Subcategorization Acquisition as an Evaluation Method for WSD

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Abstract

Evaluation of word sense disambiguation (WSD) systems is often based on machine-readable dictionaries (MRDs). Such evaluation typically employs a set of fine-grained dictionary senses and considers them all to be equally important. In this paper, we propose a novel evaluation method for WSD systems in the context of automatic subcategorization acquisition. Building on an extant subcategorization acquisition system, we show that the system would benefit from WSD and propose modifications which allow it to make use of WSD. The enhanced subcategorization acquisition system can then be used as a task-based evaluation method for WSD systems where both the notion of sense and the sense's relevance to the evaluation process is determined by the application itself.

1. Introduction

We show that using word sense disambiguation (WSD) is likely to improve the performance of a subcategorization acquisition system. We suggest using an existing subcategorization acquisition system to find out which senses and verbs are important for this task. We therefore argue that subcategorization acquisition is well suited for a task–based method of evaluating WSD and present experiments which support this claim.

It is usually not possible to directly compare WSD systems, as a number of factors can vary in the evaluation. This can be as fundamental as using a different underlying MRD (which may mean that the results cannot be easily mapped onto each other as different dictionaries tend to have different numbers of senses and different sense distinctions). But even if an identical MRD is used, evaluating on different corpora will make results incomparable. Different corpora result in a difference in average polysemy potentially making one corpus much harder than the other. For example, if corpus 1 has average polysemy 3 and corpus 2 has average polysemy 17, it is not clear that a system which has precision of 60% on corpus 2 really is worse than a system which scores 70% on corpus 1.

Due to these problems, WSD systems are now often compared by means of the SENSEVAL evaluation exercise (Kilgarriff, 1998). For example, the majority of the SENSEVAL-2 tasks expected participants to assign a sense from the WordNet 1.7 pre-release (Miller et al., 1990) to some subset of words from a text. The chosen senses were then scored against a gold standard. Thus in SENSEVAL exercises, systems are rewarded by an equal amount every time they choose a correct sense. For example, the verb *get* has 37 WordNet senses,[1] and these are all considered equally important. Given that the frequency distribution of senses is likely to be zipfian, it is not clear to us that e.g. the predominant WordNet sense of *get* "come into the possession of something concrete or abstract" (e.g. *get your results the next day*) should be considered as important as the least frequent sense "make children" (e.g. *Abraham begot Isaac*). Intuitively, it is more crucial to get frequently occurring senses correct.

It is also unclear whether evaluating WSD systems to a fine-grained level of a dictionary like WordNet is informative or even necessary. Due to elusive nature of word senses and different models used for defining and representing them lexical resources differ largely from one another in terms of sense granularity. WordNet is known to be exceptionally fine grained. For example, the Cambridge International Dictionary of English (CUP, 1995), lists only 23 senses for *get*, lumping some WordNet senses together.

The best level of sense granularity is, however, likely to be application-dependent. An alternative is thus to evaluate WSD systems in a task-based environment. This provides ultimate demonstration of success of a WSD technique and allows evaluation of senses that matter for the application in question.

Various task-based evaluation methods have been proposed in recent years, for example, in the context of machine translation. In this task, senses are defined to be the target language translations and performance is judged by the accuracy of translation. An example of this is the Japanese translation task in SENSEVAL-2 (Kurohashi, 2002) where systems were evaluated on the Japanese-English language pair.

We propose a novel task-based evaluation in the context of automatic subcategorization acquisition. Subcategorization frame (SCF) frequencies have been shown to vary across corpus type (e.g. written vs. spoken language) and genre (e.g. financial vs. balanced text) and much of this variation is reported to be due to the effects of different corpus genres on verb sense and the effect of verb sense on subcategorization (Roland et al., 2000; Roland and Jurafsky, 2001). For example, the *attack* and *bill* senses of *charge* each have a different set of SCF probabilities. The *bill* sense tends to be more frequent in a newswire corpus, while the *attack* sense is usually more common in a balanced corpus. In consequence, *charge* will have different overall SCF frequencies in these two corpora. The SCFs also vary under sense extensions. For example, in *she smiled herself an upgrade*, the entire SCF is only available under the extended sense (Briscoe, 2001). Due to this

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[1]In this paper, we refer to version 1.6. of WordNet, unless we state otherwise.

sensitivity of subcategorization to sense variation, subcategorization acquisition should provide an ideal task-based evaluation method for WSD.

