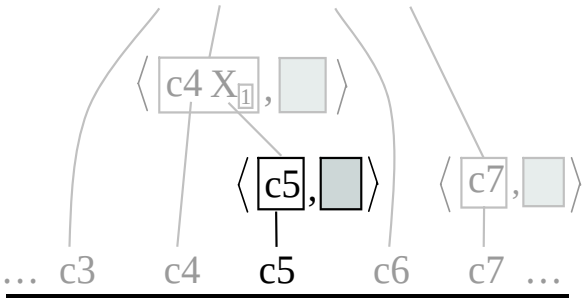


Figure 7.2: We perform WSD on the source string "c5", using the derived context dependent probability to change the original cost of the grammar rule.

has determined that for the source sentence *c1 ... c9*, the derivation in Figure 7.1 is the one with the least cost. Since each rule represents rewriting its source string as its target string, the target strings of the rule (represented by the shaded boxes) actually give the translation of the source sentence *c1 ... c9*. This means that once a particular grammar rule is used as part of the best derivation, its target string will be part of the translated output. This ties in to the *main idea* of how we use WSD to improve Hiero's translation.

To illustrate further, Figure 7.2 highlights the grammar rule with the source string "c5". This rule is part of the derivation shown in Figure 7.1. When the grammar rule is included as part of the derivation, the source string "c5" will be translated into the rule's target string, represented by the shaded box. We want to know whether our WSD system supports this translation. Hence we perform WSD on the source string "c5", given its surrounding context, to determine what is the context dependent probability of the source string "c5" translating into the target string represented by the shaded box. This information is used to change the original cost of this grammar rule, and this is done for every rule. Hence, we use the WSD system to change the costs of the grammar rules, where the change in costs is dependent upon the contextual probability of the rule's source string translating into its target string. We

hope this will help Hiero obtain a more informed derivation and thus produce a better translation.

7.2 Gathering Training Examples for WSD

Our experiments were for Chinese to English translation. Hence, in the context of our work, a synchronous CFG grammar rule X $\rightarrow \langle \gamma, \alpha \rangle$ gathered by Hiero consists of a Chinese portion γ and a corresponding English portion α, where each portion is a sequence of words and non-terminal symbols.

Our WSD classifier suggests a list of English phrases (where each phrase consists of one or more English words) with associated contextual probabilities as possible translations for each particular Chinese phrase. In general, the Chinese phrase may consist of k Chinese words, where $k = 1, 2, 3, \ldots$. However, we limit k to 1 or 2 for experiments reported here. Future work can explore enlarging k.

Whenever Hiero is about to extract a grammar rule where its Chinese portion is a phrase of one or two Chinese words with no non-terminal symbols, we note the location (sentence and token offset) in the Chinese half of the parallel corpus from which the Chinese portion of the rule is extracted. The actual sentence in the corpus containing the Chinese phrase, and the one sentence before and the one sentence after that actual sentence, will serve as the context for one training example for the Chinese phrase, with the corresponding English phrase of the grammar rule as its translation, or "sense class". Hence, unlike traditional WSD where the sense classes are tied to a specific sense inventory, our "senses" here consist of the target strings of grammar rules, which in the context of our work are English phrases extracted as translations for each Chinese phrase. This is similar to the multilingual lexical sample

task of SENSEVAL-3 (Chklovski et al., 2004) and Task 11 (English lexical sample task via English-Chinese parallel text) of SemEval-2007, where sense distinctions are decided by the use of different translations in the target language. Since the extracted training data may be noisy, for each Chinese phrase, we remove English translations that occur only once. Furthermore, we only attempt WSD classification for those Chinese phrases with at least 10 training examples.

Using the WSD classifier described in Section 3.2.2, which uses the LIBSVM implementation of SVM as its learning algorithm, we classified the words in each Chinese source sentence to be translated. We first performed POS-tagging on the Chinese texts using the tagger of (Ng and Low, 2004). Then, we performed WSD on all single Chinese words which are tagged as either noun, verb, or adjective. Next, we classified the Chinese phrases consisting of 2 consecutive Chinese words by simply treating the phrase as *a single unit*. When performing classification, we give as output the set of English translations with associated context-dependent probabilities, which are the probabilities of a Chinese word (phrase) translating into each English phrase, depending on the context of the Chinese word (phrase). After WSD, the ith word c_i in every Chinese sentence may have up to 3 sets of associated translations provided by the WSD system: a set of translations for c_i as a single word, a second set of translations for $c_{i-1}c_i$ considered as a single unit, and a third set of translations for c_ic_{i+1} considered as a single unit.

7.3 Incorporating WSD during Decoding

The following tasks are performed for each rule that is considered during decoding:

- identify Chinese words to suggest translations for

Input: rule R considered during decoding with its own associated $cost_R$
L_c = list of symbols in Chinese portion of R
WSDcost = 0
i = 1
while i $\leq$ len(L_c):
    c_i = ith symbol in L_c
    if c_i is a Chinese word (i.e., not a non-terminal symbol):
        // seenChunk is a global variable and is passed by reference to matchWSD
        seenChunk = $\emptyset$
        if (c_i is not the last symbol in L_c) and (c_{i+1} is a terminal symbol):
            then c_{i+1}=(i+1)th symbol in L_c, else c_{i+1} = NULL
        if (c_{i+1}!=NULL) and (c_i, c_{i+1}) as a *single unit* has WSD translations:
            WSD_c = set of WSD translations for (c_i,c_{i+1}) as a single unit
                    with context-dependent probabilities
            WSDcost = WSDcost + matchWSD(c_i, WSD_c, seenChunk)
            WSDcost = WSDcost + matchWSD(c_{i+1}, WSD_c, seenChunk)
            i = i + 1
        else:
            WSD_c = set of WSD translations for c_i with context-dependent probabilities
            WSDcost = WSDcost + matchWSD(c_i, WSD_c, seenChunk)
    i = i + 1
$cost_R$ = $cost_R$ + WSDcost

matchWSD(c, WSD_c, seenChunk):
    // seenChunk is the set of chunks of R already examined for possible matching WSD translations
    cost = 0
    ChunkSet = set of chunks in R aligned to c
    for $chunk_j$ in ChunkSet:
        if $chunk_j$ not in seenChunk:
            seenChunk = seenChunk $\cup$ { $chunk_j$ }
            E_{chunk_j} = set of English words in $chunk_j$ aligned to c
            $Candidate_{wsd}$ = $\emptyset$
            for wsd_k in WSD_c:
                if (wsd_k is sub-sequence of $chunk_j$) and (wsd_k contains at least one word in E_{chunk_j}):
                    $Candidate_{wsd}$ = $Candidate_{wsd}$ $\cup$ { wsd_k }
            wsd_{best} = *best matching* translation in $Candidate_{wsd}$ against $chunk_j$
            // costByWSDfeatures sums up the cost of the two WSD features
            cost = cost + costByWSDfeatures(wsd_{best})
    return cost

Figure 7.3: WSD translations affecting the cost of a rule R considered during decoding.

