You Shall Know the Most Frequent Sense by the Company it Keeps

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Abstract
Unsupervised identification of the most frequent sense of a polysemous word is an important semantic task. We introduce two concepts that can benefit MFS detection: companions, which are the most frequently co-occurring words, and the most frequent translation in a bitext. We present two novel methods that incorporate these new concepts, and show that they advance the state of the art on MFS detection.

1 Introduction
MFS detection is the task of identifying the most frequent sense of a polysemous word. The task must be defined with respect to a particular body of text. For example, one would expect bank to refer to a river bank in a geographic text, but the “repository” sense is the most frequent in general English.

MFS detection is important in word sense disambiguation (WSD), the area of research concerned with determining the meaning of words in context. WSD systems can use the MFS as a backoff method, or as an additional source of information. An MFS-based WSD system that classifies each word token according to its MFS is a strong WSD baseline that typically outperforms unsupervised WSD systems, and approaches the accuracy of supervised systems (Raganato et al., 2017a).

MFS detection is also an interesting task itself, which could be applied, for example, to provide the predominant sense of a word in an interactive dictionary look-up.

MFS detection is an unsupervised classification problem. Although sense frequency information can be approximated from a large sense-annotated corpus, such resources are expensive to create, as hundreds of thousands of word tokens need to be manually disambiguated. On the other hand, MFS detection systems require only unannotated text corpora, and so can be more easily applied to different domains and languages.

Mohammad and Hirst (2006b) generalize the famous observation of Firth (1957) as “you shall know a sense by the company it keeps.” We propose to apply this intuition to MFS detection, as stated in this paper’s title. Specifically, our hypothesis is that the most frequent sense of a given target word can be determined by referring to the set of words that most frequently co-occur with it, which we refer to as the word’s companions. In addition, following the observation that different senses of a word may translate differently, we propose that leveraging frequent word translations from a bitext can improve accuracy of a MFS detection system.

In order to test our hypothesis, we develop two novel methods for MFS detection. The first method selects the sense which is most closely related to its companions, according to a WordNet-based sense similarity measure. The second method constructs a series of vectors for words, senses, companions, and most frequent translations, and selects the MFS on the basis of the cosine similarities between them. The principal contributions of this work are the introduction and application of the concepts of companions and most frequent translations to the task of MFS detection.

We conduct an extensive evaluation of the proposed methods, which includes a series of intrinsic, extrinsic, and ablation experiments on standard datasets, as well as error analysis. The experimental results establish a new state of the art for MFS detection. In order to facilitate replication and encourage further work on MFS detection, we will publish our MFS detection results for all words covered by WordNet in a large, unannotated bitext.
2 Related Work

Buitelaar and Sacaleanu (2001) lay the groundwork for MFS detection by analyzing the relevance of GermaNet synsets to specific domains. Koeling et al. (2005) build upon this, showing that WSD performance can be improved by performing MFS detection on a corpus of the same domain as the testing data. Mohammad and Hirst (2006a) present an MFS detection method based on a published thesaurus, which they use to induce a coarse-grained sense inventory. This separates their method from other related work, which typically uses WordNet as the de facto sense inventory for WSD and MFS detection.

McCarthy et al. (2004b) present a method for MFS detection based on a thesaurus constructed from a parsed corpus. This thesaurus is used to induce a word similarity function, which they use to assess the prevalence of each sense of a given target word. They perform both intrinsic and extrinsic evaluations; we compare to their reported results to the extent their experimental setup allows. This method was subsequently applied to a WSD shared task (McCarthy et al., 2004c), and to the identification of infrequent word senses (McCarthy et al., 2004a). An extended analysis of the method was presented by McCarthy et al. (2007).

Iida et al. (2008) adapt this method to Japanese MFS detection using only the glosses of words, excluding the use of semantic networks such as WordNet.