Over the past years, several approaches have been proposed for automatic acquisition of subcategorization from corpus data (e.g. (Briscoe and Carroll, 1997; Carroll and Rooth, 1998; Sarkar and Zeman, 2000)). The different approaches vary largely according to the methods used and the number of SCFs being extracted. Regardless of this, they perform similarly. They mostly gather information about syntactic aspects of subcategorization (the type, number and/or relative frequency of SCFs given specific predicates) and do not distinguish between various predicate senses. As no lexical or semantic information is typically exploited during processing, system output is noisy and the accuracy of the resulting SCF lexicons thus shows room for improvement.

Recently, Korhonen (2002) has proposed a method which makes use of the predominant sense of a verb. Like the previous methods, this method also acquires subcategorization specific to a verb *form* rather than *sense*. However, it guides the acquisition process using back-off (i.e. probability) estimates based on the predominant sense of a verb. These estimates help to correct the acquired SCF distribution and deal with sparse data. Where the predominant sense is assigned correctly, Korhonen reports significant improvement in acquisition performance. Inaccurate senses, however, tend to degrade performance.

In this paper, we build on the method of Korhonen. We show that it could be further improved by considering non-predominant senses. We examine in detail the current system performance and investigate which verb senses would aid subcategorization acquisition the most. Finally, we consider the modifications needed to adapt the system to use WSD. The resulting system, we argue, will provide a task-based evaluation method which addresses the problems we identified with the MRD-based evaluation method for WSD.

This paper is ordered as follows: In Section 2. we introduce the framework for SCF acquisition. Section 3. considers the effect of the current predominant sense heuristics on the system performance. Section 4. reports experiments to investigate the need for WSD. Finally, we discuss the work required to modify the system for WSD (Section 5.) and present our conclusions (Section 6.).

2. Framework for SCF Acquisition

The method of Korhonen (2002) exploits the knowledge that semantically similar verbs are similar in terms of subcategorization. The motion verbs *fly* and *move*, for example, take similar SCF distributions, which differ from the ones taken e.g. by communication verbs *tell* and *say*. Levin (1993) has demonstrated that verb senses divide into semantic classes distinctive in terms of subcategorization. Korhonen (2002) shows that verb forms also divide into such classes, according to their predominant sense. For instance, the verb form specific SCF distributions for *fly* and *move* correlate well because the predominant senses of these verbs (according to the WordNet frequency data) are similar. They both belong to the Levin "Motion verbs".

Korhonen (2002) first identifies the sense, i.e. the semantic class for a predicate. The semantic classes are based on Levin classes (Levin, 1993). Levin proposes 48 broad classes for various semantic verb types which divide further into 191 sub-classes. More often than not, a broad class is employed, as it is found distinctive enough in terms of subcategorization.[2] For example, the broad class of "Motion verbs" is employed (Levin class 51), not the subclasses of this class (e.g. 51.2 "*Leave* verbs"). Semantic class assignment is done according to a verbs' predominant sense in WordNet. For class assignment a mapping is employed which establishes linking between WordNet senses and Levin classes.[3]

After the semantic class is identified, Korhonen uses the subcategorization acquisition system of Briscoe and Carroll (1997) to acquire a putative SCF distribution from corpus data. This system is capable of distinguishing 163 verbal SCFs – a superset of those found in the ANLT (Boguraev and Briscoe, 1987) and COMLEX Syntax dictionaries (Grishman et al., 1994) – and returning relative frequencies for each SCF found for a verb.