- match suggested translations against the English side of the rule
- compute features for the rule

The WSD system is able to predict translations only for a subset of Chinese words or phrases. Hence, we must first identify which parts of the Chinese side of the rule have suggested translations available. Here, we consider substrings of length up to two, and we give priority to longer substrings.

Next, we want to know, for each Chinese substring considered, whether the WSD system supports the Chinese-English translation represented by the rule. If the rule is finally chosen as part of the best derivation for translating the Chinese sentence, then all the words in the English side of the rule will appear in the translated English sentence. Hence, we need to match the translations suggested by the WSD system against the English side of the rule. It is for these matching rules that the WSD features will apply.

The translations proposed by the WSD system may be more than one word long. In order for a proposed translation to match the rule, we require two conditions. First, the proposed translation must be a substring of the English side of the rule. For example, the proposed translation "every to" would not match the string "every month to". Second, the match must contain at least one aligned Chinese-English word pair, but we do not make any other requirements about the alignment of the other Chinese or English words.[1] If there are multiple possible matches, we choose the longest proposed translation; in the case of a tie, we choose the proposed translation with the highest score according to the WSD model.

[1]In order to check this requirement, we extended Hiero to make word alignment information available to the decoder.

Define a *chunk* of a rule to be a maximal substring of terminal symbols on the English side of the rule. For instance, in Rule (7.2), the chunks would be "go to" and "every month to". Whenever we find a matching WSD translation, we mark the whole chunk on the English side as consumed.

Finally, we compute the feature values for the rule. The feature $P_{wsd}(t \mid s)$ is the sum of the costs (according to the WSD model) of all the matched translations, and the feature Pty_{wsd} is the sum of the lengths of all the matched translations.

Figure 7.3 shows the pseudocode for the rule scoring algorithm in more detail, particularly with regards to resolving conflicts between overlapping matches. To illustrate the algorithm given in Figure 7.3, consider Rule (7.2). Hereafter, we will use symbols to represent the Chinese and English words in the rule: c_1, c_2, and c_3 will represent the Chinese words "每", "月", and "到" respectively. Similarly, e_1, e_2, e_3, e_4, and e_5 will represent the English words *go*, *to*, *every*, *month*, and *to* respectively. Hence, Rule (7.2) has two chunks: e_1e_2 and $e_3e_4e_5$. When the rule is extracted from the parallel corpus, it has these alignments between the words of its Chinese and English portion: $\{c_1$–e_3, c_2–e_4, c_3–e_1, c_3–e_2, c_3–$e_5\}$, which means that c_1 is aligned to e_3, c_2 is aligned to e_4, and c_3 is aligned to e_1, e_2, and e_5. Although all words are aligned here, in general for a rule, some of its Chinese or English words may not be associated with any alignments.

In our experiment, c_1c_2 as a phrase has a list of translations proposed by the WSD system, including the English phrase "every month". *matchWSD* will first be invoked for c_1, which is aligned to only one chunk $e_3e_4e_5$ via its alignment with e_3. Since "every month" is a sub-sequence of the chunk and also contains the word e_3 ("every"), it is noted as a candidate translation. Later, it is determined that the most number of words any candidate translation has is two words. Since among

all the 2-word candidate translations, the translation "every month" has the highest translation probability as assigned by the WSD classifier, it is chosen as the best matching translation for the chunk. *matchWSD* is then invoked for c_2, which is aligned to only one chunk $e_3e_4e_5$. However, since this chunk has already been examined by c_1 with which it is considered as a phrase, no further matching is done for c_2. Next, *matchWSD* is invoked for c_3, which is aligned to both chunks of R. The English phrases "go to" and "to" are among the list of translations proposed by the WSD system for c_3, and they are eventually chosen as the best matching translations for the chunks e_1e_2 and $e_3e_4e_5$, respectively.

7.4 Experiments

As mentioned, our experiments were on Chinese to English translation. Similar to (Chiang, 2005), we trained the Hiero system on the FBIS corpus, used the NIST MT 2002 evaluation test set as our development set to tune the feature weights, and the NIST MT 2003 evaluation test set as our test data. Using the English portion of the FBIS corpus and the Xinhua portion of the Gigaword corpus, we trained a trigram language model using the SRI Language Modelling Toolkit (Stolcke, 2002). Following (Chiang, 2005), we used the version 11a NIST BLEU script with its default settings to calculate the BLEU scores (Papineni et al., 2002) based on case-insensitive n-gram matching, where n is up to 4.

First, we performed word alignment on the FBIS parallel corpus using GIZA++ (Och and Ney, 2000) in both directions. The word alignments of both directions are then combined into a single set of alignments using the "diag-and" method of (Koehn, 2003). Based on these alignments, synchronous CFG rules are then extracted from

System	BLEU-4	Individual n-gram precisions			
		1	2	3	4
Hiero	29.73	74.73	40.14	21.83	11.93
Hiero+WSD	30.30	74.82	40.40	22.45	12.42

Table 7.1: BLEU scores

	Systems	
Features	Hiero	Hiero+WSD
$P_{lm}(e)$	0.2337	0.1937
$P(\gamma\|\alpha)$	0.0882	0.0770
$P(\alpha\|\gamma)$	0.1666	0.1124
$P_w(\gamma\|\alpha)$	0.0393	0.0487
$P_w(\alpha\|\gamma)$	0.1357	0.0380
Pty_{phr}	0.0665	0.0988
$Glue$	-0.0582	-0.0305
Pty_{word}	-0.4806	-0.1747
$P_{wsd}(t\|s)$	-	0.1051
Pty_{wsd}	-	-0.1611

Table 7.2: Weights for each feature obtained by MERT training. The first eight features are those used by Hiero in Chiang (2005).

the corpus. While Hiero is extracting grammar rules, we gathered WSD training data by following the procedure described in section 7.2.

