INF5820
Distributional Semantics: Extracting Meaning from Data

Lecture 2
Distributional and distributed: inner mechanics of modern word embedding models

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Contents

Brief recap

Main approaches to produce word embeddings

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Their principal difference from previous methods is that they actively employ machine learning.

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- one can find nearest semantic associates of a given word by calculating cosine similarity between vectors.

Brief recap

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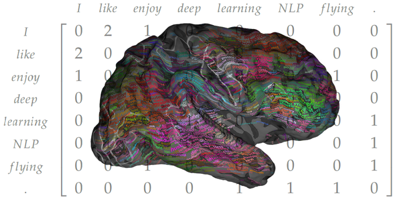

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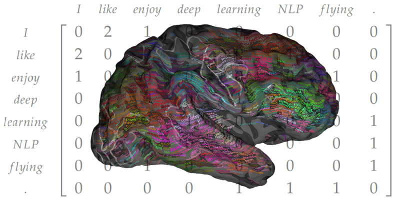

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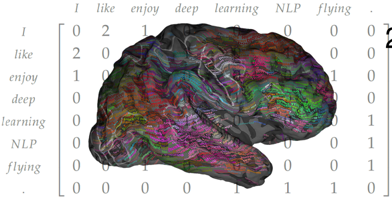

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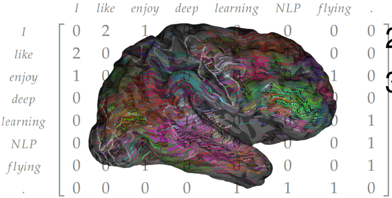

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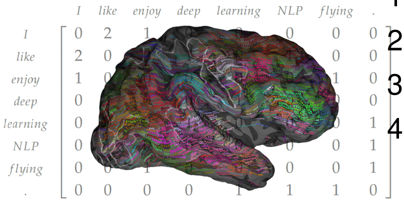

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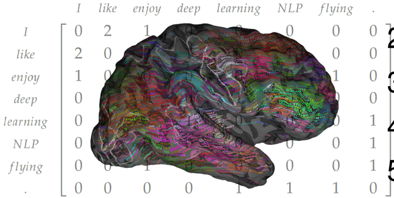

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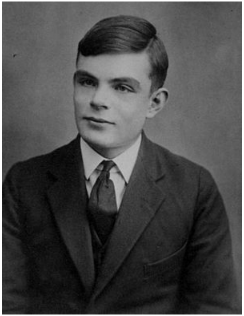

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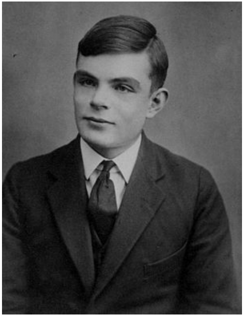

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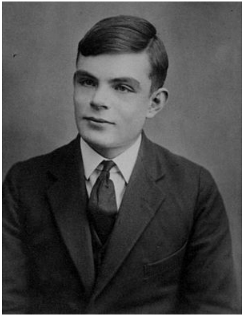

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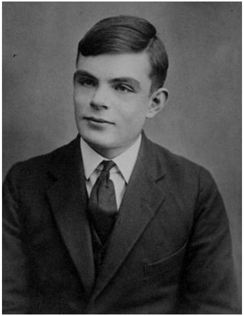

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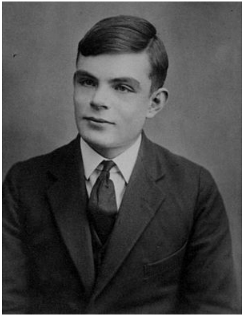

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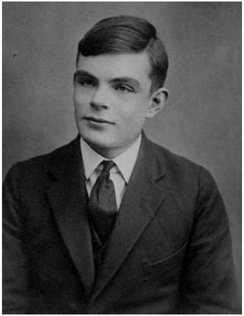

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1. compile full co-occurrence matrix on the whole corpus;
2. weigh absolute frequencies with positive point-wise mutual information (PPMI) association measure;
3. factorize the matrix with singular value decomposition (SVD) to reduce dimensionality and arrive from sparse to dense vectors.

For more details, see [Bullinaria and Levy, 2007] and methods like Latent Semantic Indexing (LSI) or Latent Semantic Analysis (LSA).

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As a result, we pay less attention to random 'noise' co-occurrences.

3. Matrix factorization

To reduce the number of dimensions in the VSM, we can use one of many matrix factorization methods. The idea is to generate a lower-rank approximation of the original matrix (to truncate it), maximally retaining the relations between the vectors. It essentially means to find the most important dimensions of the data set, along which most variation happens.

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The most popular method to generate matrix approximations of any given rank k is Singular Value Decomposition or SVD, based on extracting so called *singular values* of the initial matrix. Other methods include PCA, factor analysis, etc, but truncated SVD is probably most widely used in NLP.

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Problem: SVD is often computationally expensive, especially for large vocabularies. The alternative is given by the predict(ive) models.

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- To solve such problems, one can use machine learning: attempts to build programs which learn to make correct decisions on some training material and improve with experience;
- One of popular machine learning approaches for language modeling – artificial neural networks.