Bhingardive et al. (2015) present the first MFS detection method based on automatically learned vector word embeddings. They test their method on English and a private Hindi dataset. This is the most recent work we are aware of which considers the exact same task as we do, in the same setting; given its recency relative to other works, we consider this to be the state-of-the-art for MFS detection. We re-implement this method, and compare to it directly in our experimental evaluation.

Our methods leverage cross-lingual information and contextually related words. These concepts have previously been used to improve WSD – Yarowsky (1995); Ng et al. (2003); Navigli (2009); Apidianaki and Gong (2015), and others – but our usage of these concepts for MFS detection is novel.

3 Comp2Sense

Given a target word, our first MFS detection method uses a set of words known as its companions to determine its MFS. The method is based on a sense-similarity function which makes use of WordNet’s hierarchical semantic network. Since the method relates the companions of the target word to its senses, we name it Comp2Sense.

For each word \( w \) in a given corpus, we define the companions of \( w \) to be the \( k \) content words, other than \( w \) itself, which most frequently occur in sentences containing \( w \). The variable \( k \) is a tunable parameter. Building on prior work (Mohammad and Hirst, 2006a), the companions of a word are defined in an entirely relation-free way, re-
acquiring no external resources or pre-processing to extract (this distinguishes our method from prior work, e.g. Pantel and Lin (2002), McCarthy et al. (2004b)). We experimented with more sophisticated methods for selecting companions, such as taking the $k$ words with the highest pointwise mutual information with the target word, but in our development experiments, taking the $k$ most frequently co-occurring words gave substantially better results.

Our method uses the WordNet::SenseRelate::WordToSet (henceforth WordToSet) package (Pedersen et al., 2005) as a subroutine. WordToSet takes as input a word $w$, and a set of words $X$, and compares the senses of $w$ to the senses of each word in $X$, returning the sense of $w$ which is found to be most closely related to the words in $X$. Sense-to-sense comparison is done using (by default) the $jcn$ similarity function (Jiang and Conrath, 1997).

Given a pair of senses $s$ and $s'$, $jcn(s, s')$ is a real number, such that the more closely related the given senses are with respect to the WordNet sense hierarchy, the higher the returned value. This algorithm was developed for WSD, and variants of it are still used as strong knowledge-based WSD baselines (Raganato et al., 2017a). We apply WordToSet to MFS detection for the first time.

For a word $u$, let $C_u$ be the set containing the companions of $u$, and let $S_u$ be the set containing the senses of $u$. Note that $C_u$ is a set of words, while $S_u$ is a set of senses. To identify the MFS of a target word $w$, Comp2Sense uses WordToSet to assign a score to each $s \in S_w$ as follows:

$$score(s) = \sum_{c \in C_u} \max_{s' \in S_c} jcn(s, s')$$

The sense with the highest such score is returned.

4 WCT-VEC

Our second MFS detection method is based on vector embeddings of words, which are constructed such that cosine similarity of vectors approximates a measurement of semantic similarity. The method amalgamates these word vectors to create a sense vector for each sense of the target word, and compares each to three vectors which represent the target word itself (Section 4.1), its companions (Section 4.3), and its most frequent translation in another language (Section 4.4), respectively. These three vectors, which depend only on the target word, collectively represent the MFS, and so the sense whose vector is closest to these three vectors is taken to be the MFS. We call this method WCT-VEC, where WCT is an abbreviation of “Word, Companions, and Translation”.

4.1 Word Vectors

WCT-VEC begins from word embeddings, low-dimensional real-valued vector representations of each word in the vocabulary, which can be compared using cosine similarities as described above. We create such vectors using word2vec (Mikolov et al., 2013a), a well-known software package which learns vector embeddings from unlabelled monolingual data using a simple neural model. We denote the embedding of a word $w$ as $v_w$.

We adopt the assumption, supported by the work of Arora et al. (2016), that a vector representing a polysemous word is a composition of vectors representing each of its senses, with more frequent senses having greater influence on the word vector. Thus, the more frequent a sense of a word is, the closer its sense vector should be to the vector of the word.

