Word Sense Disambiguation using Optimised Combinations of Knowledge Sources

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Abstract

Word sense disambiguation algorithms, with few exceptions, have made use of only one lexical knowledge source. We describe a system which performs unrestricted word sense disambiguation (on all content words in free text) by combining different knowledge sources: semantic preferences, dictionary definitions and subject/domain codes along with part-of-speech tags. The usefulness of these sources is optimised by means of a learning algorithm. We also describe the creation of a new sense tagged corpus by combining existing resources. Tested accuracy of our approach on this corpus exceeds 92%, demonstrating the viability of all-word disambiguation rather than restricting oneself to a small sample.

1 Introduction

This paper describes a system that integrates a number of partial sources of information to perform word sense disambiguation (WSD) of content words in general text at a high level of accuracy.

Word sense disambiguation has become an established, separate, NLP task, and a module within more general systems to perform useful tasks like information extraction (IE) (Pazienza, 1997). However, it is still not a task with an agreed methodology or evaluation criterion, as we shall discuss below. Moreover, there is no real evidence as yet that WSD is useful for practical, general tasks like IE and machine translation (MT); the hunch that it is comes largely from the folk memory that word-sense ambiguity was a major barrier to MT. We are optimistic and already applying the system described here to IE within the ECRAN project (see below), but the fact that ECRAN’s IE performance figures improve with WSD will not, of course, be proof that WSD should get the credit. The source of scepticism comes from the old central AI tradition: that all NLP tasks, including WSD, are knowledge-dependent and therefore cannot be modularised and solved in isolation by a range of semantic and syntactic considerations of the sort investigated here. The problem with this line of argument is that it tells equally against every NLP task that has been successfully modularised, and evaluated at a high level of success, right down to part-of-speech tagging, about which many in the AI community (one of the present authors included) were sceptical fifteen years ago.

The methodology and evaluation of WSD are somewhat different from those of other NLP modules, and one can distinguish three aspects of this difference, all of which come down to evaluation problems, as does so much in NLP these days. First, researchers are divided between a general method (that attempts to apply WSD to all the content words of texts, the option taken in this paper) and one that is applied only to a small trial selection of text words (for example (Schütze, 1992) (Yarowsky, 1995)). These researchers have obtained very high levels of success in the mid-to-high ninety percents, close to the figures for other “solved” NLP modules, the issue being whether these small word sample methods and techniques will transfer to general WSD over all content words.

Others, (Wilks and Stevenson, 1997) (Mahesh et al., 1997) (Harley and Glennon, 1997) have pursued the general option on the grounds that it is the real task and should be tackled directly, but with rather lower success rates. The division between the approaches probably comes down to no more than the availability of gold standard text in sufficient quantities, which is more costly to obtain for WSD than other
tasks. In this paper we describe a method we have used for obtaining more test material by transforming one resource into another, an advance we believe is unique and helpful in this impasse.

However, there have also been deeper problems about evaluation, which has led sceptics like (Kilgarriff, 1993) to question the whole WSD enterprise, for example that it is harder for subjects to assign one and only one sense to a word in context (and hence the produce the test material itself) than to perform other NLP related tasks. We have discussed Kilgarriff’s figures elsewhere (Wilks, 1997) and argued that they are not, in fact, as gloomy as he suggests, and certainly other researchers have achieved perfectly reasonable levels (Green, 1989) of inter-subjective agreement to be a basis for this task. Again, this is probably an area where there is an “expertise effect”: some subjects can almost certainly make finer, more inter-subjective, sense distinctions than others in a reliable way, just as lexicographers do.

But there is another, quite different, source of unease about the evaluation base: everyone agrees that new senses appear in corpora that cannot be assigned to any existing dictionary sense, and this is an issue of novelty, not just one of the difficulty of discrimination. If that is the case, it tends to undermine the standard mark-up-model-and-test methodology of most recent NLP, since it will not then be possible to mark up sense assignment in advance against a dictionary if new senses are present. One of us has argued elsewhere (Wilks, 1997) that the situation may not be serious, even if such novelty is frequent, since a subject assigning the “closest” available sense may be sufficient for reliable experiments. We shall not tackle this difficult issue further here, but press on towards experiment.

