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Knowledge based word-concept model estimation and refinement for biomedical text mining

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ABSTRACT

Text mining of scientific literature has been essential for setting up large public biomedical databases, which are being widely used by the research community. In the biomedical domain, the existence of a large number of terminological resources and knowledge bases (KB) has enabled a myriad of machine learning methods for different text mining related tasks. Unfortunately, KBs have not been devised for text mining tasks but for human interpretation, thus performance of KB-based methods is usually lower when compared to supervised machine learning methods. The disadvantage of supervised methods though is they require labeled training data and therefore not useful for large scale biomedical text mining systems. KB-based methods do not have this limitation.

In this paper, we describe a novel method to generate word-concept probabilities from a KB, which can serve as a basis for several text mining tasks. This method not only takes into account the underlying patterns within the descriptions contained in the KB but also those in texts available from large unlabeled corpora such as MEDLINE. The parameters of the model have been estimated without training data. Patterns from MEDLINE have been built using MetaMap for entity recognition and related using co-occurrences.

The word-concept probabilities were evaluated on the task of word sense disambiguation (WSD). The results showed that our method obtained a higher degree of accuracy than other state-of-the-art approaches when evaluated on the MSH WSD data set. We also evaluated our method on the task of document ranking using MEDLINE citations. These results also showed an increase in performance over existing baseline retrieval approaches.

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50 1. Introduction

Text mining of biomedical literature has supported the develop-51 ment of biomedical knowledge bases (KB), which are actively used 52 by the research community [23]. These databases have contributed 53 as well in the development of methods to perform text mining 54 55 related tasks like entity recognition and relation extraction. There are a large number of KBs available for biomedical text mining pur-56 poses. Some of these resources are integrated into the Unified 57 Medical Language System[®] (UMLS[®]) [12] and many resources are 58 59 available from the Open Biological and Biomedical Ontologies (OBO) foundry [39].¹ Unfortunately, since these resources were 60 61 not developed to perform text mining tasks, knowledge based meth-62 ods usually exhibit lower performance compared to ad hoc super-

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http://dx.doi.org/10.1016/j.jbi.2014.11.015 1532-0464/© 2014 Published by Elsevier Inc. vised methods (e.g., supervised classifiers) [20]. Despite this limitation, knowledge based approaches become crucial when either there is a scarcity of labeled data to train supervised methods. Due to the heterogeneity and large scale of biomedical resources, knowledge based methods are becoming more popular.

Estimating word-concept probabilities from KBs provides an effective way to support a large range of text mining tasks in the biomedical domain [40]. Unlike supervised methods, the absence of manually labeled data can be alleviated by defining statistical approximations from either the existing data in the KBs (e.g., names, relations and descriptions) or external data such as MEDLINE[®] abstracts [20]. Other approaches are aimed at building statistical models directly from corpora, like Latent Dirichlet Allocation (LDA) [11], but it is not clear how to interpret or integrate these models within the KB structures [15].

Word sense disambiguation (WSD) and information retrieval (IR) are two tasks that benefit from word-concept probability models. Given an ambiguous word with its context, WSD attempts to

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81 select the proper sense given a set of candidate senses. An example 82 of ambiguity is the word cold which could either refer to low tem-83 *perature* or the *viral infection*. The context in which *cold* appears is 84 used to disambiguate it. WSD is an intermediate task that supports 85 other tasks such as: information extraction [5], information retrie-86 val and summarization [33]. WSD in the biomedical domain is 87 mostly based on either supervised learning or knowledge based approaches [37]. As previously mentioned, the scarcity of training 88 89 data makes knowledge based methods preferable to supervised 90 ones.

In IR, KB based methods have been proposed for either expanding queries or for performing semantic searches [14,25]. However, these methods do not provide a proper way to combine the expanded words, and just use the KB for defining improved IR queries as we have shown in [25].

This work proposes a novel method for generating word-concept statistical models from KBs that can be used directly for both IR and WSD. As mentioned earlier, this method is also able to take advantage of existing data in MEDLINE to produce a model with improved performance. These models can be integrated into IR language models to resolve ambiguity.

102 An implementation of the presented method is available from https://bitbucket.org/ajjimeno/wkpropability. 103

104 2. Related work

In the biomedical domain, there have been several big projects 105 and initiatives to build comprehensive knowledge resources such 106 as OBO and UMLS. At the same time, during the last decade 107 108 researchers have devised automatic text mining techniques to find 109 new knowledge from the scientific literature [9]. In this paper, we 110 are interested in developing a general purpose probabilistic model that can be used in several text mining tasks, such as WSD and doc-111 112 ument ranking.

