Russian Word Sense Induction by Clustering Averaged Word Embeddings

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Contents

Introducing the task

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- Method: naive clustering of contexts represented with averaged word embeddings.
- Takeaway message: small but balanced corpora are superior again.

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- WSI system for Russian is described and published.
- It successfully extracts word senses for homonyms and is based exclusively on off-the-shelf tools and models.
- Training corpus balance is very important for word embedding models in intrinsic evaluation...
- this holds for extrinsic evaluation setting as well (WSI in this case).

Contents

What we all know about WSI

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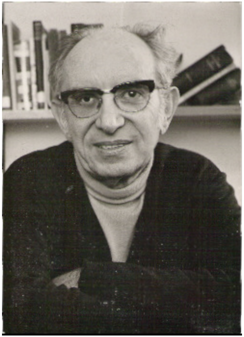
- Syntactic ambiguity is solved by PoS taggers and dependency parsers.
- ...but words can possess different senses/meanings.
- All that happens with semantics, happens at the level of word senses, not words.

What we all know about WSI



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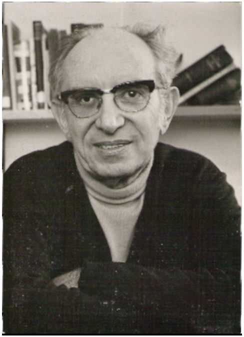
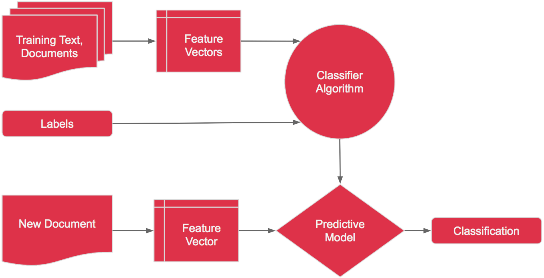


- Even word sense disambiguation is difficult for computers.
- Yehoshua Bar-Hillel:
  - '*sense ambiguity could not be resolved by electronic computer either current or imaginable*' [Bar-Hillel, 1964].
- But people learned how to disambiguate word senses in a supervised setup...
- using manually annotated semantic concordances and lexical databases.



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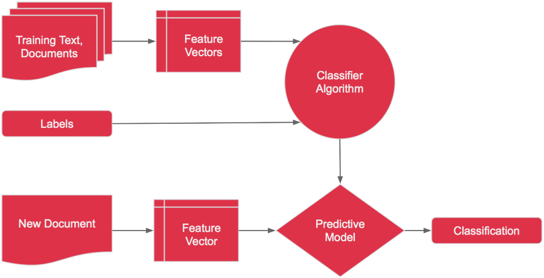

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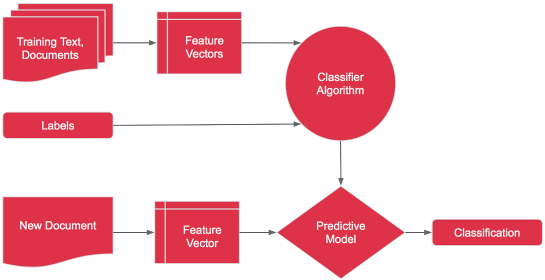

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  2. at test time collect features and predict the correct sense with the classifier.

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- Manually annotated resources quickly get outdated.
- They don't keep up with the changes in language.
- Humans simply can't annotate that fast.

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‘*Word senses are abstractions from clusters of corpus citations*’
[Kilgarriff, 1997]

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5. Centroids serve as sense vectors for WSD.

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- The approach can be enriched with additional techniques like lexical substitution [Alagić et al., 2018]

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Word embeddings

- Instead of one-hot word vectors, one can use distributional information about word meanings.
- To this end, we employ prediction-based word embedding models:
  - *Continuous Skipgram* [Mikolov et al., 2013]
  - *fastText* [Bojanowski et al., 2017]

Contents

Datasets and models overview

RUSSE'18 offered three datasets:

1. *wiki-wiki*: sense inventories and contexts from the Russian Wikipedia articles;
2. *bts-rnc*: sense inventories from 'Bolshoi Tolkovii Slovar' dictionary (BTS), contexts from the Russian National Corpus;
3. *active-dict*: sense inventories from the Active Dictionary of the Russian Language, contexts from the examples in the same dictionary.

Datasets and models overview

wiki-wiki dataset is substantially different from the other two:

Training dataset	**wiki-wiki**	**bts-rnc**	**active-dict**
Average number of senses	2	3.2	3.7
Maximum number of senses	2	8	17

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  - обед^1 (lunch) and обед^2 (lunchtime)
  - дерево^1 (tree) and дерево^2 (wood)

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Word senses represent some sort of a continuum

- There is no distinct boundary between homonymy and polysemy.
- Often difficult to tell how many senses does a word really have.
- But still:
- Inducing meanings of homonyms is a different and easier task than inducing different sense of polysemous words.