2 Knowledge Sources and Word Sense Disambiguation

One further issue must be mentioned, because it is unique to WSD as a task and is at the core of our approach. Unlike other well-known NLP modules, WSD seems to be implementable by a number of apparently different information sources. All the following have been implemented as the basis of experimental WSD at various times: part-of-speech, semantic preferences, collocating items or classes, thesaural or subject areas, dictionary definitions, synonym lists, among others (such as bilingual equivalents in parallel texts). These phenomena seem different, so how can they all be, separately or in combination, informational clues to a single phenomenon, WSD? This is a situation quite unlike syntactic parsing or part-of-speech tagging: in the latter case, for example, one can write a Cherry-style rule tagger or an HMM learning model, but there is no reason the believe these represent different types of information, just different ways of conceptualising and coding it. That seems not to be the case, at first sight, with the many forms of information for WSD. It is odd that this has not been much discussed in the field.

In this work, we shall adopt the methodology first explicitly noted in connection with WSD by (McRoy, 1992), and more recently (Ng and Lee, 1996), namely that of bringing together a number of partial sources of information about a phenomenon and combining them in a principled manner. This is in the AI tradition of combining “weak” methods for strong results (usually ascribed to Newell (Newell, 1973)) and used in the CRL-NMSU lexical work on the Eighties (Wilks et al., 1990). We shall, in this paper, offer a system that combines the three types of information listed above (plus part-of-speech filtering) and, more importantly, applies a learning algorithm to determine the optimal combination of such modules for a given word distribution; it being obvious, for example, that thesaural methods work for nouns better than for verbs, and so on.

3 The Sense Tagger

We describe a system which is designed to assign sense tags from a lexicon to general text. The lexicon we chose was the Longman Dictionary of Contemporary English (LODCE), which has been used extensively in machine-readable dictionary research (eg. Wilks et al., 1990, Cowie et al., 1992, Bruce and Guthrie, 1992). The senses for each word in LODCE are grouped into homographs, sets of senses with related meanings.
3.1 Preprocessing

Before the filters or partial taggers are applied the text is tokenised, lemmatised, split into sentences and part-of-speech tagged using the Brill part-of-speech tagger (Brill, 1992). A named entity identifier is then run over the text marking and categorising proper names.

Our system disambiguates only the content words in the text (the part-of-speech tags assigned by Brill’s tagger are used to decide which are content words) and does not attempt to disambiguate any of the words which were identified as part of a named entity. For each of the words being disambiguated, the system retrieves each of its possible senses from LDOCE and stores them with the word.

3.2 Part-of-speech

Previous work by (Wilks and Stevenson, 1998) has shown that part-of-speech tags can play an important role in the disambiguation of word senses. They carried out a small experiment on a 1700 word corpus taken from the Wall Street Journal and, using only part-of-speech tags, attempted to find the correct LDOCE homograph for each of the content words in the corpus. They part-of-speech tagged the text using Brill’s tagger and removed from consideration any homograph whose part-of-speech category did not agree with the tags assigned by Brill’s system. They then chose the most frequently occurring homograph of the remaining homographs as the tag for that word. They found that 92% of content words were assigned the correct homograph compared with manual disambiguation of the same texts.

While this method will not help us disambiguate within the homograph, since all senses which combine to form an LDOCE homograph have the same part-of-speech, it will help us to identify the senses completely inappropriate for a given context (when the homograph’s part-of-speech disagrees with that assigned by a tagger).

It could be reasonably argued that this is a dangerous strategy since, if the part-of-speech tagger made an error, the correct sense could be removed from consideration. As a precaution against this we have designed our system so that if none of the dictionary senses for a given word agree with the part-of-speech tag then they are all kept (none removed from consideration).

3.3 Dictionary Definitions

(Lesk, 1986) proposed a method for sense disambiguation using overlap of the dictionary definitions of words as a measure of their semantic closeness. In this way it is possible, at least in theory, to tag each word in a sentence with its sense from any dictionary which contains textual definitions for its senses. However, it was found that the computations which would be necessary to test every combination of senses, even for a sentence of modest length, was prohibitive.

(Cowie et al., 1992) used simulated annealing to optimise Lesk’s algorithm. By applying this method to Lesk’s heuristic Cowie et al. found that they made the process of optimising the sense choice tractable, often choosing an assignment of senses from as many as \(10^{10}\) choices. The optimisation was over a simple count of words in common in definitions, however, this meant that longer definitions were preferred over short ones, since they have more words which can contribute to the overlap, and short definitions or definitions by synonym were correspondingly penalised. We attempted to solve this problem as follows. Instead of each word contributing one we normalise its contribution by the number of words in the definition it came from. The Cowie et al. implementation returned one sense for each ambiguous word in the sentence, without any indication of the system’s confidence in its choice, but, we have adapted the system to return a set of suggested senses for each ambiguous word in the sentence. We found that the improved evaluation function led to an improvement in the algorithm’s effectiveness.