113 WSD methods are based on supervised learning or KB-based 114 approaches [37]. Supervised methods are trained on examples for 115 each one of the senses of an ambiguous word. A trained model is 116 used to disambiguate previously unseen examples. This approach 117 requires a large set of training examples, which is usually not available. For example, the 2009AB version of the UMLS contains 118 approximately 24 thousand ambiguous words, based on the exact 119 120 match of the words in the UMLS Metathesaurus. Preparing such 121 training examples would be very expensive to build and maintain 122 [44].

In the biomedical domain, KB-based methods for WSD either build a concept profile [29,28,20], develop a graph-based model [2,3] or rely on the semantic types assigned to each concept for disambiguation [19]. These derived models are compared to the context of the ambiguous word being disambiguated to select the most likely sense. In these approaches, candidate senses of the ambiguous word are UMLS concepts.

KB-based methods have been complemented with information 130 available from existing resources like MEDLINE. An example is 131 the use of MeSH indexing^{®2} as additional information [41]; 132 although this approach is dependent on the availability of MeSH 133 134 indexing. In previous work, we collected training data from MED-LINE citations for each sense of an ambiguous word [20]. PubMed 135 queries used to retrieve these citations were generated using English 136 137 monosemous relations [27] of the candidate concepts which, poten-138 tially, have an unambiguous use in MEDLINE. This approach has shown good performance compared to other KB-based methods. In 139 a subsequent study, we extended the work in [20] by considering 140

all of MEDLINE instead of the top 100 recovered citations by PubMed and by generating concept profiles that can be easily estimated on large number of examples [21]. Using a large number of examples showed an improvement over previous methods.

Semi-supervised algorithms could be used to obtain additional examples of contexts for ambiguous words. We explored this in [22], where the initial disambiguation predictions provided by an unsupervised method were used as a seed to identify better concept profiles. This method showed a significant improvement.

There are several approaches in WSD that utilize the graph structure of the resources [30,1], e.g., by applying adaptations of the page rank algorithm. Unfortunately, these methods cannot be re-used for other tasks like IR, because the generated models are only able to rank senses for given contexts, and not documents for given concepts. Conversely, approaches for IR that take into account the KB (e.g., [25]) are aimed at generating IR queries but not statistical models for other purposes.

In this paper, we claim that the generation of statistical models from both the KB and existing external corpora can provide a very valuable resource for effectively performing various text mining tasks. Furthermore, we show that the presented model generates word-concept probabilities that produce good results on these tasks.

3. Methods

In this section, we present the word-concept statistical 166 model. The estimation of the model based on the knowledge 167 base is presented in Section 3.1. The model estimates weights 168 to combine probabilities from concepts at different traversal 169 steps. In this work, the model is adjusted using it for disambig-170 uation, which is introduced in Section 3.2. The adjustment is 171 based on Expectation-Maximization as explained in Section 172 3.3. Once the model is trained, it can be refined based on exist-173 ing corpora in an unsupervised way as explained in Section 3.4. 174 The word-concept probabilities obtained from this model can be 175 used in other tasks such as IR as explained in Section 3.5. Lastly, 176 experimental set up and data sets used in this work are pre-177 sented in Section 3.6. 178

In this work, a KB is defined as an inventory of concepts C, 179 where each concept $c \in C$ is associated to a list of lexical forms 180 lex(c) (i.e., strings of text that are synonyms, variants, and so on), 181 and a set of relations to other concepts, denoted with r(c, c'). These 182 relations can be of any kind, from taxonomic is-a relations to other 183 specific biomedical domain relationships (e.g., treats). Resources 184 like the UMLS Metathesaurus fit this KB definition (see Section 185 3.6). Strings of text consist of tokens, that are their model primi-186 tives. Tokens may be punctuation or words, which are the minimal 187 semantic tokens in the text. Terms are words or multi-word 188 expressions denoting a concept (e.g., the synonyms and lexical 189 variants linked to concepts in the UMLS). 190

3.1. Word-concept probability estimation

We propose estimating the probability $P(w_i|c_i)$ by selecting a 192 word w_i given a concept c_i in a KB. This is done by selecting a word 193 from the concept c_i , step 0, or from any of the related concepts at 194 any specific step k while traversing the KB relations. The method 195 described below provides a way to estimate this probability at dif-196 ferent traversal steps. 197

The models obtained at different steps are combined using a linear combination. The weights of the linear combination are defined in the vector $\vec{\beta}$ (from Eq. (2)), whose dimension is the number of traversal steps as shown in Eq. (1).

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² NLM's controlled vocabulary used to index MEDLINE: https://www.nlm.nih.gov/ mesh.

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