4.2 Sense Vectors

Since our approach is unsupervised, we cannot train sense vectors directly using sense annotated data, as done by, for example, Mancini et al. (2017). Following prior work, we instead approximate them by identifying keywords for each sense, and taking the average of their vectors.

We differ from previous work in how we define these keywords. Chen et al. (2014) select keywords from the sense gloss whose vectors are similar to the word vector, using a threshold of cosine similarity. Bhingardive et al. (2015) add the synsets containing the synonyms, hypernyms, and hyponyms of the sense, as well as the content words from the glosses and usage examples of the sense, and of each keyword found using the above semantic relationships. We further extend the sets of keywords to include WordNet meronyms, holonyms, entailments, causes, and similar words (as encoded in WordNet).

4.3 Companions Vector

As with our Comp2Sense method, WCT-VEC also leverages the notion of companions. Rather than comparing the senses of a target word $w$ to each sense of each of its companions, WCT-VEC
represents the companions of \( w \) with a single vector, which is the average of the vectors of the companions of \( w \). We call this vector the *companions vector* of \( w \), and denote it \( c_w \). Following our hypothesis that the companions of a word are most closely related to its MFS, we expect \( c_w \) to have higher cosine similarity with the vector of the MFS of \( w \) than with the vector of any other sense of \( w \).

### 4.4 Most Frequent Translation Vector

Different senses of the same word may translate as different words in other languages (Resnik and Yarowsky, 1997; Ng et al., 2003). We leverage this fact to help identify the most frequent sense of a word by identifying its *most frequent translation (MFT)* in a sentence-aligned bilingual corpus (bitext). The intuition is that, as the different senses of a word translate differently, we should expect the most frequent translation of a word to be a translation of its most frequent sense. Without loss of generality, let the bitext represent English and French.

We word-align the bitext, and define the MFT of each English word to be the French word with which the English word is most frequently aligned. After computing vector representations for the French vocabulary using the French side of the bitext, we proceed to learn a cross-lingual linear transformation using the method of Mikolov et al. (2013b). This method takes a set \( n \) of English–French translation pairs, \( (e_i, f_i) \), represented by their word embeddings in the English and French vector spaces respectively. It then uses stochastic gradient descent to learn a *translation matrix* \( T \), by minimizing the objective function

\[
\sum_{i=1}^{n} | | T \cdot f_i - e_i | |^2
\]

This allows us to map the French word vectors into the English vector space in a way that preserves the semantic properties of the word vectors. Different from Mikolov et al. (2013b), rather than obtaining translation pairs from Google Translate, we obtain training pairs from our word-aligned bitext, using the most frequent translations of the 5000 most frequent English words as training data, as was previously demonstrated to be effective by Hauer et al. (2017).

We obtain the most frequent translation vector of \( w \), denoted \( t_w \), by computing \( t_w = T \cdot f \), where \( f \) is the embedding of the MFT of \( w \) in the French vector space. Thus, \( t_w \) represents the MFT of \( w \) in a way that allows semantic comparison to vectors in the English vector space.

### 4.5 Identifying the MFS

In the previous sections, we have identified three intuitive properties of the MFS: that the vector of the MFS should be closest to the vector of the target word (Section 4.1), that the MFS should be most closely related to the companions of the word (Section 4.3), and that the MFT of the word should be a translation of its MFS (Section 4.4). We have shown how we construct vector representations of each sense of the target word, as well as vectors which model these three sources of information regarding the target word itself. Based on prior work, these vectors admit efficient semantic comparison through computation of cosine similarities, which we use to identify the MFS.

