Embeddings: The Basics

Hinrich Schütze

Center for Information and Language Processing, LMU Munich

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Overview

1. Distributional semantics
2. WordSpace
3. Norms & scores

Outline

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2 WordSpace

3 Norms & scores

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- There is a spectrum here: synonymous, very similar, less similar, related, unrelated

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- The basic notions formalized in distributional semantics are semantic similarity and semantic relatedness.

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  - E.g., query expansion in information retrieval
  - User types in query [automobile]
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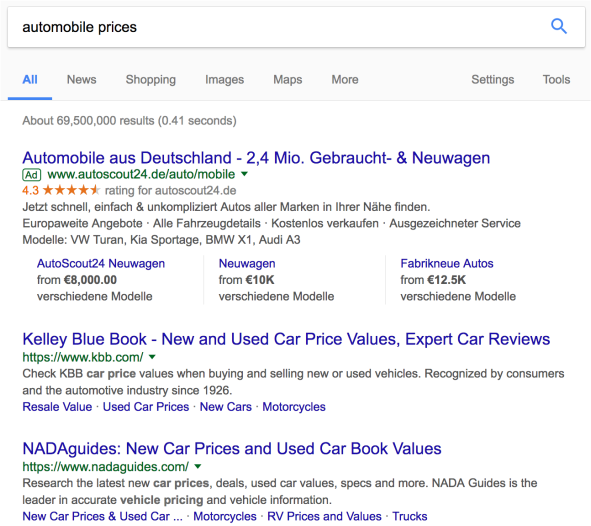
  - The search engine then uses the query [car OR automobile]
  - Better results for the user

Google: Internal model of semantic similarity



automobile prices

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Jetzt schnell, einfach & unkompliziert Autos aller Marken in Ihrer Nähe finden.
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Distributional Semantics: History

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- Leibniz
- Harris
- Firth
- Miller

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Eadem sunt quorum unum potest substitui alteri salva veritate. (17th century) – Those things are identical of which one can be substituted for the other without loss of truth. This is a definition of synonymy.

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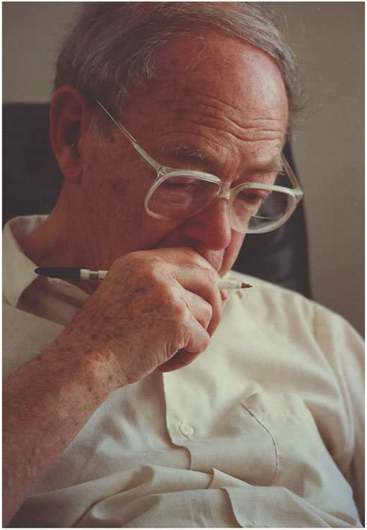

...difference in meaning correlates with difference of distribution. (1954)

John Rupert Firth

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You shall know a word by the company it keeps. (1957)

George A. Miller

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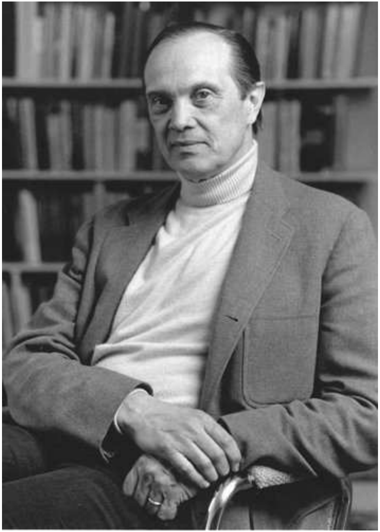

Those things are similar of which one can be substituted for the other without loss of plausibility. (1991)

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- It is doubtful there are any true synonyms if this is our definition.
- Replace "loss of truth" with "loss of plausibility": Those things are similar of which one can be substituted for the other without loss of plausibility.
- Hence: The semantic similarity [between words] is a function of the contexts in which they are used. (Miller and Charles 1991)

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  - For example, the algorithm should tell us that "car" and "automobile" are similar, but "car" and "flower" are not.

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- But perhaps this is good enough.

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  - within a distance of at most k words (where k is a parameter)

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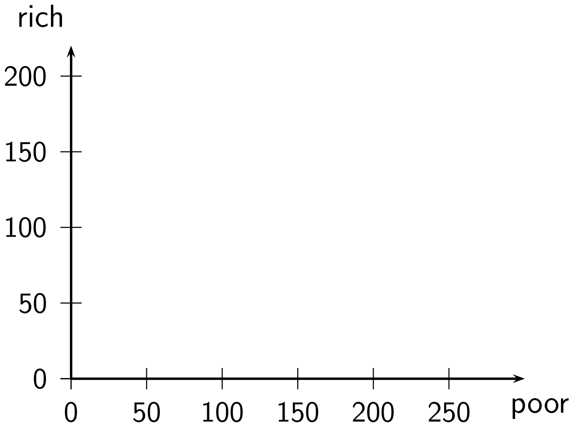