The system first tags, lemmatizes and parses corpus data using a robust statistical parser which employs a grammar written in a feature-based unification grammar formalism. This yields complete though shallow parses. Local syntactic frames including the syntactic categories and head lemmas of constituents are then extracted from parses, from sentence subanalyses which begin/end at the boundaries of predicates.

The resulting patterns are assigned to SCFs (or rejected as unclassifiable) by a comprehensive SCF classifier on the basis of the feature values of syntactic categories and head lemmas in each pattern. Finally, sets of SCFs are gathered for verbs and putative lexical entries are constructed.

Korhonen takes the putative SCF distribution from Briscoe and Carroll's system and smoothes it – using linear interpolation (e.g. Manning and Schütze (1999)) – with the "back-off" estimates of the semantic class. Back-off estimates are obtained by:

(i) choosing 4-5 representative Levin verbs from a verb class

(ii) building SCF distributions for these verbs by manually analysing c. 300 occurrences of each verb in the British National Corpus (BNC) (Leech, 1992), and

(iii) merging the resulting set of SCF distributions

For example, the back-off estimates for the "Motion verbs" are constructed by merging the SCF distributions for *fly*, *move*, *slide*, *arrive*, and *sail*.[4]

[2] The specificity of semantic class is examined beforehand by investigating (i) the syntactic similarity of Levin (sub)classes and (ii) subcategorization similarity between individual verbs from these classes.

[3] See Korhonen (2002) for details of this mapping.

[4] The verb for which subcategorization is acquired is always excluded from the back-off estimates. For example, when acquiring subcategorization for *fly*, back-off estimates are constructed using verbs other than *fly*.

After smoothing, the resulting SCF distribution is finally filtered to remove noise from the system output. This is done by setting a simple empirically determined threshold on the probability estimates after smoothing.

When back-off estimates based on the predominant sense are used for smoothing, Korhonen (2002) reports significant improvement in accuracy of subcategorization acquisition. On a test set of 45 verbs from 18 semantic classes, the proposed method yields 87% type precision (the percentage of SCF types that the method proposes which are correct) and 71% type recall (the percentage of SCF types in the gold standard that the method proposes). The baseline method, which involves no smoothing at all, yields 85% precision and 47% recall. Thus, by assuming the predominant sense we obtain 78 F measure,[5] while F measure is only 61 when no sense is assumed.

Compared to previous methods, this more semantically-driven method for subcategorization acquisition provides an effective way of dealing with low frequency associations and a means of predicting those unseen in corpus data.

3. System Performance and Predominant Sense

This work on SCF acquisition highlights several issues interesting from the WSD point of view. Firstly, significant improvement is reported with SCF acquisition by assuming the predominant sense only. This suggests that the predominant sense is the most important one and undermines the assumption that all senses are equally important. Interestingly, the predominant sense also tends to score very highly in an MRD-based evaluation of WSD systems (on real text). In SENSEVAL-2, for example, only two systems out of 21 achieved a higher precision than the most frequent sense baseline in the English all-words task.

Secondly, good subcategorization acquisition results are obtained by assuming a fairly wide notion of a sense, based on a broad Levin class. These results indicate that WordNet style fine-grained sense distinctions are not necessary for the task in hand. This, in turn, is beneficial since the method would suffer from sparse data problems if a narrow notion of sense was assumed. For example, it would be difficult (or, in some cases, impossible) to obtain adequate back-off estimates for senses (i.e. semantic classes) very low in frequency.

This observation is consistent with the SENSEVAL results: SENSEVAL-1 used Hector (Atkins, 1992 93) as its sense inventory, whereas SENSEVAL-2 used the more fine-grained WordNet. The overall results of systems participating in the English lexical sample task in SENSEVAL-2 were much lower than the results in SENSEVAL-1.

Thirdly, the results reported in Korhonen (2002) show that when the predominant sense assignment is done correctly, the method performs better with some verbs than others. This implies that assuming the predominant sense in all occurrences of a verb may not be sufficient for all verbs.