Given a target word type \( w \) with word vector \( v_w \), companions vector \( c_w \), and MFT vector \( t_w \), as well as a set of senses \( S \) with each \( s \in S \) having an associated sense vector \( s \) (Section 4.2), WCT-VEC identifies the MFS of \( w \) as follows:

\[
\text{MFS}(w) = \arg \max_{s \in S} \{ \chi_1 \cos(s, v_w) + \chi_2 \cos(s, c_w) + \chi_3 \cos(s, t_w) \}
\]

where the \( \chi_i \) are tunable non-negative parameters which sum to 1. Figure 1 illustrates a simplified
example of the vectors WCT-VEC uses to identify the MFS of a word.

5 Experiments

In this section, we describe both intrinsic and extrinsic evaluation experiments, comparing our approach against previous work on standard datasets. In addition, we perform ablation experiments and error analysis.

5.1 Experimental Setup

All sense-annotated data in our experiments comes from the WSD evaluation framework of Raganato et al. (2017a), which consists of five datasets from five shared tasks on WSD: Senseval-2 (SE2), Senseval-3 (SE3), SemEval-07 (S07), SemEval-13 (S13), and SemEval-15 (S15). The data is annotated using the WordNet 3.0 sense inventory, and POS tagged with a low-granularity tag set (nouns, verbs, adjectives, and adverbs). We treat homonyms that differ in their POS tags as distinct word types.

We designate the oldest set (SE2) as our development set, on which we tune the following parameters: the number of companion words, which we set to \( k = 20 \), and the linear weights defined in Section 4.5, which we set to \((\chi_1, \chi_2, \chi_3) = (0.5, 0.4, 0.1)\).

Our text corpus is the OpenSubtitles2018 English-French bitext (Lison and Tiedemann, 2016), which contains roughly 42M sentences from various domains. For consistency, we extract companions and induce all types of vectors from the English side of the corpus.¹ We use \textsc{word2vec} to compute 200-dimensional vector embeddings for the English and French vocabularies independently, using the skip-gram model. All other parameters are set to their default values. To identify the MFT of each word, we compute a bi-directional word alignment of the bitext using GIZA++ (Och and Ney, 2003) with the default parameter settings. While our method could certainly be applied to languages other than English, difficulty in acquiring a WordNet-like resource, and sufficient evaluation data annotated using that resource’s sense inventory, in the language on which MFS detection is to be performed, precluded such experiments here.

5.2 UMFS-WE

For the purpose of comparison, we re-implemented the UMFS-WE system (Bhingardive et al., 2015), which, to the best of our knowledge, is the most recent system to specifically consider the task of MFS detection. To make the comparison fair, we use the same English word vectors with UMFS-WE as with our method. We validated our reimplementation by replicating the results on the noun subsets of the SE2 and SE3 datasets, which are reported in the original paper. While the replication experiment was conducted on nouns only, we test on all parts of speech in the remainder of this paper.

5.3 Intrinsic Evaluation

Our principal evaluation experiment is a direct intrinsic evaluation of MFS detection systems: how frequently does each system correctly identify the MFS of the given target? This kind of an evaluation is only possible for English, thanks to the availability of SemCor (Miller et al., 1993), which is a relatively large sense-annotated corpus.² We assume that the MFS for each word type is the sense that occurs with the highest frequency in SemCor. For each method, we compute the accuracy of each method as the proportion of word types for which its prediction matches the MFS. If two or more senses are tied for the highest count, we consider any of them to be a correct prediction.

SemCor is a resource unique to English, composed of 226,034 sense-annotated word tokens, which represent 22,405 word types. 51.6% of word types are polysemous, that is, they occur in multiple WordNet synsets. A randomly selected sense has a 67.6% chance of being the MFS. It should be noted that most of the word types are relatively infrequent, with the average count of 11, and the median count of 2. The average number of

| System    | All Words | Noun Sample |
|-----------|-----------|-------------|
| Random    | 67.6      | 26.0        |
| UMFS-WE   | 73.9      | 48.0        |
| WCT-VEC   | 75.2      | 48.8        |
| COMP2SENSE| 77.9      | 58.5        |
| M04       | n/a       | 54          |

Table 1: Intrinsic evaluation on the MFS detection task on SemCor (in % accuracy).

