



Sense Embeddings in Knowledge-Based Word Sense Disambiguation

Loïc Vial, Benjamin Lecouteux, Didier Schwab

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Word Sense Disambiguation

Word Sense Disambiguation (WSD) consists in assigning the most appropriate sense to a word in a document, given a particular sense inventory. Similarity-based disambiguation systems are WSD systems composed of both:

1. A **local** algorithm, also called **similarity measure**, which computes a similarity score $sim(S_1, S_2)$ between two senses.
2. A **global** algorithm, which searches the best combination of senses at the document level, by using the local algorithm.

Common similarity measures

Among the most frequently used **similarity measures** based on definitions contained in a dictionary, there are:

- The **Lesk** algorithm [1], which computes the number of words in common between the two definitions:
 $Lesk(S_1, S_2) = |D(S_1) \cap D(S_2)|$, with $D(S) = \{w_0, w_1, \dots, w_n\}$ the definition of the sense S in the dictionary.
- The **Extended Lesk** algorithm [2], which takes into account not only the definitions of the senses, but also the definitions of all related senses in a semantic network:
 $ExtLesk(S_1, S_2) = |(D(S_1) \cup D(rel(S_1))) \cap (D(S_2) \cup D(rel(S_2)))|$, with $rel(S)$ the senses connected to S through an explicit link in WordNet [3].

Our similarity measure

The similarity measure that we propose, called $VecLesk(S_1, S_2)$, takes into account the closest senses in a sense embeddings model regarding their cosine similarity between the **vector of the lemma of S**, above a **threshold δ_1** , and also between the **vector of S**, above a **threshold δ_2** .

It is formally defined as:

$$VecLesk(S_1, S_2, \delta_1, \delta_2) = |(D(S_1) \cup D(rel(S_1, \delta_1, \delta_2))) \cap (D(S_2) \cup D(rel(S_2, \delta_1, \delta_2)))|$$

$$rel(S, \delta_1, \delta_2) = \{S' \mid cosine(\phi(lemma(S)), \phi(S')) > \delta_1, cosine(\phi(S), \phi(S')) > \delta_2\}$$

Therefore there is no more manually created semantic network used for extending the Lesk measure.

Some example results

Our sense vectors can be manipulated as word vectors.

For instance, close to **bank (financial institution)**, we find the senses **account**, **deposit** and **money**; whereas close to **bank (shore)**, we find the senses **coast**, **sandbank** and **dip**.

All sense vectors are available at the following URL:

<https://github.com/getalp/WSD-IWCS2017-Vialetal>



Sense vectors

The definition of the vector of a sense S is $\phi(S)$, and it corresponds to :

$$\phi(S) = \sum_{i=0}^n (\phi(w_n) \times weight(pos(w_n)) \times idf(w_n))$$

- $D(S) = \{w_0, w_1, \dots, w_n\}$ the definition of sense S in the dictionary
- $\phi(w_n)$ the vector of the word w_n
- $pos(w_n) = \{n, v, a, r\}$ the part of speech of the word w_n : noun, verb, adjective or adverb
- $weight(pos)$ the weight associated to the part of speech pos
- $idf(w_n)$ the IDF value of w_n

$\phi(S)$ is then normalized so its length is the same as any word vector.

Evaluation

System	SemEval 2007	SemEval 2015
S2C [4]	75.80%*	
Lesk	68.70%	50.65%
Extended Lesk	78.01%	61.42%
VecLesk (Baroni C [5])	75.29%	58.02%
VecLesk (Baroni P [5])	73.52%	53.46%
VecLesk (Deps [6])	73.02%	56.40%
VecLesk (GloVe [7])	73.00%	59.01%
VecLesk (Word2Vec [8])	73.30%	57.00%

Table 1: Results on SemEval 2007 and SemEval 2015 for each underlying word embeddings model.

*This system is comparable to our in terms of resources used, but it is biased: their threshold parameter δ is learned on the evaluation task. We would obtain **76.50%** by doing the same.

Model Parameters	Baroni C [5]		Baroni P [5]		Deps [6]		GloVe [7]		Word2Vec [8]	
	δ_1	δ_2	δ_1	δ_2	δ_1	δ_2	δ_1	δ_2	δ_1	δ_2
SemEval 2007	0.6	0.6	0.5	0.5	0.6	0.8	0.5	0.6	0.5	0.6
SemEval 2015	0.5	0.8	0.5	0.6	0.6	0.8	0.5	0.7	0.5	0.6

Table 2: Estimation of the parameters δ_1 and δ_2 on SemEval 2007 and SemEval 2015.

- The **Lesk** measure is **considerably improved** with our extension.
- The scores **almost** reach the **Extended Lesk**, **without** the need of a semantic network like the one from **WordNet**.
- Our system allows to **improve** the **word sense disambiguation** of **languages that have less resources** than English.

References

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