To identify the verbs whose performance shows room for improvement and which might benefit from WSD, we focused on polysemous verbs, i.e. verbs which have more than one sense. Table 1 shows that less than half of the verbs in WordNet are polysemous. However, if we also examine the verbs' relative frequency in WordNet (taken from the SemCor corpus), we find that polysemous verbs occur 14 times more frequently in corpus data than monosemous verbs. Thus in a piece of continuous text, we can expect the average polysemy to be higher than the 3.57 from Table 2. In fact, the average polysemy in the English all-words task in SENSEVAL-2 was around 7.

	No. of verbs	Av freq
monosemous	5752/10319	0.99
polysemous	4592/10319	14.37

Table 1: Number and frequency of polysemous and monosemous verbs in WordNet

In the context of subcategorization acquisition, we found no obvious correlation between system performance and the "degree of polysemy" of a verb, i.e. the number of senses taken by a verb. A highly polysemous verb such as *carry* (38 WordNet senses), for instance, shows better subcategorization acquisition performance than *punch*, which has 3 WordNet senses only. We did find, however, clear correlation between system performance and the frequency of a predominant sense in SemCor data.

For example, consider the verb *fly* which has 14 WordNet senses. While the predominant WordNet sense covers 0.47% of the total frequency mass, the predominant Levin sense covers 0.72%. This is because as many as 6 of the fine-grained WordNet senses are mapped to the same semantic class with the predominant Levin sense (the Levin "Motion Verbs"):

1. travel through the air, be airborne (0.47%)
2. move quickly or suddenly (0.14%)
3. fly a plane (0.08%)
4. travel in an airplane (0.01%)
5. to run away (0.01%)
6. travel over (0.01%)

The verb *stroke* has, on the other hand, 4 WordNet senses. In this case, only the predominant WordNet sense is mapped to the semantic class with the predominant Levin sense (the Levin "Verbs of Contact"). The frequency of this sense covers 0.56% of the total frequency mass.

The frequency difference between the predominant Levin senses of these two verbs is reflected in subcategorization acquisition performance. While *fly* and *stroke* both obtain 62 F measure when the baseline method is used (which assumes no notion of a sense), *fly* obtains 94 F measure when the predominant sense is assumed, while *stroke* obtains 77 F measure. Clearly *stroke* would benefit from WSD since the current method only takes into account 56% of its senses. For instance, it might help to take into account also the second most frequent sense (the Levin class "Verbs

[5] $F = \frac{2 \cdot precision \cdot recall}{precision + recall}$

of Contact by Impact") which covers 0.22% of the total frequency mass.

4. Experiments

These observations with system performance suggest that high frequency polysemous verbs whose predominant sense is not frequent enough would benefit from extra WSD knowledge. We conducted two small scale experiments to investigate which senses, in addition to the predominant, would benefit from WSD and to what extent.

We investigated the following:

1. the frequency mass distribution over senses
2. the performance of the current subcategorization acquisition system when instead of the predominant sense, we assume the second sense.[6]

For each experiment, we chose a number of test verbs and manually mapped their WordNet senses to Levin senses. By examining the relation between the number of senses and the frequency mass these cover, we found that it may be sufficient to only map a subset of the WordNet senses. The decrease in average polysemy over all polysemous verbs in WordNet with relation to frequency mass is presented in Table 2.[7] When all senses are considered, total frequency mass covered is 1.00, the average polysemy in WordNet for polysemous verbs is 3.57. If we restrict the frequency mass to 0.75, the average polysemy drops by 1, to 2.47. It is due to the highly polysemous verbs (of which there are not many) that this decrease happens. For example, for the verb *continue*, to cover 0.75 of the frequency mass, we only need to consider the first two senses out of nine. Thus by restricting our investigations to those WordNet senses which cover 0.75 of the total frequency mass, we will discard the numerous infrequent senses of the highly polysemous verbs.[8]

4.1. Experiment I

We chose 91 highly polysemous verbs from WordNet at random subject to the constraint that they occur in SemCor with frequency higher than 100. Only 150 verbs occur in SemCor with frequency higher than 100, therefore these verbs are also highly frequent.