7.4.1 Hiero Results

Using the MT 2002 test set, we ran the minimum-error rate training (MERT) (Och, 2003) with the decoder to tune the weights for each feature. The weights obtained are shown in the column *Hiero* of Table 7.2. Using these weights, we run Hiero's decoder to perform the actual translation of the MT 2003 test sentences and obtained a BLEU score of 29.73, as shown in the row *Hiero* of Table 7.1. This is higher than the score of 28.77 reported in (Chiang, 2005), perhaps due to differences in word segmentation, etc. Note that comparing with the MT systems used in (Carpuat and Wu, 2005),

(Carpuat and Wu, 2007), and (Cabezas and Resnik, 2005), the Hiero system we are using represents a much stronger baseline MT system upon which the WSD system must improve.

7.4.2 Hiero+WSD Results

We then added the WSD features of Section 7.1.1 into Hiero and reran the experiment. The weights obtained by MERT are shown in the column *Hiero+WSD* of Table 7.2. We note that a negative weight is learnt for Pty_{wsd}. This means that in general, the model prefers grammar rules having chunks that matches WSD translations. This matches our intuition. Using the weights obtained, we translated the test sentences and obtained a BLEU score of **30.30**, as shown in the row *Hiero+WSD* of Table 7.1. The improvement of 0.57 is statistically significant at $p < 0.05$ using the sign-test as described by Collins, Koehn, and Kucerova (2005), with 374 (+1), 318 (−1) and 227 (0). Using the bootstrap-sampling test described in (Koehn, 2004b), the improvement is statistically significant at $p < 0.05$. Although the improvement is modest, it is statistically significant and this positive result is important in view of the negative findings in (Carpuat and Wu, 2005) that WSD does not help MT. Furthermore, note that Hiero+WSD has higher n-gram precisions than Hiero.

7.5 Analysis

Ideally, the WSD system should be suggesting high-quality translations which are frequently part of the reference sentences. To determine this, we note the set of grammar rules used in the best derivation for translating each test sentence. From the rules of each test sentence, we tabulated the set of translations proposed by the

No. of words in WSD translations	All test sentences		+1 from Collins sign-test	
	No. of WSD translations used	% match reference	No. of WSD translations used	% match reference
1	7087	77.31	3078	77.68
2	1930	66.11	861	64.92
3	371	43.13	171	48.54
4	124	26.61	52	28.85

Table 7.3: Number of WSD translations used and proportion that matches against respective reference sentences. WSD translations longer than 4 words are very sparse (less than 10 occurrences) and thus they are not shown.

WSD system and check whether they are found in the associated reference sentences.

On the entire set of NIST MT 2003 evaluation test sentences, an average of 10.36 translations proposed by the WSD system were used for each sentence. When limited to the set of 374 sentences which were judged by the Collins sign-test to have better translations from Hiero+WSD than from Hiero, a higher number (11.14) of proposed translations were used on average. Further, for the entire set of test sentences, 73.01% of the proposed translations are found in the reference sentences. This increased to a proportion of 73.22% when limited to the set of 374 sentences. These figures show that having more, and higher-quality proposed translations contributed to the set of 374 sentences being better translations than their respective original translations from Hiero. Table 7.3 gives a detailed breakdown of these figures according to the number of words in each proposed translation. For instance, over all the test sentences, the WSD module gave 7087 translations of single-word length, and 77.31% of these translations match their respective reference sentences. We note that although the proportion of matching 2-word translations is slightly lower for the set of 374 sentences, the proportion increases for translations having more words.

After the experiments in Section 7.4 were completed, we visually inspected the

translation output of Hiero and Hiero+WSD to categorize the ways in which integrating WSD contributes to better translations. The first way in which WSD helps is when it enables the integrated Hiero+WSD system to output extra appropriate English words. For example, the translations for the Chinese sentence "...或 其他 「 恶劣 行为 」 ， 将 无法 取得 更 多 援助 或 其他 让步 。" are as follows.

- Hiero: *... or other bad behavior ", will be more aid and other concessions.*
- Hiero+WSD: *... or other bad behavior ", will be unable to obtain more aid and other concessions.*

Here, the Chinese words "无法 取得" are not translated by Hiero at all. By providing the correct translation of "*unable to obtain*" for "无法 取得", the translation output of Hiero+WSD is more complete.

A second way in which WSD helps is by correcting a previously incorrect translation. For example, for the Chinese sentence "... ， 在 全 国 各 族 人民 ， ...", the WSD system helps to correct Hiero's original translation by providing the correct translation of "*all ethnic groups*" for the Chinese phrase "各 族":

- Hiero: *..., and people of all nationalities across the country, ...*
- Hiero+WSD: *..., and people of all ethnic groups across the country, ...*

We also looked at the set of 318 sentences that were judged by the Collins sign-test to be worse translations. We found that in some situations, Hiero+WSD has provided extra appropriate English words, but those particular words are not used in the reference sentences. An interesting example is the translation of the Chinese sentence "澳洲 外长 指 北韩 行为 恶劣 将 无法 取得 更 多 援助".

- Hiero: *Australian foreign minister said that North Korea bad behavior will be more aid*
- Hiero+WSD: *Australian foreign minister said that North Korea bad behavior will be unable to obtain more aid*

This is similar to the example mentioned earlier. In this case however, those extra English words provided by Hiero+WSD, though appropriate, do not result in more *n*-gram matches as the reference sentences used phrases such as "*will not gain*", "*will not get*", etc. Since the BLEU metric is precision based, the longer sentence translation by Hiero+WSD gets a lower BLEU score instead.