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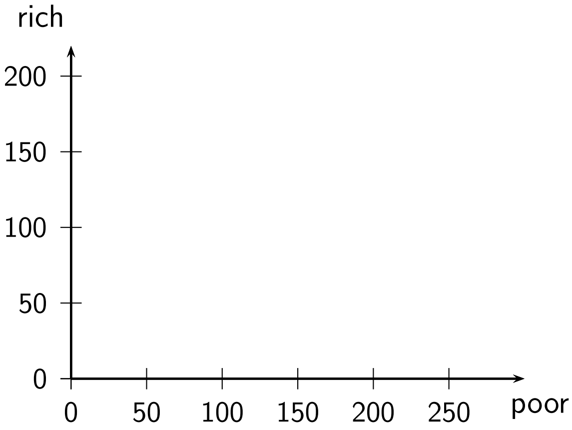

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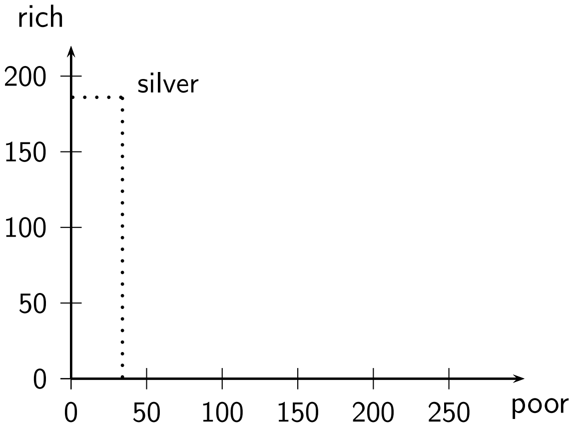

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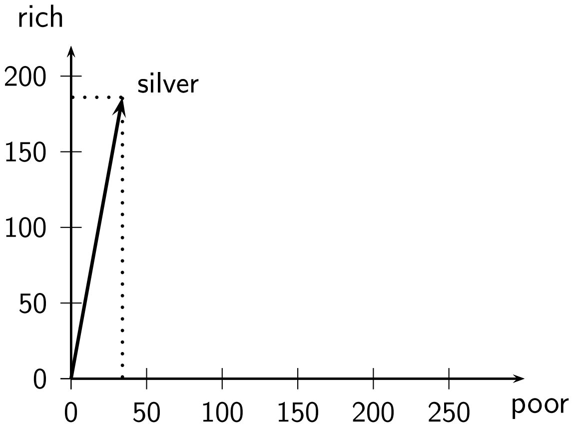

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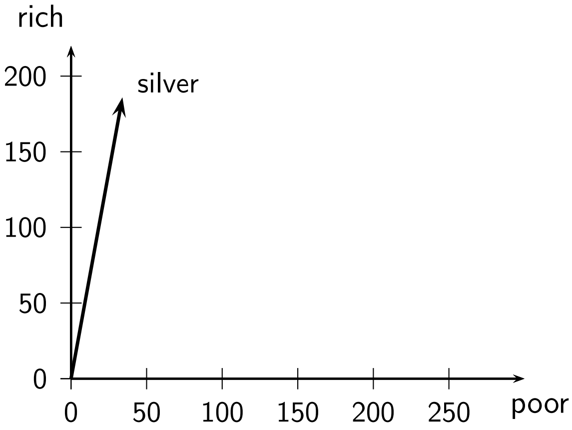

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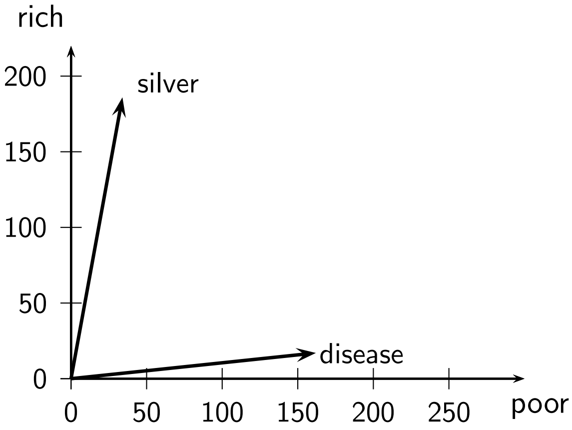

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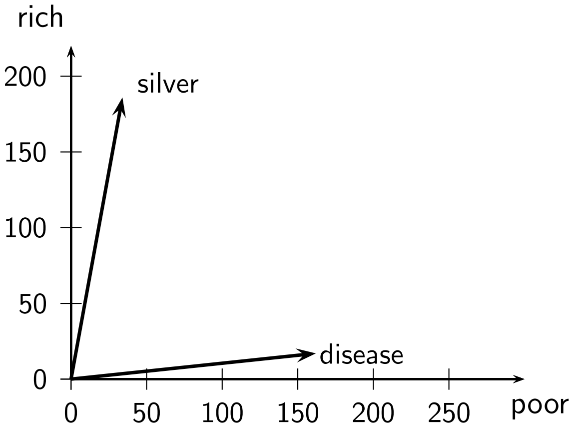

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Exercise

Add “society” to the graph.

