

Understanding and Evaluating Medical Concept Embeddings

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Word embeddings, also known as distributed representations, have seen rapid adoption in natural language processing (NLP) and machine learning. Though they are now standard practice in many areas of NLP and machine learning, they are just now beginning to attract interest in biomedical and clinical informatics. In this article, we present an overview of the existing word embedding methodology and investigate their use for biomedical concepts. In addition, we propose a set of benchmarks so that researchers can evaluate concept embeddings and understand what aspects of the source data they capture. We provide the benchmarks and a set of reference embeddings as an R package to the community to encourage quick, easy, and reproducible comparisons of new embeddings in the future.

Keywords: Machine Learning; Distributed Representations; Word Vectors; Concept Embeddings; Unsupervised Learning

1. Distributed Representations for Words and Concepts

Word embeddings have ignited a furious amount of research after the the results of Mikolov¹ et. al demonstrated that they are capable of capturing a surprising amount of semantic information. The central idea of a word embedding is to represent a word as a dense, real-valued vector that projects the word into a d -dimensional space. Words that are similar in this space encode certain semantic and linguistic regularities from the source text. While classic NLP tasks, such as sentiment analysis and text classification, have been shown to benefit from distributed representations, what caused this approach to gain considerable attention was the observation that analogies could be solved using arithmetic vector operations. The now famous example of *king : queen :: man : ?* can be solved by the following operations on their corresponding word vectors:

$$king - man + woman \approx queen \tag{1}$$

Thus, the analogy task of analogy is reduced to addition and subtraction of the word vectors.

The idea of a vectorized or distribution representation of a word has its roots in the neural language model of Bengio,¹ though this model is actually a formalization of the ideas first put forth in [paper from the 50s]. However, it wasn't until the paper² underpinning the wildly

successful *word2vec* software package which demonstrated that collapsing the neural language model of Bengio¹ to a linear model enabled greater accuracy through training on much larger datasets that the idea of word embeddings finally came of age. Though they are often conflated, current distributed representations are not an instance of deep learning, but are actually a specific kind of linear model, with explicit connections to many well known forms of matrix factorization.³

1.1. *Word2Vec and Glove*

1.2. *Medical Concept Embeddings*

2. Benchmarks

Here is where we will put the description of all of the benchmarks, put in `\subsection{}` tags

3. Results

Here is where we will present the results for all of the different embeddings.

References

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