Our work gives evidence that to successfully integrate WSD into NLP applications, it is important to properly tailor the method of integration according to the particular NLP application. In particular, due consideration has to be given to the definition of the sense inventory. For instance, we feel that a contributing factor to the success of our work in (Chan, Ng, and Chiang, 2007) when prior work such as (Carpuat and Wu, 2005) reported that WSD decreases MT performance, is that unlike traditional WSD where the sense classes are tied to a specific sense inventory, we define our "senses" as strings in the target language. More recently, Agirre et al. (2008) used sense information to substitute words with their semantic classes. For instance, word sense information could help to determine whether an occurrence of the word *crane* should be substituted with the semantic class of ANIMAL or ARTIFACT. They showed that this process helps in generalizing the information learnt and thus improves parsing performance. Overall, while the sense inventory may change depending on the specific NLP application, the *same* WSD algorithm still applies to select the correct sense or semantic class in the application.

7.6 Summary

We have shown that WSD improves the translation performance of a state-of-the-art hierarchical phrase-based statistical MT system and this improvement is statistically significant. We have also demonstrated one way to integrate a WSD system into an MT system. For future work, an immediate step would be for the WSD classifier to provide translations for longer Chinese phrases. Also, different alternatives could be tried to match the translations provided by the WSD classifier against the chunks of rules. Finally, besides our proposed approach of integrating WSD into statistical MT via the introduction of two new features, we could explore other alternative ways of integration.

Chapter 8

Conclusion

As mentioned at the start of this thesis, we are interested in exploring three important issues of WSD research: tackling the data acquisition bottleneck for WSD, domain adaptation of WSD systems, and whether WSD can help to improve MT performance.

With regards to the first issue, we have shown that the approach of gathering training examples from parallel texts is promising. When we evaluate WSD systems trained on parallel text examples on the test data of SENSEVAL-2 and SENSEVAL-3 English all-words task, we always outperform the strategy of choosing the first sense of WordNet. Note that, as mentioned in Chapter 1, this is a baseline strategy that few participating systems could beat (moreover, these systems rely on manually annotated examples for training). On both sets of test data, we show that adding parallel text examples can help to further improve the performance of classifiers trained on the manually annotated examples of SemCor and DSO. We also participated in the coarse-grained English all-words task and fine-grained English all-words task of the recent SemEval-2007 evaluation exercise. Using training examples gathered from parallel texts, SemCor, and the DSO corpus, we trained supervised WSD systems. Evaluation

results show that this approach achieves good performance in both tasks.

With regards to the issue of domain adaptation, we have highlighted that differences in sense priors between training and target domain data result in a loss of WSD accuracy. By using an EM-based algorithm, we estimate the sense priors in the target domain. In estimating these sense priors, we show that it is important to use well calibrated probabilities, such as those obtained from logistic regression. We have also explored another complementary approach to domain adaptation of WSD systems, by adding examples from the new domain as additional training data to a WSD system. Besides showing that active learning is effective in reducing the annotation effort required, we use the predominant sense information predicted by the EM-based algorithm, and incorporate a count-merging technique. With these enhancements, we improve the effectiveness of the original adaptation process achieved by the basic active learning approach.

Finally, we show how we integrate a WSD system into the state-of-the-art hierarchical phrase-based statistical MT system, Hiero. Through our experiments, we show that WSD improves the translation performance of Hiero and that this improvement is statistically significant.

8.1 Future Work

In the following sub-sections, we outline some potential future work.

8.1.1 Acquiring Examples from Parallel Texts for All English Words

We have shown that our approach of gathering examples from parallel texts is promising. So far, however, we have only gathered parallel text examples for a set of frequently occurring words. A future direction would be to extend the approach to all the content words of English. To achieve this, the process of assigning Chinese translations to the senses of words has to be automated as much as possible. A potential solution for this will be to make use of some suitable English-Chinese lexicon that includes Chinese translations of WordNet word senses.

8.1.2 Word Sense Disambiguation for Machine Translation

In existing statistical phrase-based MT systems such as Hiero and Pharaoh, translation probabilities are calculated from an aligned parallel corpus during training. In particular, each source-target phrase pair s and t will be associated with a single translation probability. These probabilities are context independent in that once a probability is calculated for a pair of phrases s and t, the same probability will be used in every occurrence of translating s to t. Instead of the approach taken in our work where we introduce two features for WSD into the MT model of Hiero, we could instead replace these phrase translation probabilities with context-sensitive probabilities. This is similar to the approach in (Carpuat and Wu, 2007) where the authors attempted to incorporate WSD into the Pharaoh MT system by dynamically changing the phrase translation lexicon of Pharaoh, according to each source sentence to be translated.

Another potential direction is to investigate whether BLEU is an appropriate

evaluation metric for our current research. In scoring translation output, BLEU rewards systems that produce the correct words in the correct word order. However, the aim of incorporating WSD into MT is on producing more semantically meaningful translations. Thus, human judgment might be better suited for evaluation of our current work. For instance, in a related work (Callison-Burch, Osborne, and Koehn, 2006), the authors conclude that while BLEU is appropriate for tracking incremental changes to a single system, or for comparing performance across systems employing similar translation strategies (such as phrase-based versus phrase-based statistical MT), BLEU does not always correlate well with human judgments.

References

Agirre, Eneko, Timothy Baldwin, and David Martinez. 2008. Improving parsing and PP attachment performance with sense information. In *Proceedings of ACL08:HLT*, pages 317–325, Columbus, Ohio.

Agirre, Eneko, Bernardo Magnini, Oier Lopez de Lacalle, Arantxa Otegi, German Rigau, and Piek Vossen. 2007. SemEval-2007 task 01: Evaluating WSD on cross-language information retrieval. In *Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007)*, pages 1–6, Prague, Czech Republic.

Agirre, Eneko, Lluís Márquez, and Richard Wicentowski. 2007. *Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007)*. Association for Computational Linguistics, Prague, Czech Republic.

Agirre, Eneko and David Martinez. 2004. Unsupervised WSD based on automatically retrieved examples: The importance of bias. In *Proceedings of EMNLP04*, pages 25–32, Barcelona, Spain.

Atkins, Sue. 1992. Tools for computer-aided corpus lexicography: the Hector project. In *Papers in Computational Lexicography: Complex 92*, pages 1–60, Budapest, Hungary.