In the case of our 91 test verbs, the predominant WordNet sense covers (on average) about 45% of the frequency mass and together the first and second most frequent WordNet sense cover about 63% of the frequency mass (Table 3).[9] Mapped to Levin, the first sense covers about 55%,

Freq	Polysemy	Total	Average
1.00	16314	4567	3.57
0.95	14954	4551	3.29
0.90	13731	4503	3.05
0.85	12658	4425	2.86
0.80	11489	4343	2.65
0.75	10363	4202	2.47
0.70	9559	3926	2.43
0.65	7855	3394	2.31
0.60	7111	3270	2.17
0.55	6440	2965	2.17

Table 2: Polysemy in relation to total frequency mass (polysemous verbs only)

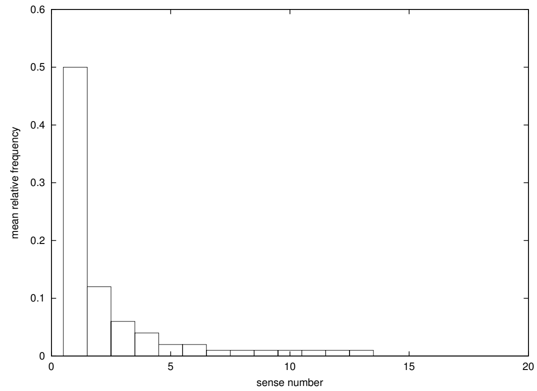

Figure 1: Frequency distribution of all polysemous verbs

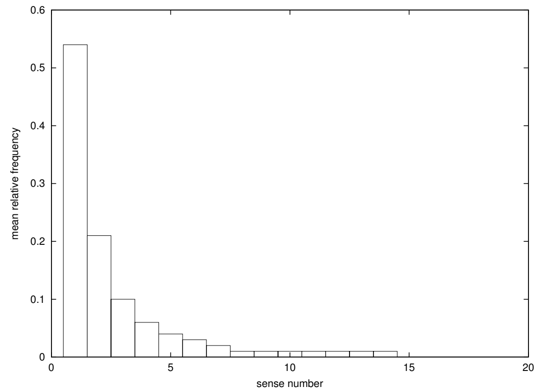

Figure 2: Frequency distribution of high frequency polysemous verbs

whereas the first and second most frequent senses mapped to Levin cover 93%. We therefore conclude that the most frequent senses of polysemous high frequency verbs from WordNet tend to be mapped to distinct Levin classes. Presumably if a verb is frequently used in two different senses, these have to be sufficiently semantically different to be distinguishable.

We can make another interesting observation: the frequency distribution over WordNet senses is slightly different for all polysemous verbs and for high frequency polysemous verbs. A histogram presenting the mean of the relative frequencies for all polysemous verbs is shown in

[6] A number of results in this paper are presented only for the first and second sense to make them easier to understand. However it is important to note that we are not proposing to introduce a numerical cut-off on the number of senses. Rather, we propose to introduce a cut-off based on the sense frequency.

[7] This experiment uses the frequency distribution in WordNet which was derived from the SemCor corpus. Due to the small size of SemCor, we also smooth the frequencies.

[8] This turns out to be necessary, as there will not be enough data for the rare senses to acquire new subcategorization frames.

[9] Note that these percentages refer to the 75% frequency mass which we are considering, i.e. 45% corresponds to 45% out of 75%.

	Frequency mass (%)
predominant WN sense	45.17
second WN sense	17.35
predominant Levin sense	55.44
second Levin sense	38.03

Table 3: The frequency mass covered by the predominant and second WordNet and Levin sense

Figure 1 and a histogram presenting the mean for all highly frequent (frequency of occurrence greater than 100 in SemCor) verb is shown in Figure 2. Although the overall shape of the graphs is zipfian, the means of the relative frequencies are higher for the initial senses in the polysemous frequent verbs. This implies that it is important to consider more than the most frequent sense for high frequency polysemous verbs.

