
Compressed Sensing Project

A compressed sensing view of unsupervised text embeddings

Salomé Do, Lucas Zanini

March, 22nd 2019

Introduction

Text documents have been, until recently, an underexploited source of information due to their complex, non-numerical structure. Low level natural language processing (NLP) tasks as text classification, sequence tagging (POS-tagging, named entity recognition, ...) and parsing have long been tackled through bag-of-words methods and hidden markov models. The application of deep learning to NLP tasks (started around 2010s) has opened new, complementary and effective ways to solve these problems, eventually leading to core innovations in high-level tasks such as question answering or language generation. Using feed-forward networks to generate low-dimensionnal representation of sparse, high dimensionnal word vectors; recurrent neural networks as LSTMs to fit the sequential nature of sentences; and later on attention mechanisms, deep learning techniques have set new baselines on traditional benchmarks. However, the efficiency of these results is totally empirical and is not backed by theoretical results, in addition to having high computational costs. The article studied in this project [1] aims at giving some results on unsupervised text embeddings.

To do so, it focusses on a compressed sensing view of the text embedding problem, which aims at providing low-dimensionnal representation for texts. As words can be viewed as very sparse vectors in the vocabulary space, providing a low-dimensionnal representation of a text can be seen as measuring words signals in a compressed way. The article explores this idea, and links compressed sensing to some LSTMs-learned text representations. In order to evaluate such representations (through their performances on text classification), authors adapts a result in [2] on the quality of low-dimensionnal compressed sensing representations as inputs for a classification problem.

In this work, we will first recall what are words and text embeddings, in order to recall the basic NLP background for a non-specialized reader, and we will present author's text embeddings. Then, we will focuss on the core part of this project : the compressed sensing part, and its application in text embeddings. Finally, we will present a reproduction of author's results, and discuss their statings and their implications.

Contents

1	Text embeddings	3
1.1	Word embeddings	3
1.2	From word embeddings to text embeddings	5
1.2.1	LSTMs	5
1.2.2	Bag of n-Grams	5
1.2.3	DisC embeddings	5
1.3	Why text embeddings?	5
2	Text embedding as a Compressed Sensing problem	6
2.1	Results on compressed sensing for classification	6
2.2	Links with LSTMs	6
2.3	Sparse recovery with pretrained embeddings	6
3	Experiments and discussion	7
3.1	Results reproduction	7
3.2	Testing DisC embeddings on real life data	7
3.3	Discussion	7

1 Text embeddings

A text embedding is a vector representing a text. Usually, we want this representation to be low-dimensionnal, and to keep some information on the meaning of the text. By necessity, these representations are generally unsupervised : it would be hard to define a "standard" representation to be learned in a supervised way. In this section, we recall usual ways to learn to generate word embeddings - upon which lie LSTMs text embeddings -, text embeddings, and we explain in which ways they can be used for tasks as text classification.

1.1 Word embeddings

The very beginning of most popular text embeddings is word embeddings. In this part we will briefly explain how such embeddings are learned, and we will set the definitions and the general context for the rest of the work.

Supposing that we have a vocabulary $\mathcal{V} = \{w_1, \dots, w_V\}$, of size $|\mathcal{V}| = V$, a natural vector representation of any word $w_i, i = 1, \dots, V$ is the following :

$$w_i = \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \leftarrow i, \quad w_i \in \mathbb{R}^V$$

The problem with this simple representation is the dimension (V) and its sparsity ($\|w_i\|_0 = 1, \forall i = 1, \dots, V$) of the vectors. To adress this issue, many techniques have been proposed, especially in recent deep learning developments. Non-deep learning techniques are based on co-occurrence matrices : given a set \mathcal{D} of documents, we first build a matrix containing the number of co-occurrences of every word in all documents in a context window of size c , for instance :