Ayer, Miriam, H. D. Brunk, G. M. Ewing, W. T. Reid, and Edward Silverman. 1955. An empirical distribution function for sampling with incomplete information. *Annals of Mathematical Statistics*, 26(4):641–647.

Bacchiani, Michiel and Brian Roark. 2003. Unsupervised language model adaptation.

In *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, pages 224–227.

Bhattacharya, Indrajit, Lise Getoor, and Yoshua Bengio. 2004. Unsupervised sense disambiguation using bilingual probabilistic models. In *Proceedings of ACL04*, pages 287–294, Barcelona, Spain.

Black, Ezra. 1988. An experiment in computational discrimination of English word senses. *IBM Journal of Research and Development*, 32(2):185–194.

Brown, Peter F., Stephen A. Della Pietra, Vincent J. Della Pietra, and Robert L. Mercer. 1991. Word-sense disambiguation using statistical methods. In *Proceedings of ACL91*, pages 264–270, Berkeley, California, USA.

Bruce, Rebecca and Janyce Wiebe. 1994. Word-sense disambiguation using decomposable models. In *Proceedings of ACL94*, pages 139–146, New Mexico, USA.

Cabezas, Clara and Philip Resnik. 2005. Using WSD techniques for lexical selection in statistical machine translation. Technical report, University of Maryland.

Callison-Burch, Chris, Miles Osborne, and Philipp Koehn. 2006. Re-evaluating the role of BLEU in machine translation research. In *Proceedings of EACL06*, pages 249–256, Trento, Italy.

Carpuat, Marine, Weifeng Su, and Dekai Wu. 2004. Augmenting ensemble classification for word sense disambiguation with a kernel PCA model. In *Proceedings of SENSEVAL-3*, pages 88–92, Barcelona, Spain.

Carpuat, Marine and Dekai Wu. 2005. Word sense disambiguation vs. statistical machine translation. In *Proceedings of ACL05*, pages 387–394, Ann Arbor, USA.

Carpuat, Marine and Dekai Wu. 2007. Improving statistical machine translation using word sense disambiguation. In *Proceedings of EMNLP-CoNLL07*, pages 61–72, Prague, Czech Republic.

Chan, Yee Seng and Hwee Tou Ng. 2005a. Scaling up word sense disambiguation via parallel texts. In *Proceedings of AAAI05*, pages 1037–1042, Pittsburgh, Pennsylvania, USA.

Chan, Yee Seng and Hwee Tou Ng. 2005b. Word sense disambiguation with distribution estimation. In *Proceedings of IJCAI05*, pages 1010–1015, Edinburgh, Scotland.

Chan, Yee Seng and Hwee Tou Ng. 2006. Estimating class priors in domain adaptation for word sense disambiguation. In *Proceedings of COLING/ACL06*, pages 89–96, Sydney, Australia.

Chan, Yee Seng and Hwee Tou Ng. 2007. Domain adaptation with active learning for word sense disambiguation. In *Proceedings of ACL07*, pages 49–56, Prague, Czech Republic.

Chan, Yee Seng, Hwee Tou Ng, and David Chiang. 2007. Word sense disambiguation improves statistical machine translation. In *Proceedings of ACL07*, pages 33–40, Prague, Czech Republic.

Chan, Yee Seng, Hwee Tou Ng, and Zhi Zhong. 2007. NUS-PT: Exploiting parallel texts for word sense disambiguation in the English all-words tasks. In *Proceedings of the 4th International Workshop on Semantic Evaluations (SemEval-2007)*, pages 253–256, Prague, Czech Republic.

Chang, Chih-Chung and Chih-Jen Lin, 2001. *LIBSVM: a library for support vector machines*. Software available at http://www.csie.ntu.edu.tw/ cjlin/libsvm.

Chen, Jinying, Andrew Schein, Lyle Ungar, and Martha Palmer. 2006. An empirical study of the behavior of active learning for word sense disambiguation. In *Proceedings of HLT/NAACL06*, pages 120–127, New York, USA.

Chiang, David. 2005. A hierarchical phrase-based model for statistical machine translation. In *Proceedings of ACL05*, pages 263–270, Ann Arbor, USA.

Chiang, David. 2007. Hierarchical phrase-based translation. *Computational Linguistics*, 33(2):201–228.

Chklovski, Timothy and Rada Mihalcea. 2002. Building a sense tagged corpus with Open Mind Word Expert. In *Proceedings of ACL02 Workshop on Word Sense Disambiguation: Recent Successes and Future Directions*, pages 116–122, Philadelphia, Pennsylvania, USA.

Chklovski, Timothy, Rada Mihalcea, Ted Pedersen, and Amruta Purandare. 2004. The Senseval-3 multilingual English-Hindi lexical sample task. In *Senseval-3: Third International Workshop on the Evaluation of Systems for the Semantic Analysis of Text*, pages 5–8, Barcelona, Spain.

Chugur, Irina, Julio Gonzalo, and Felisa Verdejo. 2002. Polysemy and sense proximity in the SENSEVAL-2 test suite. In *Proceedings of ACL SIGLEX Workshop on Word Sense Disambiguation: Recent Successes and Future Directions*, pages 32–39, Philadelphia, USA.

Collins, Michael, Philipp Koehn, and Ivona Kucerova. 2005. Clause restructuring

for statistical machine translation. In *Proceedings of ACL05*, pages 531–540, Ann Arbor, USA.

Crestan, Eric, Marc El-Beze, and Claude De Loupy. 2001. Improving WSD with multi-level view of context monitored by similarity measure. In *Proceedings of SENSEVAL-2*, pages 67–70, Toulouse, France.

Daelemans, Walter, Antal van den Bosch, and Jakub Zavrel. 1999. Forgetting exceptions is harmful in language learning. *Machine Learning*, 34(1–3):11–41.

Dagan, Ido and Alon Itai. 1994. Word sense disambiguation using a second language monolingual corpus. *Computational Linguistics*, 20(4):563–596.

Dang, Hoa Trang. 2004. *Investigations into the Role of Lexical Semantics in Word Sense Disambiguation*. PhD dissertation, University of Pennsylvania.

Daude, Jordi, Lluis Padro, and German Rigau. 2000. Mapping WordNets using structural information. In *Proceedings of ACL 2000*, pages 504–511, Hong Kong.