4.2. Experiment II

For the second experiment, we selected 16 polysemous high frequency verbs whose predominant sense belongs to one of 8 Levin classes. We took a sample of 20 million words of the BNC corpus and extracted all sentences containing an occurrence of one the verbs. After the extraction process, we retained 1000 citations, on average, for each verb.

The sentences containing these verbs were processed by the SCF acquisition system, using the method outlined in Section 2. Three lexicons were acquired for each verb so that we assumed (i) the predominant Levin sense (i.e. back-off estimates of the predominant Levin sense were used for smoothing), (ii) the second most frequent one (i.e. back-off estimates of the second sense were used)[10], and, as a baseline, (iii) no sense at all (i.e. no smoothing was done).

The results were evaluated against a manual analysis of the corpus data. This was obtained by analyzing a maximum of 300 occurrences for each test verb in the BNC corpus. Type precision, type recall and F measure were calculated (see Section 2. for details).

The average frequency mass for the predominant and the second senses for our verbs is shown in the second column of Table 4. The results included in the third, fourth and fifth column show that by assuming both the predominant and the second senses, we obtain clearly better performance (in terms of the F measure) than when assuming no sense at all. The predominant sense yields 6.2 better F measure than the second sense. The fact that the difference is not bigger (i.e. the performance with the second sense is surprisingly high considering that its frequency mass is 17% on average) is due to our restricting the evaluation to Levin classes which – despite being semantically different – are syntactically somewhat similar (they mainly cover verbs taking NP and PP complements). However, these results confirm the importance of the second most frequent sense and suggest that disambiguating both senses together should help to improve subcategorization acquisition performance.

[10]Note that the subcategorization acquisition system uses the back-off estimates for the second sense only. The system does not combine predominant sense and second sense back-off estimates in any way.

	Freq mass (%)	Precision	Recall	F
Predominant Levin sense	0.55	93.7	83.3	88.2
Second Levin sense	0.17	90.8	74.8	82.0
Baseline (no sense)		91.1	50.7	65.2

Table 4: SCF acquisition results

5. Future Work

The framework outlined in Section 2. requires modification in order to benefit from WSD and before the system can be used for task-based WSD evaluation.

The mapping between predominant WordNet and Levin senses needs to be extended to cover all senses corresponding to 75% of frequency mass. This work is required, however, for polysemous high frequency verbs only. Once the mapping is obtained, the corpus data can be disambiguated and for each verb, the resulting data divided into the first few senses (as many as cover 75% of frequency mass) and any other sense occurrences. Subcategorization can then be acquired for these data sets separately, using back-off estimates of the corresponding senses and using no back-off in the case of “other senses”.

To carry this work out, we must find a suitable WSD method. Current WSD systems do not tend to significantly outperform the most frequent sense baseline. However, as our task-based evaluation is only required WSD for high frequency polysemous verbs, we believe that an existing supervised system could be adapted to generate accurate word sense disambiguation for the chosen verbs. Supervised systems tend to have a higher accuracy than unsupervised systems. A system such as that described in Mihalcea and Moldovan (2002) was one of the two systems which outperformed the most frequent sense baseline in SENSEVAL-2.

Immediate future work will include modifying the system as proposed and carrying out a small scale experiment on evaluation of WSD in this framework.

6. Conclusion

We showed that SCF lexicon acquisition can be used as a novel task-based evaluation for WSD systems. With a few modifications the system discussed will provide a framework which allows evaluation of senses and verbs that really matter for the application. Our results show that in our subcategorization acquisition framework, it is sufficient to assume a fairly broad notion of sense and disambiguate the most frequent senses of polysemous highly frequent verbs only. This contrasts with the MRD-based evaluation, which typically examines exhaustively a set of fine-grained senses and gives equal weight to both frequent and infrequent senses.

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