IN5550: Neural Methods in Natural Language Processing
Sub-lecture 5.4
Word embeddings: miscellaneous

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Contents



1. Training word embeddings
2. The followers
3. Practical aspects
4. Demo web service and pre-trained vectors repository
5. Next group session: February 22

Training word embeddings

Prediction-based training algorithms

'the **vector** of a word w is "dragged" back-and-forth by the **vectors** of w's co-occurring words, as if there are physical strings between w and its neighbors...like gravity, or force-directed graph layout.' [Rong, 2014]

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Useful demo of *word2vec* algorithms: `https://ronxin.github.io/wevi/`

Contents



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The followers



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These approaches were implemented in third-party software: Gensim, PyTorch, TensorFlow...

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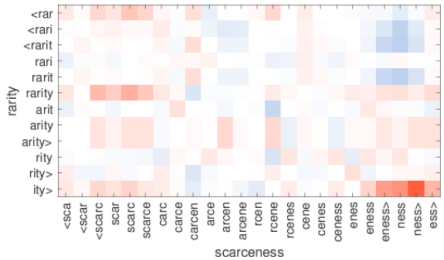
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- `https://fasttext.cc/`
- `http://vectors.nlpl.eu/repository/`



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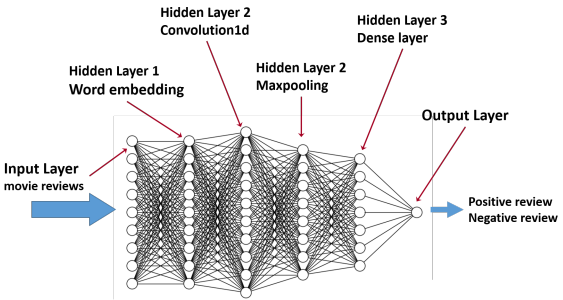
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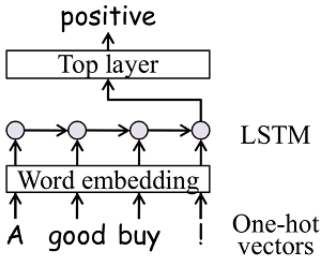
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Embeddings themselves can be updated at the training time along with the rest of the network weights or 'frozen' (protected from updating).





Contents



1. Training word embeddings
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Software to train word embeddings on your data

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6. fastText official implementation by *Facebook* [Bojanowski et al., 2017] (`https://fasttext.cc/`).

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Pre-trained word embedding models can come in several formats:

1. Simple text format, `*.txt` or `*.vec`:
   - words and sequences of values representing their vectors, one word per line;
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Gensim works with all these formats (also if compressed). Recommended for the Obligatory 2.
On Fox: `module load nlpl-gensim/4.2.0-foss-2021a-Python-3.9.5`



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- they represent lexical meanings as dense vectors (embeddings);
- the models are also distributed: meaning is expressed via values of multiple vector entries;
- particular vector entries (features) are not directly related to any particular semantic 'properties', and thus not directly interpretable;
- words occurring in similar contexts have similar vectors.

Contents



1. Training word embeddings
2. The followers
3. Practical aspects
4. Demo web service and pre-trained vectors repository
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Demo web service and pre-trained vectors repository



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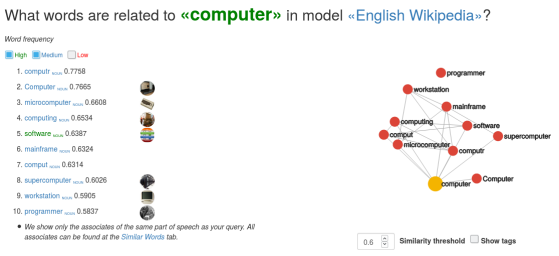
You can try the *WebVectors* service developed by our Language Technology group

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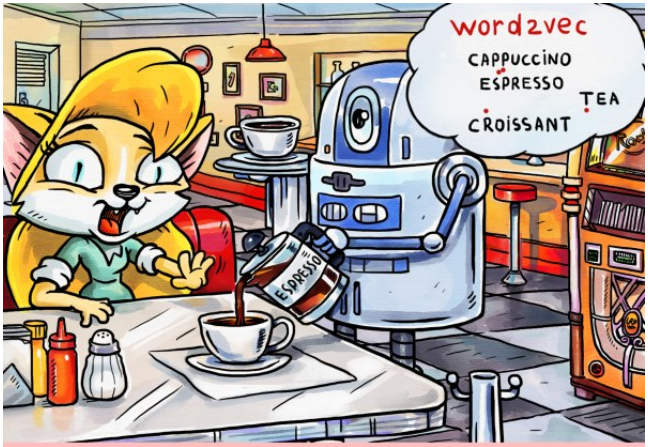
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`http://vectors.nlpl.eu/explore/embeddings/`
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Demo web service and pre-trained vectors repository



- Espresso? But I ordered a cappuccino!
- Don't worry, the cosine distance between them is so small that they are almost the same thing.

(by Dmitry Malkov)

Contents



1. Training word embeddings
2. The followers
3. Practical aspects
4. Demo web service and pre-trained vectors repository
5. Next group session: February 22

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- Discussing Obligatory 1
- Training *word2vec* embeddings using *Gensim* and *PyTorch*.

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