¹Note that we could use any bitext for this purpose, and that all vectors except the MFT vectors could also be derived from other monolingual corpora.

²For consistency, we use the version of SemCor made available by Raganato et al. (2017a).
word tokens per sense is 6.8, and the corresponding median is again 2.

The evaluation results are shown in Table 1. Both methods proposed in this paper outperform UMFS-WE. Our WordNet-based Comp2sense method has a higher MFS detection accuracy than either of the methods based on word embeddings, UMFS-WE and WCT-VEC. This result confirms the utility of the concept of word companions, and provides strong support to our hypothesis that they convey a strong signal about the word’s MFS.

To make our comparison more robust, we replicate, as closely as possible, the intrinsic evaluation performed by McCarthy et al. (2004b), henceforth referred to for brevity as “M04”. To this end, this evaluation is performed on a sample of the words in SemCor; specifically, evaluation is performed only on polysemous nouns (with respect to WordNet 3.0) which occur at least three times in SemCor and which have a single MFS (i.e. no ties). This is slightly different from the M04 evaluation, which uses an older version of WordNet (1.6) and a correspondingly older version of SemCor, and which further samples the nouns to be evaluated on by choosing nouns for which a certain amount of grammatical information is available in a parsed corpus which they use as a resource. Since these differences do not make the task easier, it is fair to compare our results to what M04 report.

The results of this “noun sample” intrinsic evaluation on SemCor are also reported in Table 1. Again, the random selection baseline is outperformed by all other systems. Our Comp2sense method clearly outperforms the reported result of McCarthy et al. (2004b)3. Interestingly, both Comp2sense and M04 outperform the vector-based methods. This highlights the particularly strong performance of the jcn similarity measure on nouns as compared to other parts of speech.

5.4 WSD Evaluation

An indirect, extrinsic evaluation of an MFS detection system is to apply it to the WSD task by simply predicting the most frequent sense for each word, regardless of its context. Unlike the intrinsic evaluation above, WSD evaluation is conducted on the level on word tokens, rather than types, with multiple instances of the same word contributing independently to the results.

In addition to the systems evaluated in the previous section, we also include the results of two other methods, as reported by Raganato et al. (2017a,b). Supervised MFS outputs the most frequent sense according to the SemCor annotations, demonstrating what a “perfect” MFS detection system (applied to SemCor) could achieve. Leskext (Banerjee and Pedersen, 2003) is a WordNet-based extension of the classic Lesk algorithm (Lesk, 1986), and is a strong unsupervised baseline WSD system. Unlike the MFS detection systems, it disambiguates words at the level of individual tokens, rather than word types, according to the context of each instance.

The results are reported in Table 2. WCT-VEC is the top-performing unsupervised method on the development set (SE2), two of the other data sets (SE3 and S07), and is within 1% of the best result on the other two data sets (S13 and S15). Following the example of recent work (Raganato et al., 2017b; Pasini andNavigli, 2018), we also test on the concatenation of the five datasets. It also obtains the best result on the concatenated dataset (of which the development set is a small part).

Another interesting observation is that all three MFS-based approaches outperform the Leskext method, even though it has the ability to select different senses for different tokens of the same type depending on context, an advantage MFS detection methods applied to WSD lack by definition. This shows that a strong MFS detection method, applied to WSD, can outperform a strong unsupervised WSD baseline. These results, together with the high supervised MFS ceilings shown in Table 2 confirm the importance of accurate MFS detection for the WSD task.

Finally, a key difference from the intrinsic evaluation results reported in Section 5.3, is that here, our vector-based WCT-VEC method outperforms the WordNet-based Comp2sense method. These results show that an MFS detection system which is strictly better at detecting the most frequent sense of a word may not produce the best results when its output is used for WSD. This also demonstrates that both of the systems which we have developed in this paper have merit, depending on the proposed application: Comp2Sense gives better type-level accuracy when the MFS itself is desired, while WCT-VEC provides better token-level results when the goal is to apply the output to perform WSD.

