Expanding a Dictionary of Marker Words for Uncertainty and Negation Using Distributional Semantics

Alfalahi, Alyaa; Ahlblom, Rickard; Skeppstedt, Maira; Baskalayci, Roza; Henriksson, Aron; Asker, Lars; Paradis, Carita; Kerren, Andreas

Published in:
[Host publication title missing]

2015

Citation for published version (APA):

General rights
Unless other specific re-use rights are stated the following general rights apply:
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.
• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
  • You may not further distribute the material or use it for any profit-making activity or commercial gain
  • You may freely distribute the URL identifying the publication in the public portal

Read more about Creative commons licenses: https://creativecommons.org/licenses/

Take down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.
Expanding a dictionary of marker words for uncertainty and negation using distributional semantics

Alyaa Alfalahi¹, Maria Skeppstedt², Rickard Ahlbom¹, Roza Baskalayci¹, Aron Henriksson¹, Lars Asker¹, Carita Paradis⁴, Andreas Kerren³

¹DSV, Stockholm University, Stockholm, Sweden ²Gavagai AB, Stockholm, Sweden ³Computer Science Department, Linnaeus University, Växjö, Sweden ⁴Centre for Languages and Literature, Lund University, Lund, Sweden

Corresponding authors: maria@gavagai.se, aronhen@dsv.su.se

Abstract

Approaches to determining the factuality of diagnoses and findings in clinical text tend to rely on dictionaries of marker words for uncertainty and negation. Here, a method for semi-automatically expanding a dictionary of marker words using distributional semantics is presented and evaluated. It is shown that ranking candidates for inclusion according to their proximity to cluster centroids of semantically similar seed words is more successful than ranking them according to proximity to each individual seed word.

1 Introduction

Clinical text, i.e., the narrative sections of health records, has recently received much attention with regards to automatic detection of uncertainty and negation (Uzuner et al., 2011; Velupillai, 2012; Mowery et al., 2014). Methods for automatic detection of which diagnoses and findings are mentioned as negated or uncertain typically rely on a dictionary of marker words, either as a resource for rule-based methods or when constructing features for machine learning (Uzuner et al., 2011). Dictionaries of marker words have previously been constructed by manual annotation or by translation of dictionaries from one language to another (Velupillai et al., 2014). Alternative methods for automating marker word dictionary construction would, however, be useful since manual annotation is time-consuming, and translation results in incomplete dictionaries due to differences between languages in how negation and uncertainty are expressed. The aim of the present study was to explore one such possible method for semi-automatic dictionary expansion: using distributional semantics to extract possible marker words from a large unannotated corpus and, more specifically, attempting to obtain improved performance by applying clustering to the semantic vectors in the resulting semantic space.

Given a dictionary of known uncertainty and negation markers to use as seed words, the task of the system explored here was to rank words not included in the seed dictionary according to their suitability as marker words, with the aim of having good candidates for inclusion in the dictionary among the top-ranked words.

An experiment was carried out to determine if a method whereby words are ranked according to proximity to the centroids of seed word clusters outperforms – in the sense of ranking true marker words higher – a ranking method that instead uses proximity to each individual seed word. The seed words are here represented as vectors comprising word co-occurrence information, created using a model of distributional semantics called random indexing.

2 Background

For the English language, there are a number of large corpora annotated for speculation and negation: bio-medical corpora (Vincze et al., 2008; Uzuner et al., 2011), as well as corpora in other domains (Konstantinova et al., 2012). Systems for detecting negation and speculation are typically constructed by training machine learning models on these corpora (Farkas et al., 2010; Uzuner et al., 2011). For most other languages, there are, however, often only smaller annotated corpora or none at all (Velupillai et al., 2011; Aramaki et al., 2014). In such cases, methods for detecting uncertainty and negation that rely on lexicon/dictionary-matching to lists of marker words for uncertainty or negation are a possible alternative. Such an approach has been shown to perform in line with machine learning methods trained on corpora with fewer training instances (Velupillai et al., 2014; Aramaki et al., 2014).
For a dictionary-matching approach, extensive dictionaries of marker words are, however, required, and to build such a resource manually can also be prohibitively expensive. An alternative to creating a dictionary of marker words manually is to use automatic methods for creating lists of candidate words to include in the dictionary. For semi-automatically creating vocabulary resources of other types than marker words, there are a number of previous studies wherein various methods are used. Those that rely on terms being explicitly defined in the text (Hearst, 1992; Yu and Agichtein, 2003; Cohen et al., 2005; McCrae and Collier, 2008; Neelakantan and Collins, 2014) are unlikely to be successful for negation and uncertainty terms. Term extraction methods that measure similarity between words according to how frequently they occur in similar contexts (Lin, 1998), on the other hand, might be more suitable. Such distributional semantic properties are often represented by spatial models, i.e., given a geometric representation in the form of a vector space (Cohen and Widdows, 2009), and there are examples in which such spatial models have been used for vocabulary expansion (Zhang and Elhadad, 2013; Skeppstedt et al., 2013; Henriksson et al., 2014), as well as for related tasks (Jonnalagadda et al., 2012), in the bio-medical domain.