Decadt, Bart, Veronique Hoste, and Walter Daelemans. 2004. GAMBL, genetic algorithm optimization of memory-based WSD. In *Proceedings of SENSEVAL-3*, pages 108–112, Barcelona, Spain.

Diab, Mona. 2004. Relieving the data acquisition bottleneck in word sense disambiguation. In *Proceedings of ACL04*, pages 303–310, Barcelona, Spain.

Diab, Mona and Philip Resnik. 2002. An unsupervised method for word sense tagging using parallel corpora. In *Proceedings of ACL02*, pages 255–262, Philadelphia, Pennsylvania, USA.

Domingos, Pedro and Michael Pazzani. 1996. Beyond independence: Conditions for the optimality of the simple Bayesian classifier. In *Proceedings of ICML96*, pages 105–112, Bari, Italy.

Dong, Zhendong. 2000. HowNet. http://www.keenage.com.

Duda, Richard O. and Peter E. Hart. 1973. *Pattern Classification and Scene Analysis*. Wiley, New York.

Edmonds, Philip and Scott Cotton. 2001. SENSEVAL-2: Overview. In *Proceedings of SENSEVAL-2*, pages 1–5, Toulouse, France.

Efron, Bradley and Robert J. Tibshirani. 1993. *An Introduction to the Bootstrap*. Chapman & Hall, New York.

Escudero, Gerard, Lluis Marquez, and German Rigau. 2000. An empirical study of the domain dependence of supervised word sense disambiguation systems. In *Proceedings of EMNLP/VLC'00*, pages 172–180, Hong Kong.

Fujii, Atsushi, Kentaro Inui, Takenobu Tokunaga, and Hozumi Tanaka. 1998. Selective sampling for example-based word sense disambiguation. *Computational Linguistics*, 24(4):573–597.

Gale, William A., Kenneth W. Church, and David Yarowsky. 1992. A method for disambiguating word senses in a large corpus. *Computers and the Humanities*, 26(5–6):415–439.

Germann, Ulrich. 2003. Greedy decoding for statistical machine translation in almost linear time. In *Proceedings of HLT-NAACL03*, pages 72–79, Edmonton, Canada.

Hakkani-Tür, Dilek, Gokhan Tur, Mazin Rahim, and Giuseppe Riccardi. 2004. Unsupervised and active learning in automatic speech recognition for call classification. In *Proceedings of IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, pages 429–432, Montreal, Canada.

Hearst, Marti A. 1991. Noun homograph disambiguation using local context in large text corpora. In *Proceedings of the 7th Annual Conference of the University of Waterloo Centre for the New OED and Text Research*, pages 1–22, Oxford, UK.

Hoste, Véronique, Walter Daelemans, I. Hendrickx, and Antal van den Bosch. 2002. Evaluating the results of a memory-based word-expert approach to unrestricted word sense disambiguation. In *Proceedings of the Workshop on Word Sense Disambiguation: Recent Successes and Future Directions*, pages 95–101, Philadelphia, PA, USA.

Hoste, Véronique, Anne Kool, and Walter Daelemans. 2001. Classifier optimization and combination in the English all words task. In *Proceedings of SENSEVAL-2*, pages 83–86, Toulouse, France.

Hovy, Eduard, Mitchell Marcus, Martha Palmer, Lance Ramshaw, and Ralph Weischedel. 2006. Ontonotes: The 90% solution. In *Proceedings of the HLT-NAACL06*, New York, USA.

Ide, Nancy, Tomaz Erjavec, and Dan Tufis. 2002. Sense discrimination with parallel corpora. In *Proceedings of ACL SIGLEX Workshop on Word Sense Disambiguation: Recent Successes and Future Directions*, pages 54–60, Philadelphia, USA.

Kilgarriff, Adam. 1998. SENSEVAL: An exercise in evaluating word sense disambiguation programs. In *Proceedings of First International Conference on Language Resources and Evaluation (LREC)*, pages 581–588, Granada.

Kilgarriff, Adam. 2001. English lexical sample task description. In *Proceedings of SENSEVAL-2*, pages 17–20, Toulouse, France.

Koehn, Philipp. 2003. *Noun Phrase Translation.* Ph.D. thesis, University of Southern California.

Koehn, Philipp. 2004a. Pharaoh: A beam search decoder for phrase-based statistical machine translation models. In *Proceedings of the 6th Conference of the Association for Machine Translation in the Americas (AMTA04)*, pages 115–124, Washington D.C., USA.

Koehn, Philipp. 2004b. Statistical significance tests for machine translation evaluation. In *Proceedings of EMNLP04*, pages 388–395, Barcelona, Spain.

Koehn, Philipp, F. J. Och, and D. Marcu. 2003. Statistical phrase-based translation. In *Proceedings of HLT-NAACL03*, pages 48–54, Edmonton, Canada.

Koeling, Rob, Diana McCarthy, and John Carroll. 2005. Domain-specific sense distributions and predominant sense acquisition. In *Proceedings of Joint HLT-EMNLP05*, pages 419–426, Vancouver, British Columbia, Canada.

Kohomban, Upali Sathyajith and Wee Sun Lee. 2005. Learning semantic classes for word sense disambiguation. In *Proceedings of ACL05*, pages 34–41, Ann Arbor, Michigan.

Krovets, Robert and W. Bruce Croft. 1992. Lexical ambiguity and information retrieval. *ACM Transactions on Information Systems*, 10(2):115–141.

Kucera, Henri and Winthrop N. Francis. 1967. *Computational Analysis of Present-Day American English*. Brown University Press.

Leacock, Claudia, Geoffrey Towell, and Ellen Voorhees. 1993. Corpus-based statistical sense resolution. In *Proceedings of the ARPA Workshop on Human Language Technology*, pages 260–265.

Lee, Yoong Keok and Hwee Tou Ng. 2002. An empirical evaluation of knowledge sources and learning algorithms for word sense disambiguation. In *Proceedings of EMNLP02*, pages 41–48, Philadelphia, Pennsylvania, USA.

Lee, Yoong Keok, Hwee Tou Ng, and Tee Kiah Chia. 2004. Supervised word sense disambiguation with support vector machines and multiple knowledge sources. In *Proceedings of SENSEVAL-3*, pages 137–140, Barcelona, Spain.

