IN5550: Neural Methods in Natural Language Processing
Sub-lecture 5.2
Count-based (explicit) vector semantic models

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University of Oslo

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Count-based ('explicit') vector space models



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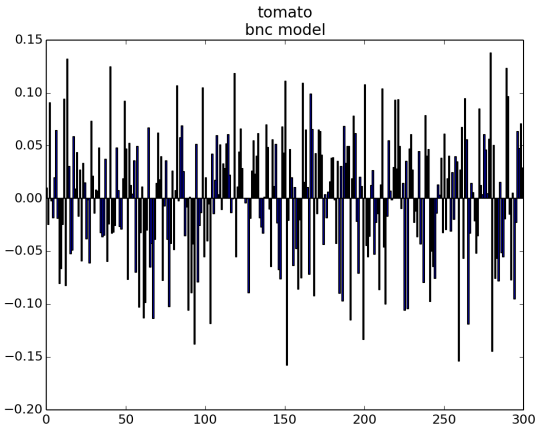
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- Interpretability is an important property of sparse representations (could be employed in the Obligatory 1!).

Count-based ('explicit') vector space models

300-D vector of 'tomato'



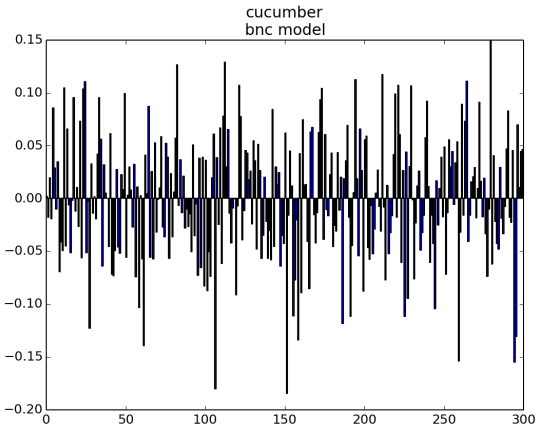


In this toy example, $|V| = 300$. Co-occurrence frequencies are normalized.

Count-based ('explicit') vector space models

300-D vector of 'cucumber'

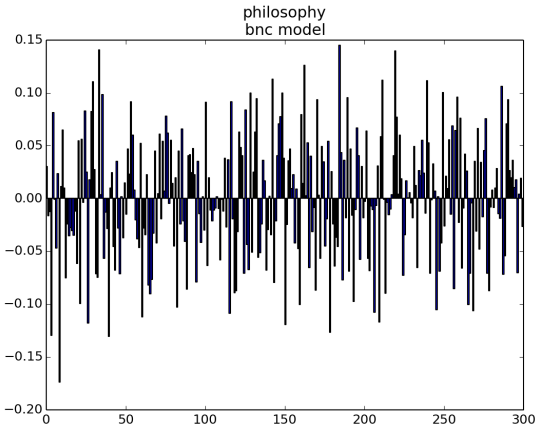




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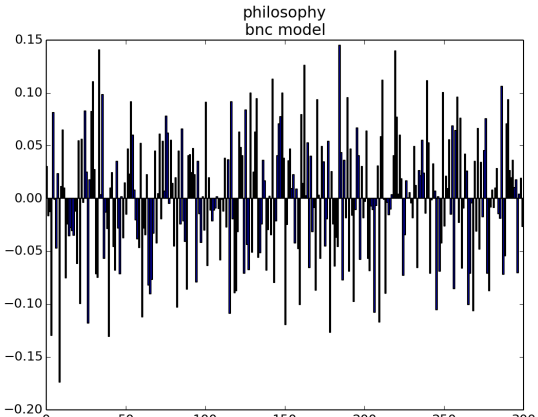
Count-based ('explicit') vector space models

300-D vector of 'philosophy'



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Can we prove that tomatoes are more similar to cucumbers than to philosophy?

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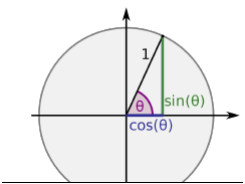
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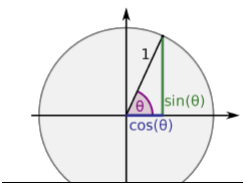


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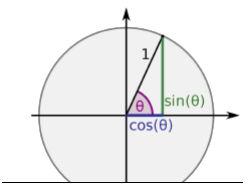
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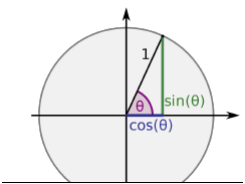
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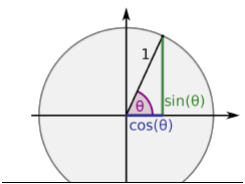
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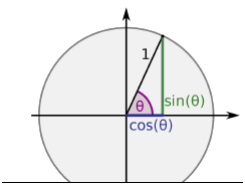
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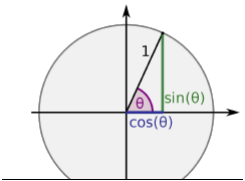
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$cos(tomato, cucumber) = 0.66$

Question: why not simply use dot product?