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- In the count models we count co-occurrence frequencies and use them as word vectors; in the predict models it is vice versa:
- We try to find (to learn) for each word such a vector/embedding that it is maximally similar to the vectors of its paradigmatic neighbors and minimally similar to the vectors of the words which in the training corpus are not second-order neighbors of the given word.

When using artificial neural networks, such learned vectors are called neural embeddings.

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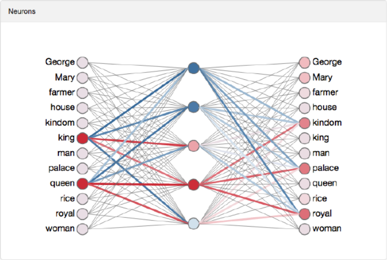

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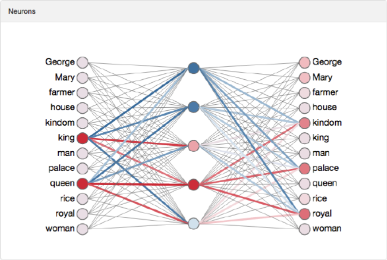

Artificial neural networks try to imitate this process.

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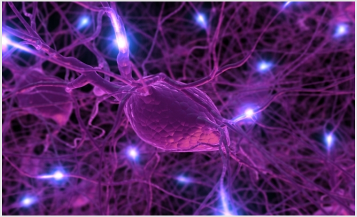

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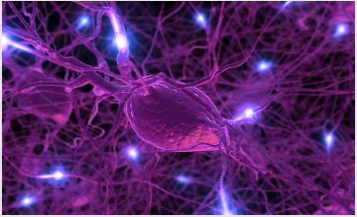

Concepts are represented by vectors of n dimensions (aka neurons), and each neuron is responsible for many concepts or rough 'semantic components'.

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word2vec turned out to be very fast and efficient.

NB: it actually features two different algorithms: Continuous Bag-of-Words (CBOW) and Continuous Skipgram.

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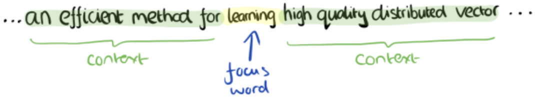

Learning good vectors

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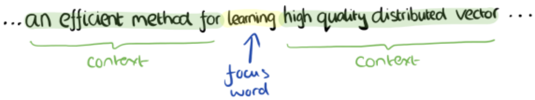

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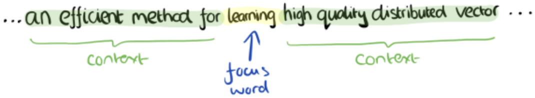

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It is important that prediction here is not an aim in itself: it is just a proxy to learn vector representations good for other downstream tasks.

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At training time, CBOW learns to predict current word based on its context, while Skip-Gram learns to predict context based on the current word.

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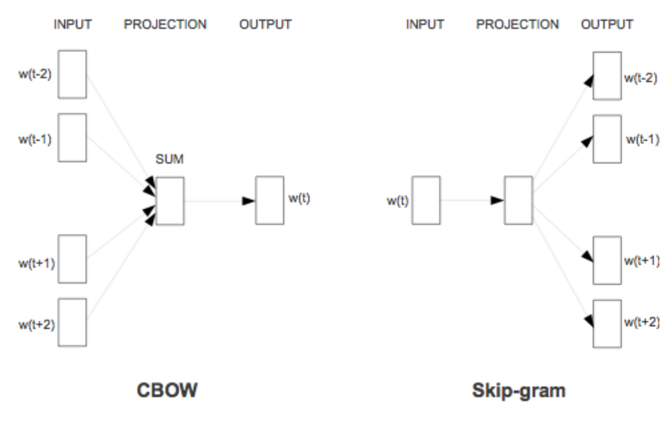
Continuous Bag-of-Words and Continuous Skip-Gram: two algorithms in the *word2vec* paper



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and the learning itself is implemented with stochastic gradient descent and (optionally) adaptive learning rate.

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Prediction for each training instance is basically:

- CBOW: **average vector for all context words.** We check whether the current word vector is the closest to it among all vocabulary words.
- SkipGram: **current word vector.** We check whether each of context words vector is the closest to it among all vocabulary words.

Predictive distributional models: Word2Vec revolution

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- CBOW: **average vector for all context words.** We check whether the current word vector is the closest to it among all vocabulary words.
- SkipGram: **current word vector.** We check whether each of context words vector is the closest to it among all vocabulary words.

Reminder: this ‘closeness’ is calculated with the help of cosine similarity and then turned into probabilities using softmax.

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During the training, we are updating 2 weight matrices: of context vectors (from the input to the hidden layer) and of output vectors (from hidden layer to the output). As a rule, they share the same lexicon, and only output vectors are used in practical tasks.

