IN5550: Neural Methods in Natural Language Processing
Sub-lecture 4.4
Machine learning based distributional models: word2vec

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1. Machine learning based distributional models
   - Word2Vec revolution
2. Training word embeddings
3. Practical aspects
4. Demo web service and pre-trained embeddings repository

Machine learning based distributional models



Approaches to produce (static) word embeddings

1. *Word-context* co-occurrence matrices, factorized by *SVD* (count-based approaches);

Machine learning based distributional models



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Machine learning based distributional models



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   - fastText [Bojanowski et al., 2017];

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   - Continuous Bag-of-Words (CBOW),
   - Continuous Skip-Gram (skipgram);
   - fastText [Bojanowski et al., 2017];
3. Hybrid approaches like Global Vectors for Word Representation (GloVe) [Pennington et al., 2014].

1 is not used much any more.
Static embeddings from 2 and 3 are now increasingly replaced with contextualized embedding models; more on that in later lectures.

Machine learning based distributional models



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- We do it using word co-occurrences in corpora as a supervision signal...

Word2Vec revolution



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- ...and a distributional model trained on the large Google News corpus
- Just a set of vectors for English words.

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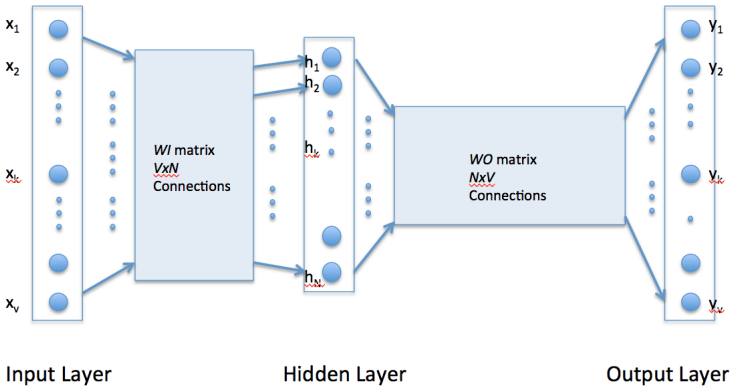
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- *word2vec* turned out to be very fast and efficient.
- It actually featured two different algorithms:
  1. Continuous Bag-of-Words (CBOW),
  2. Continuous Skipgram.
- Both use a very simple feed-forward neural network.
- No non-linear activations, can hardly be considered a neural network at all!
- But this is why it is so fast.

Word2Vec revolution





Model initializing

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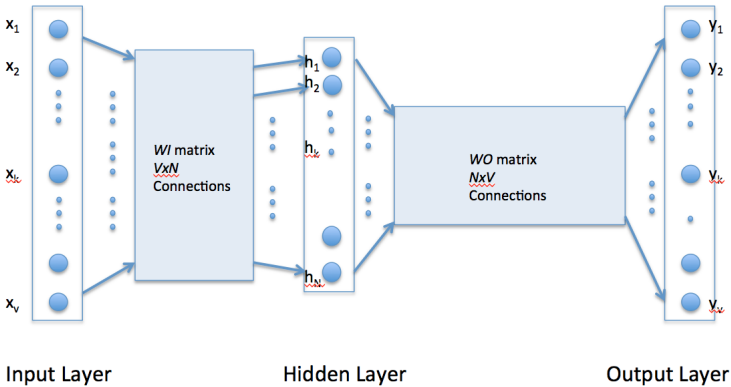
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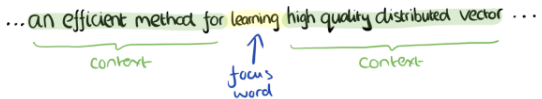
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What happens next?

Word2Vec revolution



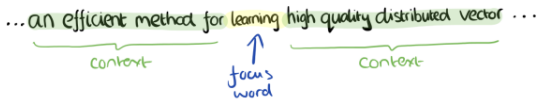
Word2Vec revolution



Learning good vectors

- While training, we move through the corpus with a sliding window.

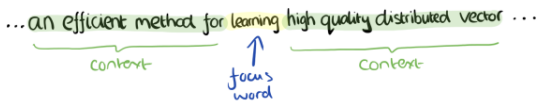
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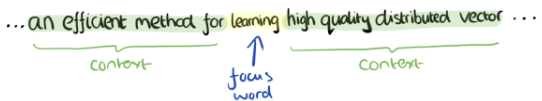
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Prediction is not an aim in itself: it is just a proxy to learn vector representations for words, useful for other downstream tasks.