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3McCarthy et al. (2004b) do not provide greater numerical precision than what we report.
| System              | SE2 (dev) | SE3 | S07 | S13 | S15 | ALL |
|---------------------|-----------|-----|-----|-----|-----|-----|
| UMFS-WE             | 54.8      | 52.0| 38.2| **55.2** | 54.5 | 53.1|
| WCT-VEC             | **56.4**  | **53.8** | **40.6** | 54.9 | 54.0 | **54.1** |
| COMP2SENSE          | 51.5      | 47.0| 37.5| 54.1 | **55.0** | 50.7|
| Supervised MFS      | 65.6      | 66.0| 54.5| 63.8 | 67.1 | 65.5|
| Lesk                | 50.6      | 44.5| 32.0| 53.6 | 51.0 | n/a |

Table 2: Extrinsic evaluation of the MFS detection systems on the WSD task (in % $F_1$-score). The first three rows present extrinsic evaluation results for MFS detection systems; the best of these results in each column is in bold. The rightmost column gives the combined result for all five datasets.

| WCT-VEC Variant     | Intrinsic (SemCor) | Extrinsic (SE2) |
|---------------------|--------------------|-----------------|
| Full system         | **75.2**           | **56.4**        |
| Word vector         | 74.5               | 55.2            |
| Companions vector   | 67.4               | 53.2            |
| MFT vector          | 71.9               | 49.8            |
| Knowledge-light     | 71.9               | 52.7            |

Table 3: Intrinsic (SemCor) and extrinsic (SE2) evaluation results for our ablation experiments. Results are measured in % accuracy and $F_1$-score respectively.

### 5.5 Ablation Experiments

WCT-VEC has a highly modular structure, making it adaptable to a variety of alternative settings. In this section, we perform a series of ablation experiments, in which various components or sources of information are removed from WCT-VEC to measure their impact. We perform intrinsic evaluation experiments on SemCor (all words), and extrinsic evaluation experiments on the SE2 WSD dataset.

Our first ablation experiments evaluate the utility of the three sources of information used by WCT-VEC: the vector of the target word, the average of the vectors of its companions, and the transformed vector of its most frequent translation. We run three feature ablation experiments, each using only one of these vectors, with the $\chi$ coefficients corresponding to the other vectors set to 0.

The results of this experiment, shown in Table 3, show that, if only one of these three vectors can be constructed, sense vectors are best compared to word vectors, as using only this vector gives better results than using only one of the other vectors. For intrinsic evaluation, using only the MFT vector gives better results using only the companions vector; on the extrinsic evaluation, the reverse is true. This once again shows the potential for disagreement between intrinsic and extrinsic evaluations of MFS detection systems.

In order to measure the impact of WordNet as a source of linguistic knowledge, we also perform a knowledge ablation experiment, in which WCT-VEC only has access to WordNet’s glosses and examples, and not to the WordNet synset hierarchy or any of its information on semantic relationships such as synonymy or hypernymy. This limits the keyword available for the construction of sense vectors, and essentially reduces WordNet to a machine-readable dictionary. This setting, which we refer to as knowledge-light, emulates the circumstances of working with less well-studied languages, for which machine-readable dictionaries are available, but WordNet-like knowledge bases are not. In this setting, our parameter tuning procedure for WCT-VEC yields the values of $(\chi_1, \chi_2, \chi_3) = (0.4, 0.1, 0.5)$ on the development set, which suggests that our innovation of leveraging a parallel corpus helps recover some linguistic information lost in this setting.

Table 3 shows that the decline in the performance of WCT-VEC in the knowledge-light setting compared to the standard “knowledge-heavy (KH)” version is relatively small, with a drop in accuracy of only 3.3% on MFS detection on SemCor. This shows that WCT-VEC ultimately has lower information requirements compared to prior work, and is applicable for low-resource settings.