Lewis, David D. and William A. Gale. 1994. A sequential algorithm for training text classifiers. In *Proceedings of SIGIR94*, pages 13–19, Dublin, Ireland.

Lewis, P. M. II and R. E. Stearns. 1968. Syntax-directed transduction. *Journal of the ACM*, 15(3):465–488.

Li, Cong and Hang Li. 2002. Word translation disambiguation using bilingual bootstrapping. In *Proceedings of ACL02*, pages 343–351, Philadelphia, USA.

Lin, Dekang. 1998. Automatic retrieval and clustering of similar words. In *Proceedings of COLING-ACL98*, pages 768–774, Montreal, Quebec, Canada.

Low, Jin Kiat, Hwee Tou Ng, and Wenyuan Guo. 2005. A maximum entropy approach to Chinese word segmentation. In *Proceedings of the Fourth SIGHAN Workshop on Chinese Language Processing*, pages 161–164, Jeju Island, Korea.

Magnini, Bernardo and Gabriela Cavaglià. 2000. Integrating subject field codes into WordNet. In *Proceedings of LREC-2000*, pages 1413–1418, Athens, Greece.

Marcu, Daniel and William Wong. 2002. A phrase-based, joint probability model for statistical machine translation. In *Proceedings of EMNLP02*, pages 133–139, Philadelphia, PA, USA.

Marcus, Mitchell P., Beatrice Santorini, and Mary Ann Marcinkiewicz. 1993. Building a large annotated corpus of english: the penn treebank. *Computational Linguistics*, 19(2):313–330.

Martinez, David and Eneko Agirre. 2000. One sense per collocation and genre/topic variations. In *Proceedings of EMNLP/VLC00*, pages 207–215, Hong Kong.

McCarthy, Diana, Rob Koeling, Julie Weeds, and John Carroll. 2004a. Automatic identification of infrequent word senses. In *Proceedings of COLING04*, pages 1220–1226, Geneva, Switzerland.

McCarthy, Diana, Rob Koeling, Julie Weeds, and John Carroll. 2004b. Finding predominant word senses in untagged text. In *Proceedings of ACL04*, pages 280–287, Barcelona, Spain.

Mihalcea, Rada. 2002a. Bootstrapping large sense tagged corpora. In *Proceedings of the 3rd International Conference on Languages Resources and Evaluation (LREC)*, pages 1407–1411, Canary Islands, Spain.

Mihalcea, Rada. 2002b. Word sense disambiguation using pattern learning and automatic feature selection. *Journal of Natural Language and Engineering*, 8(4):343–358.

Mihalcea, Rada, Timothy Chklovski, and Adam Kilgarriff. 2004. The SENSEVAL-3 English lexical sample task. In *Proceedings of SENSEVAL-3*, pages 25–28, Barcelona, Spain.

Mihalcea, Rada and Ehsanul Faruque. 2004. Senselearner: Minimally supervised word sense disambiguation for all words in open text. In *Proceedings of SENSEVAL-3*, pages 155–158, Barcelona, Spain.

Mihalcea, Rada and Dan Moldovan. 2001. Pattern learning and active feature selection for word sense disambiguation. In *Proceedings of SENSEVAL-2*, pages 127–130, Toulouse, France.

Miller, George A. 1990. WordNet: An on-line lexical database. *International Journal of Lexicography*, 3(4):235–312.

Miller, George A., Martin Chodorow, Shari Landes, Claudia Leacock, and Robert G. Thomas. 1994. Using a semantic concordance for sense identification. In *Proceedings of ARPA Human Language Technology Workshop*, pages 240–243, Plainsboro, New Jersey, USA.

Navigli, Roberto, Kenneth C. Litkowski, and Orin Hargraves. 2007. Semeval-2007 task 07: Coarse-grained English all-words task. In *Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007)*, pages 30–35, Prague, Czech Republic.

Navigli, Roberto and Paola Velardi. 2005. Structural semantic interconnections: A knowledge-based approach to word sense disambiguation. *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*, 27(7):1063–1074.

Ng, Andrew Y. and Michael I. Jordan. 2001. On discriminative vs. generative classifiers: A comparison of logistic regression and naive Bayes. In *Proceedings of NIPS01*, pages 605–610, Vancouver, British Columbia, Canada.

Ng, Hwee Tou. 1997a. Exemplar-based word sense disambiguation: Some recent improvements. In *Proceedings of EMNLP97*, pages 208–213, Providence, Rhode Island, USA.

Ng, Hwee Tou. 1997b. Getting serious about word sense disambiguation. In *Proceedings of the ACL SIGLEX Workshop on Tagging Text with Lexical Semantics: Why, What, and How?*, pages 1–7, Washington, D.C., USA. Invited paper.

Ng, Hwee Tou and Yee Seng Chan. 2007. Task 11: English lexical sample task via English-Chinese parallel text. In *Proceedings of the 4th International Workshop on Semantic Evaluations (SemEval-2007)*, pages 54–58, Prague, Czech Republic.

Ng, Hwee Tou and Hian Beng Lee. 1996. Integrating multiple knowledge sources to disambiguate word sense: An exemplar-based approach. In *Proceedings of ACL96*, pages 40–47, Santa Cruz, California, USA.

Ng, Hwee Tou and Jin Kiat Low. 2004. Chinese part-of-speech tagging: One-at-a-time or all-at-once? word-based or character-based? In *Proceedings of EMNLP04*, pages 277–284, Barcelona, Spain.

Ng, Hwee Tou, Bin Wang, and Yee Seng Chan. 2003. Exploiting parallel texts for

word sense disambiguation: An empirical study. In *Proceedings of ACL03*, pages 455–462, Sapporo, Japan.

Ng, Hwee Tou and John Zelle. 1997. Corpus-based approaches to semantic interpretation in natural language processing. *AI Magazine (Special Issue on Natural Language Processing)*, 18(4):45–64.

Niculescu-Mizil, Alexandru and Rich Caruana. 2005. Predicting good probabilities with supervised learning. In *Proceedings of ICML05*, pages 625–632, Bonn, Germany.