Random indexing is a computationally light-weight method for producing spatial models of distributional semantics (Kanerva et al., 2000; Sahlgren, 2006). Random indexing requires two types of vectors: index vectors, which are used only for semantic space construction, and context vectors, which represent the meaning of words and collectively make up the resulting semantic space. Each unique word \( w_j \) in the corpus vocabulary \( W \) is assigned an index vector \( \vec{w}_j \) and a context vector \( \vec{w}_j^c \) of dimensionality \( d \). The index vectors are static representations of contexts (here, these are unique words) that are approximately uncorrelated to each other, which is achieved by creating very sparse vectors that are randomly assigned a small number of non-zero elements (1s and -1s). A \( \vec{w}_j^c \) – containing the distributional profile of the word \( w_j \) – is then the (weighted) sum of all the index vectors of the words with which \( w_j \) co-occurs within a (typically symmetric) window of a certain size. Spatial proximity between two context vectors is taken to indicate the semantic similarity between the two words they represent. The context vectors can also be further analysed, for instance by applying different kinds of clustering (Rosell et al., 2009; Pyysalo et al., 2013).

### 3 Method

The conducted experiment consisted of the following steps: 1) constructing a semantic space with random indexing; 2) applying hierarchical clustering to context vectors representing seed words; 3) for different levels in the cluster tree, producing a ranked list of the words in the corpus according to their proximity to the centroids of the constructed clusters; 4) evaluating the recall of the top-ranked words in the produced lists against a reference standard.

1) A semantic space was constructed with random indexing on a freely available subset (years 1996–2005) of the Läkartidningen (Journal of the Swedish Medical Association) corpus (Kokkinakis, 2012). This subset contains 21,447,900 tokens and 444,601 unique terms. In order also to allow inflected forms of marker words to be captured, the corpus was not lemmatised. 1,000-dimensional vectors were used in a context window of two preceding and two following words and double weight was given to the two words closest to the target word. Since the sentences in the corpus appear in a randomised order, no context windows were allowed to cross sentence boundaries.

2) Single-linkage agglomerative hierarchical clustering (Sibson, 1973) was applied to the context vectors representing the seed words. A tree-formed cluster hierarchy was thereby created, with progressively larger clusters, starting from clusters in which each seed word formed its own cluster (cluster level 0 on the x-axis in Figure 1), until all seed words collectively formed a single cluster (cluster level 79 on the x-axis in Figure 1).

3) For each cluster level (0 to 79), a ranked list of all words in the corpus (except those used as seed words) was produced. The words were ranked according to the Euclidean distance between their length-normalised context vector and their most closely located cluster centroid (also length-normalised). That is, the word with the context vector that was closest to any of the centroid vectors achieved the highest ranking, the word with the context vector that was second closest to any of the centroid vectors was ranked as number two on the list, and so on. For cluster level
4) As a final step, the method was evaluated using an existing, freely available, dictionary of Swedish marker words for uncertainty and negation. This dictionary was developed through translation of English marker words and through manual annotation of clinical text (Velupillai et al., 2014). Markers in the dictionary were used as seed words as well as for evaluation data.

The dictionary was filtered by removing multi-word terms, since the constructed semantic space only contains single-word terms. In addition, words occurring fewer than 50 times in the corpus were removed, since a certain number of observations of a word is required for its context vector to be modeled reliably in semantic space. The performed filtering resulted in a set of 161 marker words for uncertainty and negation. The vocabulary used is shown in Figure 3.

This set of vocabulary terms was used in the evaluation by randomly splitting it into two equally large subsets: one set of seed words and one set of words to use as reference standard. In addition, words occurring fewer than 50 times in the corpus were removed, since a certain number of observations of a word is required for its context vector to be modeled reliably in semantic space. The performed filtering resulted in a set of 161 marker words for uncertainty and negation. The vocabulary used is shown in Figure 3.