Predictive distributional models: Word2Vec revolution

CBOW and SkipGram 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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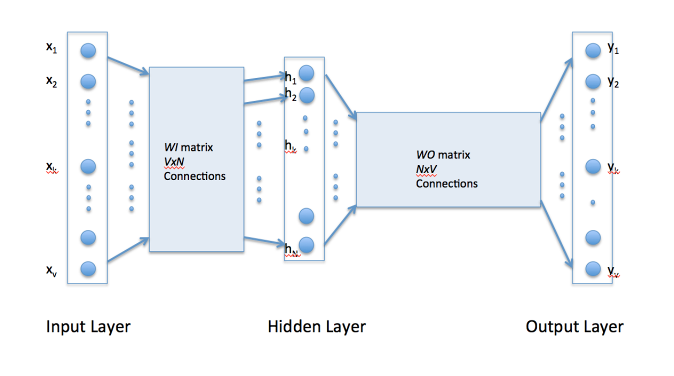

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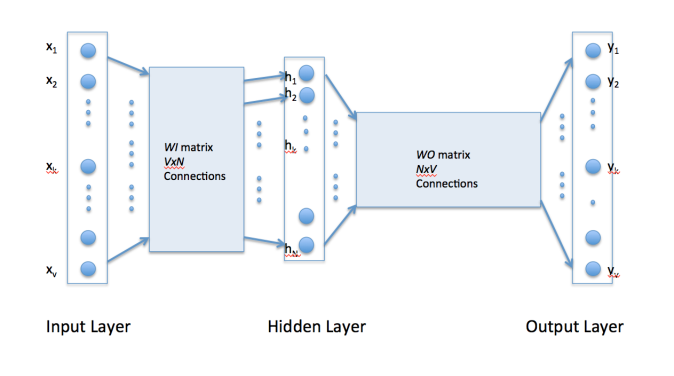

Useful demo of *word2vec* algorithms: `https://ronxin.github.io/wevi/`

Predictive distributional models: Word2Vec revolution

Selection of learning material

At each training instance, to find out whether the prediction is true, we have to iterate over all words in the vocabulary and calculate their dot products with the input word(s).

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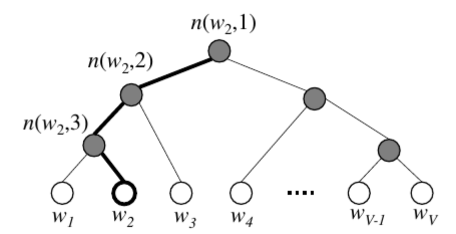
This is not feasible. That's why *word2vec* uses one of these two smart tricks:

1. Hierarchical softmax;
2. Negative samping.

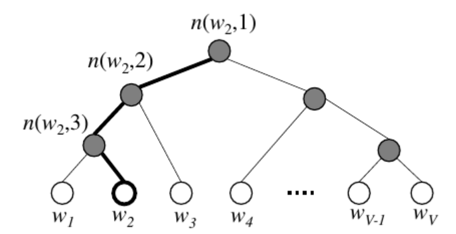
Predictive distributional models: Word2Vec revolution

Hierarchical softmax



Predictive distributional models: Word2Vec revolution

Hierarchical softmax



Calculate joint probability of all items in the binary tree path to the true word. This will be the probability of choosing the right word.
Now for vocabulary size V, the complexity of each prediction is $O(log(V))$ instead of $O(V)$.

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Calculating probabilities for 15 words is of course much faster than iterating over all the vocabulary

Predictive distributional models: Word2Vec revolution

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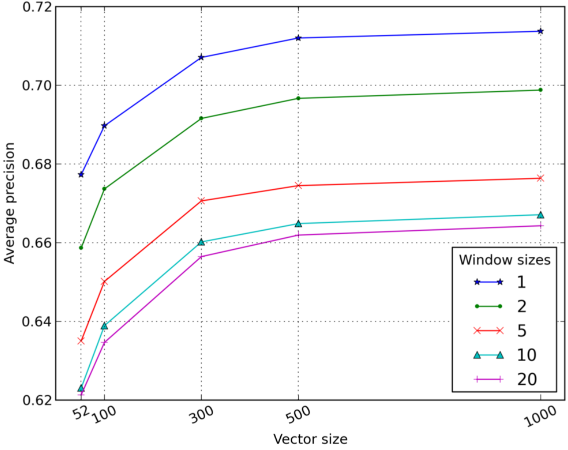
6. Number of iterations on our training data, etc...

Predictive distributional models: Word2Vec revolution



Model performance in semantic relatedness task depending on context width and vector size.

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- These approaches were implemented in third-party open-source software, for example, Gensim or TensorFlow.

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- The objective is to learn word vectors such that their dot product equals the logarithm of the words' probability of co-occurrence.
- Code and pre-trained embeddings available at `http://nlp.stanford.edu/projects/glove/`.

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Questions?

INF5820
Distributional Semantics: Extracting Meaning from Data
Lecture 2
Distributional and distributed: inner mechanics of modern word embedding models

Homework: play with
`http://ltr.uio.no/semvec`,
install *Gensim* library for *Python* (`http://radimrehurek.com/gensim/`).

Contents

In the next week

Practical aspects of training and using distributional models

- Models hyperparameters;
- Models evaluation;
- Models' formats;
- Off-the-shelf tools to train and use models.