3.4 Pragmatic Codes

Our next partial tagger is based on the technique of disambiguation by examining thesaural hierarchies (such as Roget and WordNet). LDOCE contains a hierarchy of subject codes which indicate the subject of a text; these are divided into primary, of which there are around 300, and secondary codes (around 2,500). The pragmatic code associated with a sense consists of four letters, for example ECZA, the first two

\footnote{We define content words as nouns, verbs, adjectives and adverbs, prepositions are not included in this class.}
letters of which indicate the primary code (economics in this case) and the final two the subclass of the primary code (accounting in this case). The hierarchy is therefore shallow (since there are only two levels) but wide (since there are many subject codes at each level).

We carried out disambiguation using a modified version of the simulated annealing algorithm, which attempts to optimise the number of pragmatic codes of the same type in the sentence. However, the method has been modified from the application to word overlap in three ways: first, we maximise the overlap of the pragmatic codes associated with the word senses rather than the content words in their definitions. Secondly, we optimise over entire paragraphs rather than just sentences, because there is good evidence (Gale et al., 1992) that a wide context, of around 100 words, is optimal when disambiguating using domain codes. Finally, we only optimise the pragmatic codes for nouns, since (Yarowsky, 1993) has shown that, in general, nouns are disambiguated by “broad context” considerations, such as the general subject of the text they are in, while other parts of speech are disambiguated by “local context”, such as the semantic types of the words they modify.

3.5 Selectional Restrictions

LDOCE senses contain simple selectional restrictions for each content word in the dictionary. A set of 35 semantic classes are used, such as H = Human, M = Human male, P = Plant, S = Solid and so on. Each word sense for a noun is given one of these semantic types, senses for adjectives list the type which they expect for the noun they modify, senses for adverbs the type they expect of their modifier and verbs list between one and three types (depending on their transitivity) which are the expected semantic types of the verb’s subject, direct object and indirect object.

We identify grammatical links between verbs, adjectives and adverbs and the head noun of their arguments using a specially constructed shallow syntactic analyser.

The semantic classes in LDOCE are not provided with a hierarchy, but, Bruce and Guthrie (Bruce and Guthrie, 1992) manually identified hierarchical relations between the semantic classes, constructing them into a hierarchy which we use to resolve the restrictions.

The selectional restriction resolution algorithm makes use of the information provided by the shallow syntactic analyser and the named entity identifier. Although we are not disambiguating named entities they are still useful to help disambiguate other words: for example, if a verb has two senses one of which places the restriction H (=Human) on its object, the other I (=Inanimate) and the object was a named entity marked PERSON then we would prefer the first sense. Restrictions are resolved by returning all the senses which agree with their restrictions (that is, those whose semantic category is at the same, or a lower, level in the hierarchy).

4 Combining Knowledge Sources

Since each of our partial taggers suggests only possible senses for each word it is necessary to have some method to combine their results. We trained decision lists (Rivest, 1987) using a supervised learning approach. Decision lists have already been successfully applied to lexical ambiguity resolution in (Yarowsky, 1993) where they performed well.

We present the decision list system with a number of training words for which the correct sense is known. For each of the words we supply each of its possible senses (apart from those removed from consideration by the part-of-speech filter (Section 3.2)) within a context consisting of the results from each of the partial taggers, frequency information and 10 simple collocations (first noun/verb/preposition to the left/right and first/second word to the left/right). Each sense is marked as either appropriate (if it is the correct sense given the context) or inappropriate. A learning algorithm infers a decision list which classifies senses as appropriate or inappropriate in context. The partial taggers and filters can then be run over new text and the decision list applied to the results, so as to identify the appropriate senses for words in novel contexts.

Although the decision lists are trained on a fixed vocabulary of words this does not limit the decision lists produced to those words, and our system can assign a sense to any word, provided it has a definition in LDOCE. The decision list produced consists of rules such as “if the part-of-speech is a noun and the pragmatic
codes partial tagger returned a confident value for that word then that sense is appropriate for the context”.

5 Producing an Evaluation Corpus
Rather than expend a vast amount of effort on manual tagging we decided to adapt two existing resources to our purposes. We took SEMCOR, a 200,000 word corpus with the content words manually tagged as part of the WordNet project. The semantic tagging was carried out under disciplined conditions using trained lexicographers with tagging inconsistencies between manual annotators controlled. SENSUS (Knight and Luk, 1993) is a large-scale ontology designed for machine-translation and was produced by merging the ontological hierarchies in WordNet and LDOCE (Bruce and Guthrie, 1992). To facilitate this merging it was necessary to derive a mapping between the senses in the two lexical resources. We used this mapping to translate the WordNet-tagged content words in SEMCOR to LDOCE tags.