Word2Vec revolution



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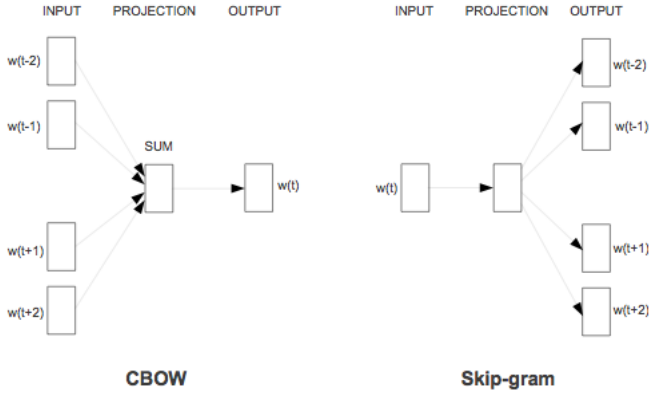
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- NB: context (window size and nature) can be defined in many different ways;
- this greatly influences the resulting models.
- Both CBOW and Skip-Gram outperformed traditional count DSMs in various semantic tasks [Baroni et al., 2014]

Word2Vec revolution



Continuous Bag-of-Words and Continuous Skip-Gram:
two algorithms in the *word2vec* paper [Mikolov et al., 2013]



What we are updating during the training?

- weight matrix of input vectors W^I (from the input layer to the hidden layer)
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Reminder: this 'closeness' is calculated with the help of dot product or cosine similarity and then turned into probabilities using softmax.

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and the learning itself is implemented with stochastic gradient descent.



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That's why *word2vec* employs one of these two smart tricks:

1. Hierarchical softmax (rarely used nowadays);
2. Negative sampling.



Negative sampling

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SkipGram model with Negative Sampling is sometimes called simply 'SGNS'.
SGNS is still often seen in NLP papers, despite the newer pre-trained Transformer-based language models (covered later in this course).

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Training word embeddings

Prediction-based training algorithms

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

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Software to train word embeddings on your data

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4. word2vec implementation in *TensorFlow* (`https://www.tensorflow.org/tutorials/text/word2vec`).

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Practical aspects



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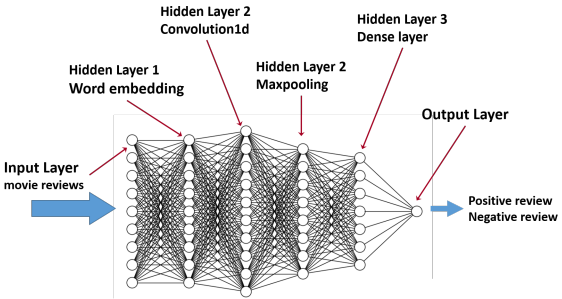
- feed-forward networks,
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- etc.

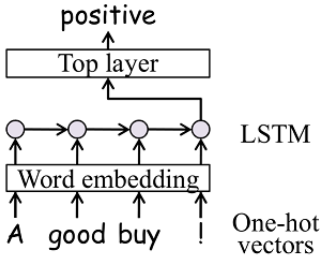
Practical aspects

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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).





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 1.
On Fox: `module load nlpl-gensim/4.3.2-foss-2022b-Python-3.10.8`



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- 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.

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Demo web service and pre-trained embeddings reposito



Distributional semantic models for English and Norwegian online

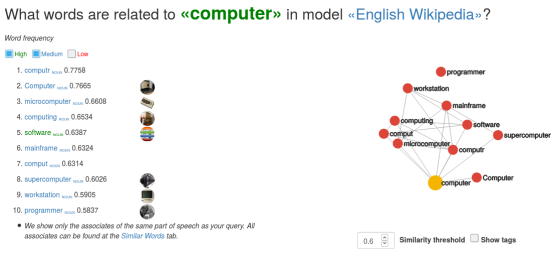
You can try the *WebVectors* service developed by our Language Technology group

Demo web service and pre-trained embeddings reposito

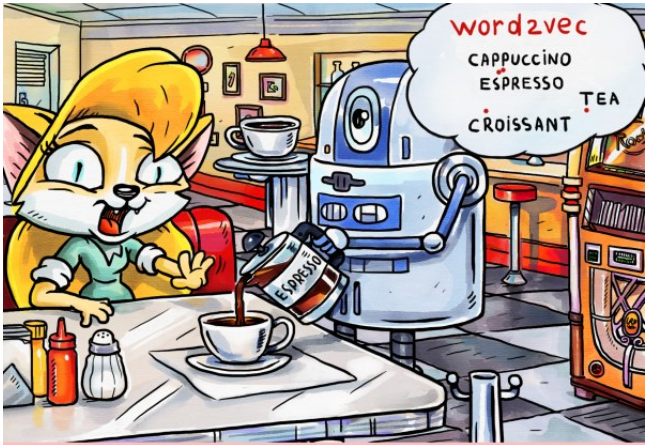
Distributional semantic models for English and Norwegian online

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

`https://vectors.nlpl.eu/explore/embeddings/`
`https://vectors.nlpl.eu/repository/`



Demo web service and pre-trained embeddings reposito



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

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