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

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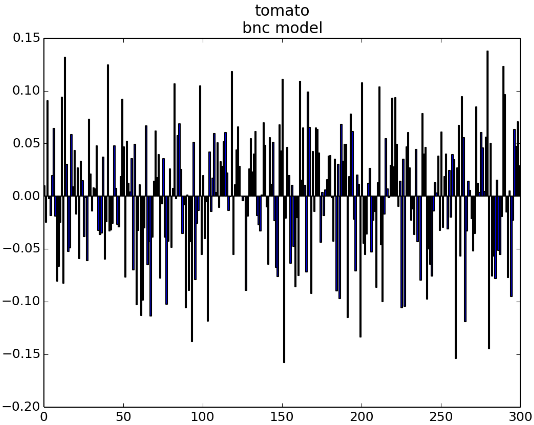
- Dimensions of a word vector are interpretable: they are associated with particular context words...
- ...or other types of contexts: documents, sentences, even characters.
- Interpretability is an important property of sparse representations (could be employed in the Obligatory 1!).

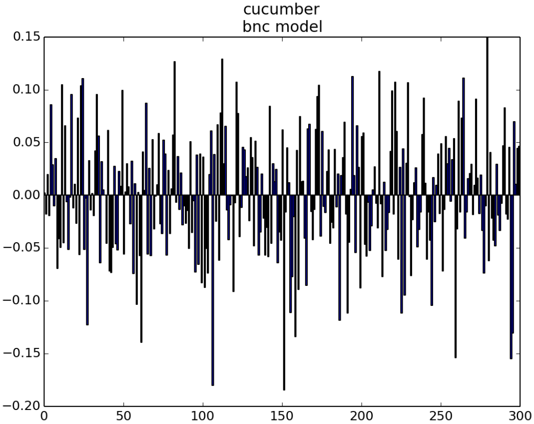
Count-based ('explicit') vector space models

300-D vector of 'tomato'



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

300-D vector of 'cucumber'



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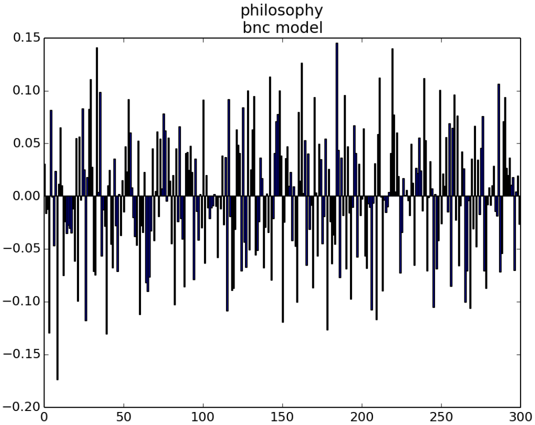
300-D vector of 'philosophy'



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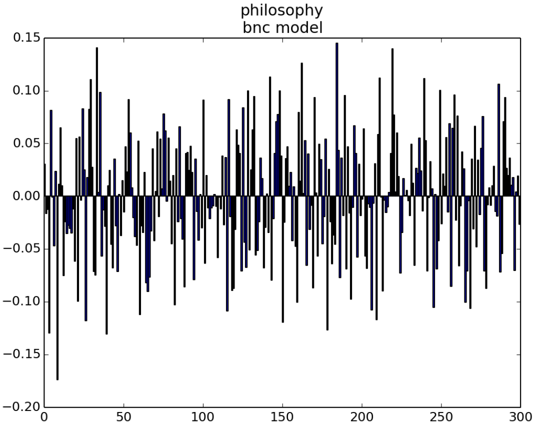

Can we prove that tomatoes are more similar to cucumbers than to philosophy?

