Multilingual Vector Representations of Words, Sentences, and Documents

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Abstract

Neural vector representations are now ubiquitous in all subfields of natural language processing and text mining. While methods such as word2vec and GloVe are wellknown, *multilingual* and *cross-lingual* vector representations have also become important. In particular, such representations can not only describe words, but also of entire sentences and documents as well.

1 Introduction

Vector representations are ubiquitous in all subfields of natural language processing and text mining. Well-known neural methods such as word2vec and GloVe enable us to obtain distributed vector representations of words, overcoming some of the sparsity issues faced by traditional distributional semantics methods. Such representations are learnt from co-occurrence information drawn from large monolingual corpora.

Oftentimes, however, we are interested in representations that enable us to transition across language boundaries. Thus, it is useful to consider *multilingual* vector representations, covering multiple languages, and in particular *cross-lingual* vector representations, which capture the semantics of different items in the same vector space, even when said items stem from different source languages.

This is useful for representations of individual words (Section 2), but also of entire sentences (Section 3) and documents (Section 4) as well.

2 Multilingual Word Vectors

One can distinguish several broad classes of algorithms for inducing cross-lingual word vectors.

Projection Approaches. The first strategy is to train multiple separate vector spaces using standard

methods and then align them cross-lingually. The latter can be achieved using techniques such as linear projections (Mikolov et al., 2013), Canonical Correlation Analysis (Faruqui and Dyer, 2014), or the approach by Gouws et al. (2015).

Parallel Corpora Approaches. The second strategy is to rely on parallel corpora and directly optimize a cross-lingual objective that considers sentence translations. Examples include the methods proposed by Klementiev et al. (2012), Kočiský et al. (2014), and Gouws and Søgaard (2015). Some of these simply use aligned sentences, while others require word alignments. Vulić and Moens (2015a) showed that comparable documents may suffice to learn bilingual embeddings.

External Supervision. Alternatively, a third strategy is to draw on supplementary sources of supervision. For this, one can extract more explicit semantic information from text and then incorporate the mined knowledge into the objective function (Chen and de Melo, 2015; Chen et al., 2016). Loza Mencía et al. (2016) propose exploiting document labels as a surrogate form of supervision for higher-quality embeddings.

Finally, one can also draw on lexical knowledge graphs such as WordNet and its multilingual extensions (de Melo and Weikum, 2010), or on Wikipedia (de Melo and Weikum, 2014). These resources provide a rich source of information to induce massively multilingual word vectors covering hundreds of languages in the same space (de Melo, 2015; de Melo, 2017), with the additional advantage of also yielding sense- or concept-specific representations.

3 Multilingual Sentence Vectors

Next, we turn to vector representations of sentences. **Word Vector-inspired Approaches.** A widely used strategy is to simply average the word vectors of words in a given sentence. Despite its simplicity, this method often works surprisingly well (Wieting et al., 2015; Arora et al., 2017).

An early attempt to incorporate sentences more explicitly into the objective function was proposed with the Paragraph Vectors approach (Le and Mikolov, 2014). This method is also occasionally referred to as doc2vec, as it straightforwardly extends word2vec to additionally create representations of sentences or other longer units. Several authors have devised bilingual variants of the Paragraph Vector approach (Pham et al., 2015; Mogadala and Rettinger, 2016).

The Skip-Thought Vector approach (Kiros et al., 2015), while also inspired by the word2vec skipgram method, instead draws on recurrent units to encode and decode sentence representations such that the resulting representations are optimized for predicting neighbouring sentences.

External Supervision. Wieting et al. (2015) explored using supervision from paraphrase information to obtain custom-tailored word vectors that give rise to high-quality sentence embeddings. The InferSent approach (Conneau et al., 2017) relies on supervision from the Stanford Natural Language Inference data as an auxiliary task to obtain sentence representations. In terms of cross-lingual methods, neural machine translation based on sequence-to-sequence learning can give rise to vector encodings of multilingual input sentences (Luong et al., 2015). These have been shown to be semantically meaningful (Schwenk and Douze, 2017).

4 Multilingual Document Vectors

Finally, we consider representations of entire text documents.

Word Vector-inspired Approaches. To obtain document representations, a common choice is again to simply take the average of word vectors, or a suitably weighted sum. In doing so, one can directly rely on multilingual word vectors to generate cross-lingual documents representations (Klementiev et al., 2012) that can be used for tasks such as cross-lingual text classification (de Melo and Siersdorfer, 2007).

A fallback strategy is to translate all documents to a single language and then consider monolingual document similarity metrics. This approach may be more costly in terms of the resources used, and may neglect language-specific subtleties. Still, in practice, it does appear to be a strong baseline (de Melo and Siersdorfer, 2007).

Modeling Document Semantics. While many methods treat sentences and documents as interchangeable, there are significant differences between the two. Methods that focus specifically on properties of documents have the potential to yield higher-quality document-level embeddings. Bagof-words vectors can be rendered cross-lingual by translating individual words (Song et al., 2016), or by moving from original words to bag-of-concept representations (de Melo and Siersdorfer, 2007), optionally drawing on distributed vectors for concepts (de Melo, 2017). Representations may also account for the salience of different parts of the text (Yang et al., 2016, 2017). Hermann and Blunsom (2014) train a siamese-style network architecture on a parallel corpus such that it learns to compose sentence representations into document representations. Finally, when documents are to be compared against short queries, it is important to consider the peculiarities of relevance modeling (Vulić and Moens, 2015b; Hui et al., 2017), which differs from semantic similarity modeling.

5 Conclusion

In summary, vector representations have made it easier to target multilingual and cross-lingual semantics. This is possible both at the level of individual words as well as at the level of sentences or even entire documents.

Biography

Gerard de Melo is an Assistant Professor of Computer Science at Rutgers University, heading a team of researchers working on NLP, Big Data analytics, and web mining. He has published over 80 papers on these topics, with Best Paper/Demo awards at WWW 2011, CIKM 2010, ICGL 2008, the NAACL 2015 Workshop on Vector Space Modeling, as well as an ACL 2014 Best Paper Honorable Mention, a Best Student Paper Award nomination at ESWC 2015, and a thesis award for his work on graph algorithms for knowledge modeling. Notable research projects include UWN/MENTA, the first massively multilingual version of Word-Net, and Lexvo.org, an important hub in the Web of Data. For further information, please refer to http://gerard.demelo.org.

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