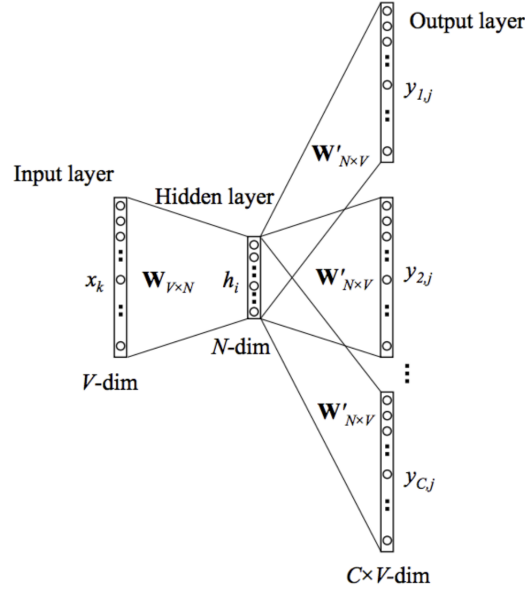
$$M = \begin{pmatrix} C(w_1, w_1) & \dots & C(w_1, w_V) \\ \vdots & \ddots & \vdots \\ C(w_V, w_1) & \dots & C(w_V, w_V) \end{pmatrix} \in \mathbb{R}^{V \times V}$$

Where $C(w_i, w_j)$ is the number of times that the word w_j appears in the context of w_i , the context being defined as the words far from at most c words from w_i in any of the documents in \mathcal{D} . This matrix is usually regularized using positive pointwise mutual information (PPMI). A word w_i is then represented as the i -th line of M , or its PPMI counterpart. However, this representation does not get rid of dimension neither sparsity problems. Assuming the PPMI matrix is very sparse, we use, as it is frequently done in high-dimensionnal statistics, a singular value decomposition $M^{\text{PPMI}} = W \times D \times C$, keeping only the k most important singular values and vectors, leading to a new truncated version of W , of size $V \times k$, which becomes the embedding matrix, each line being a word's embedding. This decomposition has good denoising and generalization properties.

In parallel, the most popular deep learning embedding is the Word2Vec embedding, proposed in [3]. This embedding is learned by trying to predict a word from its context (CBOW), or vice

versa to predict a context from a given word (skip-gram); using a 1-hidden layer feed-forward neural network (Figure 1).

Figure 1: Skip-gram architecture for Word2Vec



Using some regularization and computational tricks during the training, as replacing the softmax output function computation by a hierarchical softmax computation, or as using negative sampling loss as an objective function, or doing frequency subsampling; which are detailed in [4]; Word2Vec embeddings achieved better generalization and denoising properties than SVD. The main idea behind both Word2Vec and SVD embeddings, which makes them coherent as a good semantic representation, is called the distributional hypothesis. This linguistic hypothesis is built upon Firth's statement that *"a word is characterized by the company that it keeps"*. Thus, words employed in similar contexts are more likely to have similar meanings. However, latest deep learning developments seem to have abandoned this approach, replaced by language modelling as in [5, 6, 7], which are outside the scope of this project.

The evaluation of such embeddings is difficult, as they are learned in an unsupervised way. However, two techniques are generally used to assess embeddings representation quality : the evaluation of the embedding through a downstream task, i.e. for instance the evaluation of classic text classifiers using the evaluated embedding as an input; and an evaluation through word similarities, with the objective that near vectors (regarding cosine distance) represent words with similar meanings. This evaluation techniques are used in the same manner for text embeddings.

1.2 From word embeddings to text embeddings

1.2.1 LSTMs

1.2.2 Bag of n-Grams

1.2.3 DisC embeddings

1.3 Why text embeddings?

2 Text embedding as a Compressed Sensing problem

2.1 Results on compressed sensing for classification

2.2 Links with LSTMs

2.3 Sparse recovery with pretrained embeddings

3 Experiments and discussion

3.1 Results reproduction

3.2 Testing DisC embeddings on real life data

3.3 Discussion

References

- [1] S. Arora, M. Khodak, N. Saunshi, and K. Vodrahalli, “A compressed sensing view of unsupervised text embeddings, bag-of-n-grams, and lstms,” in Proceedings of the 6th International Conference on Learning Representations (ICLR), 2018.
- [2] R. Calderbank, “Compressed learning : Universal sparse dimensionality reduction and learning in the measurement domain,” 2009.
- [3] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed Representations of Words and Phrases and their Compositionality,” in Advances in Neural Information Processing Systems 26 (C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger, eds.), pp. 3111–3119, Curran Associates, Inc., 2013.
- [4] T. Mikolov, K. Chen, G. Corrado, and J. Dean, “Efficient Estimation of Word Representations in Vector Space,” pp. 1–12, 2013.
- [5] J. Howard and S. Ruder, “Universal language model fine-tuning for text classification,” 2018.
- [6] M. Peters, M. Neumann, M. Iyyer, M. Gardner, C. Clark, K. Lee, and L. Zettlemoyer, “Deep contextualized word representations,” Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), 2018.
- [7] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” 2018.