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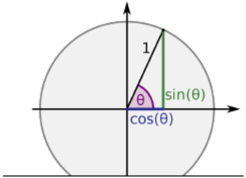

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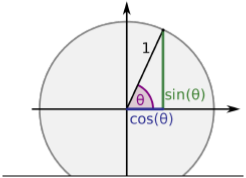

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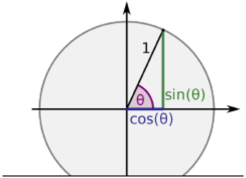

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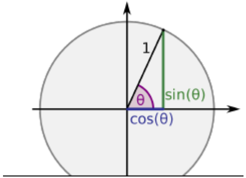

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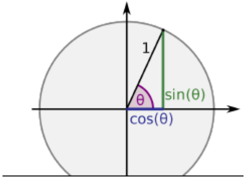

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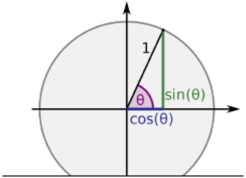

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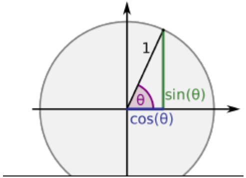

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Question: why not simply use dot product?

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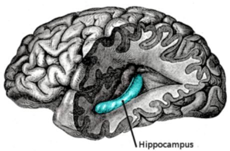

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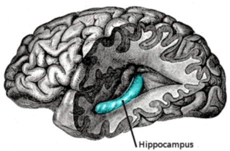

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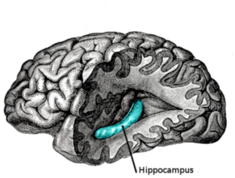

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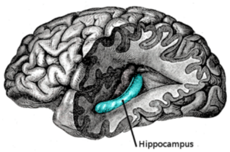

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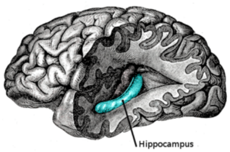

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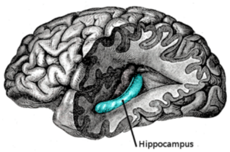

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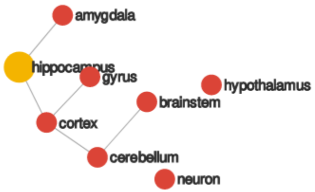

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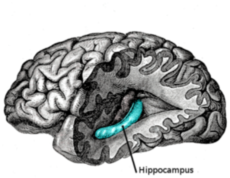

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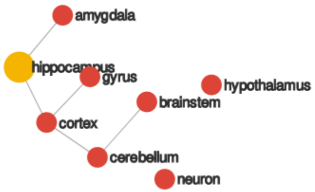

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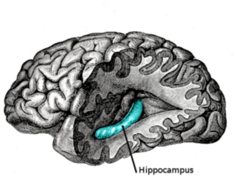

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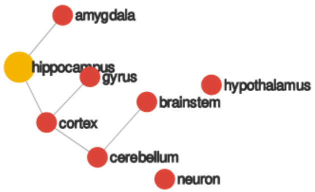

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Question: what do the edges in the graph denote?

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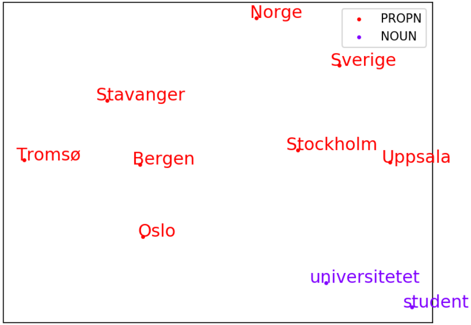
- Can even reduce to the dimensionality of 2 or 1.
- Such reduced 'implicit' vectors are usually dense and have much more rights to be called 'word embeddings'.
- NB: still nothing 'neural' or 'deep' here!

Word embeddings

An extreme case: 2-dimensional word embeddings:



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[Van der Maaten and Hinton, 2008]

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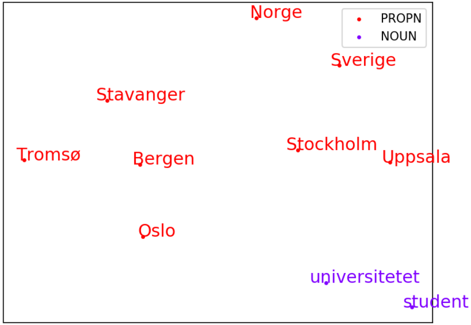

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Vector components (x and y) are not directly interpretable any more, of course.
An 'explicit' model turned to an 'implicit' one. Semantic information is distributed across the remaining dimensions.

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But where is machine learning and neural networks? See sub-lecture 5.3!

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).
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Visualizing data using t-SNE.
Journal of Machine Learning Research, 9(2579-2605):85.