The mapping is not one-to-one, and some WordNet senses are mapped onto two or three LDOCE senses when the WordNet sense does not distinguish between them. The mapping also contained significant gaps (words and senses not in the translation). SEMCOR contains 91,368 words tagged with WordNet synsets, 6,071 of which are proper names which we ignore, leaving 85,377 words which could potentially be translated. The translation contains only 36,869 words tagged with LDOCE senses, although this is a reasonable size for an evaluation corpus given this type of task (it is several orders of magnitude larger than those used by (Cowie et al., 1992), (Harley and Glennon, 1997), (McRoy, 1992), (Veronis and Ide, 1990) and (Mahesh et al., 1997)). This corpus was also constructed without the excessive cost of additional hand-tagging and does not introduce any inconsistencies which may occur with a poorly controlled tagging strategy.

6 Results
To date we have tested our system on only a portion of the text we derived from SEMCOR, which consisted of 2021 words tagged with LDOCE senses (and 12,208 words in total). The 2021 word occurrences are made up from 1068 different types, with an average polysemy of 7.65. As a baseline against which to compare results we computed the percentage of words which are correctly tagged if we chose the first sense for each, which resulted in 49.8% correct disambiguation.

We trained a decision list using 1821 of the occurrences (containing 1000 different types) and kept 200 (129 types) as held-back training data. When the decision list was applied to the held-back data we found 70% of the first senses correctly tagged. We also found that the system correctly identified one of the correct senses 83.4% of the time. Assuming that our tagger will perform to a similar level over all content words in our corpus if test data was available, and we have no evidence to the contrary, this figure equates to 92.8% correct tagging over all words in text (since, in our corpus, 42% of words tokens are ambiguous in LDOCE).

Comparative evaluation is generally difficult in word sense disambiguation due to the variation in approach and the evaluation corpora. As (Resnik and Yarowsky, 1997) said “there are nearly as many test suites as there are researchers in the field”. However, it is fair to compare our work against other approaches which have attempted to disambiguate all content words in a text against some standard lexical resource. Examples of this are (Cowie et al., 1992), (Harley and Glennon, 1997), (McRoy, 1992), (Veronis and Ide, 1990) and (Mahesh et al., 1997). Neither McRoy nor Veronis & Ide provide a quantitative evaluation of their system and so our performance cannot be easily compared with theirs. Mahesh et al. claim high levels of sense tagging accuracy (about 89%) from a single knowledge source, the Mikrokosmos knowledge representation, but our results are not directly comparable since its authors explicitly reject the conventional markup-training-test method used here. Cowie et al. used LDOCE and so we can compare results using the same set of senses. Harley and Glennon used the Cambridge International Dictionary of English which is a comparable resource containing similar lexical information and levels of semantic distinction to LDOCE. Our result of 83% compares well with the two systems above who report 47% and 73% correct disambiguation for their most detailed level of semantic distinction. Our result is also higher than
both systems at their most rough grained level of distinction (72% and 78%). These results are summarised in Table 1.

In order to compare the contribution of the separate taggers we implemented a simple voting system. By comparing the results obtained from the voting system with those from the decision list we get some idea of the advantage gained by optimising the combination of knowledge sources. The voting system provided 59% correct disambiguation, at identifying the first of the possible senses, which is little more than each knowledge source used separately (see Table 2). This provides a clear indication that there is a considerable benefit to be gained from combining disambiguation evidence in an optimal way. In future work we plan to investigate whether the apparently orthogonal, independent, sources of information are in fact so.

7 Conclusion

Our conclusion is that all content words can be disambiguated as a close to acceptable level by an optimised combination of lexical knowledge sources and a part-of-speech filter: 92% of all words in text can be disambiguated in this way.

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| System                          | Resource | Ambiguity level | Result |
|--------------------------------|----------|-----------------|--------|
| (Cowie et al., 1992)           | LDOCE    | homograph       | 72%    |
|                                |          | sense           | 47%    |
| (Harley and Glennon, 1997)     | CIDE     | 'coarse' level  | 78%    |
|                                |          | 'fine' level    | 73%    |
| Reported system                | LDOCE    | sense           | 83%    |

Table 1: Comparison of tagger with similar systems

| Knowledge Sources              | Result |
|--------------------------------|--------|
| Dictionary definitions         | 58.1%  |
| Pragmatic codes                | 55.1%  |
| Selectional Restrictions       | 57%    |
| All                            | 59%    |

Table 2: Results from different knowledge sources

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