Och, Franz Josef. 2003. Minimum error rate training in statistical machine translation. In *Proceedings of ACL03*, pages 160–167, Sapporo, Japan.

Och, Franz Josef and Hermann Ney. 2000. Improved statistical alignment models. In *Proceedings of ACL 2000*, pages 440–447, Hong Kong.

Och, Franz Josef and Hermann Ney. 2002. Discriminative training and maximum entropy models for statistical machine translation. In *Proceedings of ACL02*, pages 295–302, Philadelphia, PA, USA.

Och, Franz Josef and Hermann Ney. 2004. The alignment template approach to statistical machine translation. *Computational Linguistics*, 30(4):417–449.

Palmer, Martha, Christiane Fellbaum, Scott Cotton, Lauren Delfs, and Hoa Trang Dang. 2001. English tasks: All-words and verb lexical sample. In *Proceedings of SENSEVAL-2*, pages 21–24, Toulouse, France.

Papineni, Kishore, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. BLEU: A

method for automatic evaluation of machine translation. In *Proceedings of ACL02*, pages 311–318, Philadelphia, PA, USA.

Pedersen, Ted, Siddharth Patwardhan, and Jason Michelizzi. 2004. WordNet::Similarity - measuring the relatedness of concepts. In *Proceedings of AAAI04, Intelligent Systems Demonstration*, pages 1024–1025, San Jose, CA.

Pradhan, Sameer, Edward Loper, Dmitriy Dligach, and Martha Palmer. 2007. Semeval-2007 task-17: English lexical sample, SRL and all words. In *Proceedings of the Fourth International Workshop on Semantic Evaluations (SemEval-2007)*, pages 87–92, Prague, Czech Republic.

Ratnaparkhi, Adwait. 1996. A maximum entropy model for part-of-speech tagging. In *Proceedings of EMNLP96*, pages 133–142.

Resnik, Philip and David Yarowsky. 1997. A perspective on word sense disambiguation methods and their evaluation. In *Proceedings of ACL97 SIGLEX Workshop on Tagging Text with Lexical Semantics: Why, What, and How?*, pages 79–86, Washington, D.C., USA.

Resnik, Philip and David Yarowsky. 2000. Distinguishing systems and distinguishing senses: New evaluation methods for word sense disambiguation. *Natural Language Engineering*, 5(2):113–133.

Reynar, Jeffrey C. and Adwait Ratnaparkhi. 1997. A maximum entropy approach to identifying sentence boundaries. In *Proceedings of the Fifth Conference on Applied Natural Language Processing*, pages 16–19, Washington, D.C., USA.

Roark, Brian and Michiel Bacchiani. 2003. Supervised and unsupervised PCFG

adaptation to novel domains. In *Proceedings of HLT-NAACL03*, pages 126–133, Edmonton, Canada.

Robertson, Tim, Farrol T. Wright, and Richard L. Dykstra. 1988. Chapter 1. Isotonic Regression. In *Order Restricted Statistical Inference*. John Wiley & Sons.

Saerens, Marco, Patrice Latinne, and Christine Decaestecker. 2002. Adjusting the outputs of a classifier to new a priori probabilities: A simple procedure. *Neural Computation*, 14(1):21–41.

Sanderson, Mark. 1994. Word sense disambiguation and information retrieval. In *Proceedings of SIGIR94*, pages 142–151, Dublin, Ireland.

Schütze, Hinrich and Jan Pedersen. 1995. Information retrieval based on word senses. In *Proceedings of the Fourth Annual Symposium on Document Analysis and Information Retrieval (SDAIR)*, pages 161–175, Las Vegas, Nevada.

Snyder, Benjamin and Martha Palmer. 2004. The English all-words task. In *Proceedings of SENSEVAL-3*, pages 41–43, Barcelona, Spain.

Stolcke, Andreas. 2002. SRILM - an extensible language modeling toolkit. In *Proceedings of the International Conference on Spoken Language Processing*, pages 901–904, Denver, CO.

Vapnik, Vladimir N. 1995. *The Nature of Statistical Learning Theory*. Springer-Verlag, New York.

Vickrey, David, Luke Biewald, Mark Teyssier, and Daphne Koller. 2005. Word-sense disambiguation for machine translation. In *Proceedings of HLT/EMNLP 2005*, pages 771–778, Vancouver, B.C., Canada.

Vucetic, Slobodan and Zoran Obradovic. 2001. Classification on data with biased class distribution. In *Proceedings of ECML01*, pages 527–538, Freiburg, Germany.

Weaver, Warren. 1955. Translation. In William N. Locke and A. Donald Booth, editors, *Machine Translation of Languages*. John Wiley & Sons, New York, pages 15–23. (Reprint of mimeographed version, 1949.).

Witten, Ian H. and Eibe Frank. 2000. *Data Mining: Practical Machine Learning Tools and Techniques with Java Implementations*. Morgan Kaufmann, San Francisco.

Wu, Dekai. 1996. A polynomial-time algorithm for statistical machine translation. In *Proceedings of ACL96*, pages 152–158, Santa Cruz, California, USA.

Yarowsky, David. 1995. Unsupervised word sense disambiguation rivaling supervised methods. In *Proceedings of ACL95*, pages 189–196, Cambridge, Massachusetts, USA.

Yuret, Deniz. 2004. Some experiments with a naive Bayes WSD system. In *Proceedings of SENSEVAL-3*, pages 265–268, Barcelona, Spain.

Zadrozny, Bianca and Charles Elkan. 2002. Transforming classifier scores into accurate multiclass probability estimates. In *Proceedings of KDD02*, pages 694–699, Edmonton, Alberta, Canada.

Zhang, Jian and Yiming Yang. 2004. Probabilistic score estimation with piecewise logistic regression. In *Proceedings of ICML04*, Banff, Alberta, Canada.

Zhang, Tong, Fred Damerau, and David Johnson. 2003. Updating an NLP system

to fit new domains: an empirical study on the sentence segmentation problem. In *Proceedings of CONLL03*, pages 56–62, Edmonton, Canada.

Zhu, Jingbo and Eduard Hovy. 2007. Active learning for word sense disambiguation with methods for addressing the class imbalance problem. In *Proceedings of EMNLP-CoNLL07*, pages 783–790, Prague, Czech Republic.