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If one can measure similarity between words, one can rank words by similarity to a target word!

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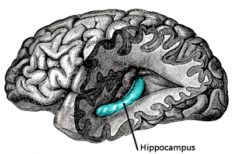
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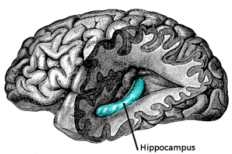
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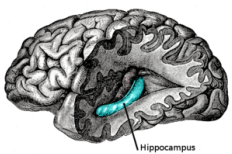
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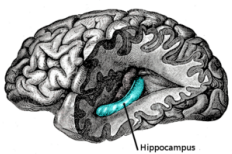
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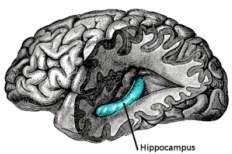
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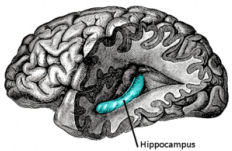
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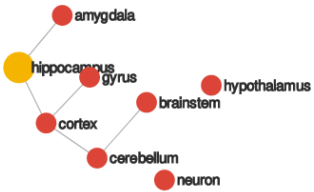


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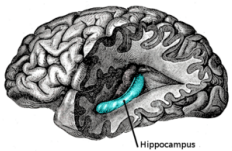
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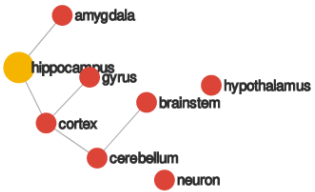


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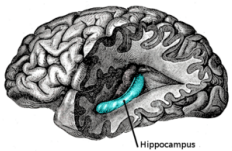


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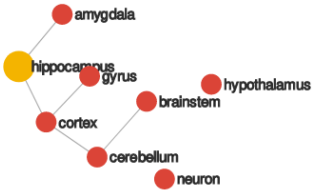


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Question: what do the edges in the graph denote?



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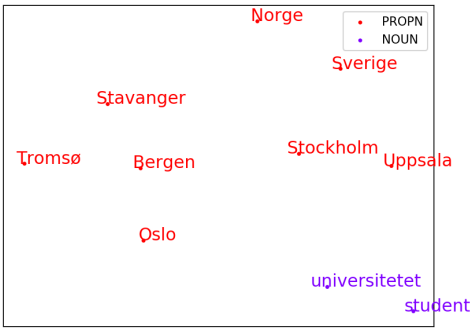
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- Can even reduce to the dimensionality of 2 or 1.
- Such reduced 'implicit' vectors are usually dense and have much more rights to be called 'word embeddings'.
- NB: still nothing 'neural' or 'deep' here!

Word embeddings

An extreme case: 2-dimensional word embeddings:

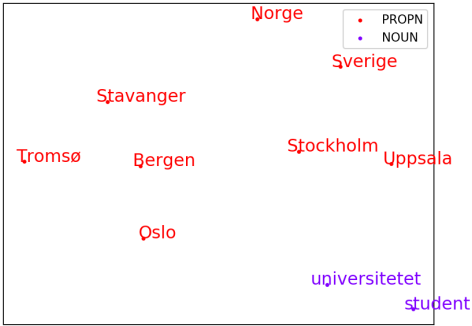


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[Van der Maaten and Hinton, 2008]

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Vector components (x and y) are not directly interpretable any more, of course.
An 'explicit' model turned to an 'implicit' one. Semantic information is distributed across the remaining dimensions.

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For more details, see [Bullinaria and Levy, 2007] and [Goldberg, 2017].

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3. factorize the matrix with singular value decomposition (SVD) or Principal Components Analysis (PCA) to reduce dimensionality to $d \ll |V|$.
4. Semantically similar words are still represented with similar vectors...
5. ...but the matrix is no longer square, the number of columns is d and each row $\boldsymbol{a} \in \mathbb{R}^d$.
6. The word vectors are now dense and small: embedded in the d-dimensional space.

For more details, see [Bullinaria and Levy, 2007] and [Goldberg, 2017].
But where is machine learning and neural networks? See sub-lecture 5.3!

References I

Bullinaria, J. A. and Levy, J. P. (2007).
Extracting semantic representations from word co-occurrence statistics: A computational study.
Behavior research methods, 39(3):510–526.

Goldberg, Y. (2017).
Neural network methods for natural language processing.
Synthesis Lectures on Human Language Technologies, 10(1):1–309.

Van der Maaten, L. and Hinton, G. (2008).
Visualizing data using t-SNE.
Journal of Machine Learning Research, 9(2579-2605):85.