WordNet glosses may include usage examples for a given sense. As a final ablation experiment, we measure the effect of removing these examples from WCT-VEC, in both the the knowledge-heavy and knowledge-light settings, as well as from UMFS-WE.

We found that, in all cases, the removal of examples lowered the results, however, the magnitude of the effect varied across the three systems. In an extrinsic evaluation on the SE2 WSD
dataset, WCT-VEC obtained F1 scores of 49.8% in the knowledge-light setting, and 55.9% in the KH setting, while UMFS-WE obtains an F1 score of 53.5%. This represents a decrease of 0.5% F1 for WCT-VEC in the knowledge-heavy setting, but 2.9% in the knowledge-light setting, with UMFS-WE losing 1.3% F1 when examples were excluded. A pattern is apparent in these results: the more linguistic knowledge a system uses, the less it benefits from the inclusion of examples.

5.6 Error Analysis

An example illustrating the advantage of using translations involves the noun *brow*, which has three principal senses: “hair above the eye” (MFS), “part of the face”, and “peak of a hill.” The COMP2SENSE approach incorrectly selects the last sense, which is actually the least frequent sense. WCT-VEC is able to identify the MFS by leveraging the fact that each of the senses translates into a different French word (*sourcil*, *front*, and *sommet*, respectively).

The difficulty of the task is illustrated by the verb *bow*. The MFS is “bend one’s knee or body, or lower one’s head”, but WordNet contains also two other similar senses: “bend the head or the upper part of the body in a gesture of respect or greeting”, and “bend one’s back forward from the waist on down.” The challenge of distinguishing between these senses is highlighted by the fact that all three sense include an almost identical usage example: “she/he bowed before the king/queen”. We conclude that, although WordNet is a standard evaluation resource, its fine-grained sense inventory may not be optimal for the WSD task. This is in accordance with prior work which has shown that WSD performance improves when performed with respect to less granular sense inventories (Navigli, 2006).

Although our knowledge-light version commits errors on a number of instances for which the WordNet information is crucial, there are also hundreds of words where it outdoes all other tested methods. For example, it correctly identifies the MFS of the verb *bore* as “cause to be bored.” The fact that the other methods choose instead the sense of “make a hole, especially with a pointed power or hand tool” can be attributed to the fact that this sense has a more detailed gloss, and is accompanied by 4 usage examples, as opposed to no examples for the MFS. It seems that the varying amounts of extra information available in WordNet for different senses may be a source of confusion for the knowledge-intensive methods.

This finding should motivate further research into knowledge-light MFS detection and WSD. Indeed, the trend in recent years has been to augment WSD systems with increasingly rich, increasingly complex sources of linguistic knowledge, such as BabelNet (Navigli and Ponzetto, 2012). That systems with more resources available perform better in general is unsurprising, and raises the question of whether recent advances in WSD are primarily due to the addition of new sources of linguistic knowledge, rather than algorithmic innovation. Development and comparison of systems in resource-controlled settings, such as our knowledge-light setting, could provide useful insights into how both WSD and MFS detection could be improved.

6 Conclusion

We have presented two novel MFS detection methods, one which uses a sense-to-sense similarity measure to find the sense which is most related to the companions of the target, and another which uses cross-lingual vector representations of words derived using a bitext. Our intrinsic and extrinsic evaluations show that the two methods perform well in comparison to previous work, and that they outperform a strong knowledge-based baseline when applied to word sense disambiguation. The ablation experiments demonstrate that our innovation of leveraging a bitext helps recover some of the lost information, improving results. In short, we have established that our contributions of defining and applying the companions and most frequent translations lead to improved performance in MFS detection.

In the future, we plan to explore ways of applying these concepts directly to word sense disambiguation, as well as leveraging WordNet-based similarity measures in a cross-lingual setting, and enhancing such measures with word vectors.

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