Datasets and models overview

Pre-trained word embedding models from the RusVectōrēs web service [Kutuzov and Kuzmenko, 2016]

Model id	corpus	corpus size, words	algorithm
ruscorpora_upos_skipgram_300_5_2018	Russian National Corpus (RNC)	250M	word2vec skipgram
ruwikiruscorpora_upos_skipgram_300_2_2018	RNC + Wikipedia	600M	word2vec skipgram
news_upos_cbow_600_2_2018	News corpus	5000M	word2vec CBOW
araneum_upos_skipgram_300_2_2018	Araneum Russicum Maximum	10000M	word2vec skipgram
araneum_none_fasttextskipgram_300_5_2018	Araneum Russicum Maximum	10000M	fastText (char 3-grams)

Prior to training, all the corpora were tokenized, split into sentences, lemmatized and PoS-tagged using *UDPipe* [Straka and Straková, 2017]. All the models use vector size 300.

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Averaging embeddings to get senses

Our approach consisted of the following steps:

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Our approach consisted of the following steps:

1. Lemmatize and PoS-tag contexts;
2. Represent each context as a fixed-length vector manifesting its semantics;
3. Determine the number of clusters in the set of contexts, using the *Affinity Propagation* algorithm;
4. Group the contexts into clusters representing word senses, using either *Affinity Propagation* or other clustering algorithm.

Contexts representation

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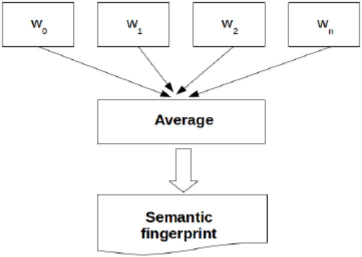
1. Each word in the context is mapped to its vector in the model;
2. Ambiguous query word itself is removed;
3. For each context utterance, a 'semantic fingerprint' [Kutuzov et al., 2016] is created:
4. Weighted average of all words' vectors.
5. This dense vector is our semantic representation of the context utterance.



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1. Multiple occurrences of the same lemma counted as one occurrence:
   - binary bag-of-words, to discard local word frequencies in the contexts;
2. The average was weighted by word frequencies in the training corpus of the embedding model used:
   - globally frequent words get less influence,
   - globally rare words are more influential.

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  - This gave the best performance.

Contexts clustering

A simple system, but reasonable clusterings:

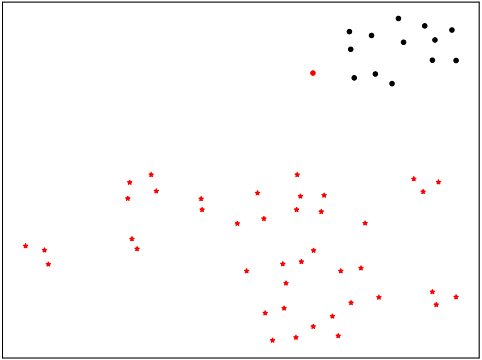

Figure: Clustering of the бор contexts (‘pine wood’ and ‘Boron’). Each point is a context, 2-dimensional t-SNE projection. Colors are clusters assigned by the system, shapes are gold clusters.

Contents

And what? The results

ARI on the training data, dependent on the word embedding model

Model id	wiki-wiki	bts-rnc	active-dict
ruscorpora_upos_skipgram_300_5_2018	**0.772**	**0.176**	**0.260**
ruwikiruscorpora_upos_skipgram_300_2_2018	0.669	0.162	0.210
news_upos_cbow_600_2_2018	0.653	0.174	0.143
araneum_upos_skipgram_300_2_2018	0.492	0.162	0.197
araneum_none_fasttextskipgram_300_5_2018	0.695	0.171	0.178

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The RNC wins, despite being significantly smaller.
Properly compiling and balancing the training corpora for word embedding models is extremely important: even in an extrinsic evaluation setting like WSI.

And what? The results

ARI on the training data, dependent on the parameters of word vector averaging

Dataset	Original	+binary BOW	+weights
wiki-wiki	0.579	0.717	**0.772**
bts-rnc	0.169	0.167	0.176
active-dict	0.250	0.254	0.260

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The effect of binary bag-of-words and weights is most visible on the *wiki-wiki* dataset.

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Dataset	Our ARI	Rank (of 17)	The best ARI
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- Probably, RUSSE'18, SemEval-2013, and WWSI datasets are different, but still interesting.

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- Python source code of the system is available, results are reproducible: `https://github.com/akutuzov/russian_wsi`

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- Quite successful for *wiki-wiki*.
- Less successful for *bts-rnc* and *active-dict*
  - May be, because of polysemous words with highly inter-related senses.
- Word embedding models trained on well-balanced and clean corpora (like RNC) are superior in the extrinsic WSI task to the models trained on large but noisy and unbalanced web or news corpora.
- Python source code of the system is available, results are reproducible: `https://github.com/akutuzov/russian_wsi`

Thanks to the RUSSE'18 organizers! Questions?

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