This set of vocabulary terms was used in the evaluation by randomly splitting it into two equally large subsets: one set of seed words and one set of words to use as reference standard. In addition, words occurring fewer than 50 times in the corpus were removed, since a certain number of observations of a word is required for its context vector to be modeled reliably in semantic space. The performed filtering resulted in a set of 161 marker words for uncertainty and negation. The vocabulary used is shown in Figure 3.

4 Results and Discussion

As can be seen in Figure 1, results achieved with a moderate cluster level (20–40) were better than those achieved when proximity to each individual seed word was used as the ranking method (level 0). When the clusters grew larger (cluster level > 50), however, recall started to decrease, and using proximity to the centroid of a cluster containing all seed words resulted in much lower recall than when using proximity to each individual seed word, indicating that there are important differences in the usage of marker words. As a method for ranking the words in the corpus, it was thus better to use proximity to the centroid of a
Figure 1: Recall for different levels of clustering. Cluster level 0 means that each seed word forms its own cluster. The higher the cluster level, the larger the clusters created. Cluster level 79 means that all seed words form one large cluster. Recall is shown in Figure 1 from among the top 100 best candidates up to among the top 5,000 best candidates (with a step size of 100). The improvement that is achieved with a larger number of candidate words slowly levels out with an increasing number of candidates. The average result among the top 5,000 best candidates was a recall of just above 50%. A possible reason for these relatively low recall scores could be that the dictionary of marker words for uncertainty and negation contains many semantic outliers, i.e., words that do not occur in contexts similar to the other words in the list. The statistics shown in Figure 2 support this theory. The first stack in each of the three histograms, which shows the number of words that are very rarely found, is large in all three histograms. This indicates that regardless of which seed words are used, there is a large number of words that are never or very rarely found. It might, therefore, be the case that methods based on distributional semantics cannot be used for constructing a complete dictionary of negation and uncertainty markers, as such a dictionary includes semantic outliers, although the methods are useful for expanding a dictionary with typical marker words. Figure 3 shows the vocabulary used and how often a word was retrieved among the top 1,000 candidates when used as evaluation data.

It should be noted that the used list of marker words has been constructed using clinical text and has the aim of being used for clinical text, while this study was carried out on medical journal text. The used medical corpus has the advantage of being freely available, in contrast to large clinical corpora, which are only rarely available for research, and it also makes it possible for anyone to repeat the experiments carried out in this study. As there are many differences between medical journal text and clinical text (Smith et al., 2014), some marker words might be used in other contexts in clinical text than in medical journal text.
and there might be fewer semantic outliers if the experiments were to be repeated using a clinical corpus.

There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

The experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms). There were also 54 negation and uncertainty markers in the used dictionary that were excluded from the study since they occurred fewer than 50 times in the corpus. The existence of these words, which were mainly inflected forms, abbreviations and a few misspellings that are unusual outside of the clinical language, e.g., beaktandes (taking into consideration), alt (alternatively), diffdiagnos (diifferential diagnosis), is also a reason for why the experiment should be repeated with a clinical corpus. Multi-word terms formed an even larger proportion of the terms than described in previous work and uncertainty and negation markers in the vocabulary used for the experiments (376 terms).

It could, therefore, be difficult to retrieve standard language single-word terms for negation and uncertainty not already included in this dictionary. There might, however, still be a need to add abbreviated forms and multi-word terms. The methods evaluated here could also be applied to other languages, for which resources of marker words for negation and uncertainty, used in main text, have not yet been constructed.

5 Conclusion

It was shown that proximity to the centroid of the a number of semantically similar seed words was a more successful method for ranking the words in the corpus as candidates for negation and uncertainty markers than to use proximity to each individual seed word as the ranking method. However, many of the marked words used in the evaluation were never, or very rarely, ranked highly on the candidate list, regardless of which seed words were used.

Acknowledgements

This work was partly funded through the project StaViCTA by the framework grant “the Digitized Society Past, Present, and Future” with No. 2012-5659 from the Swedish Research Council (Vetenskapsrådet) and partly by the Swedish Foundation for Strategic Research through the project High-Performance Data Mining for Drug Effect Detection (ref. no. IIS11-0053) at Stockholm University. The authors would also like to direct thanks to the reviewers for valuable comments.
References