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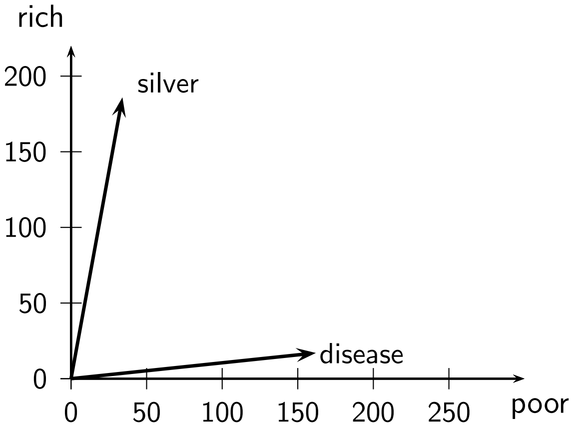

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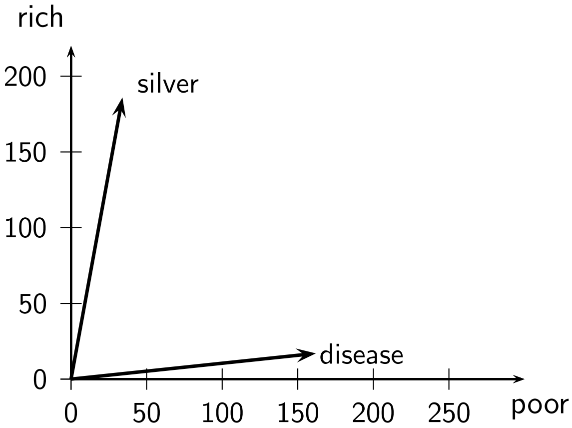

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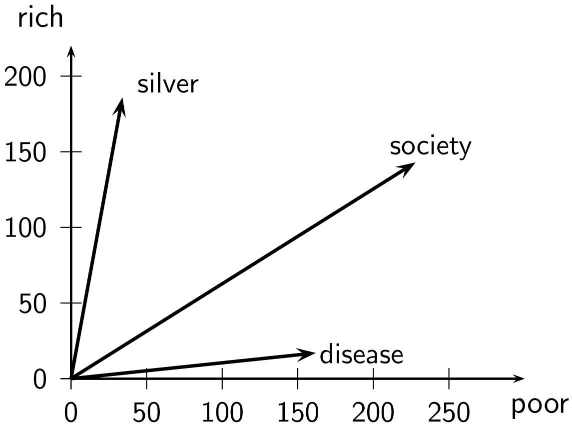

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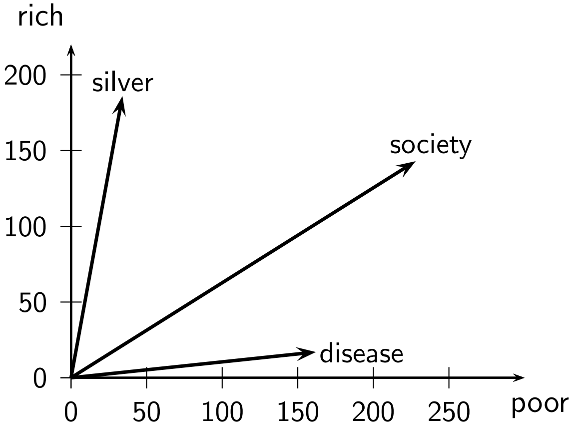

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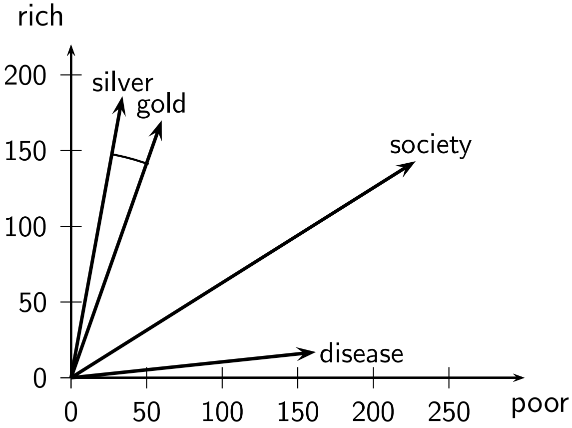

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Small angle: silver and gold are similar.

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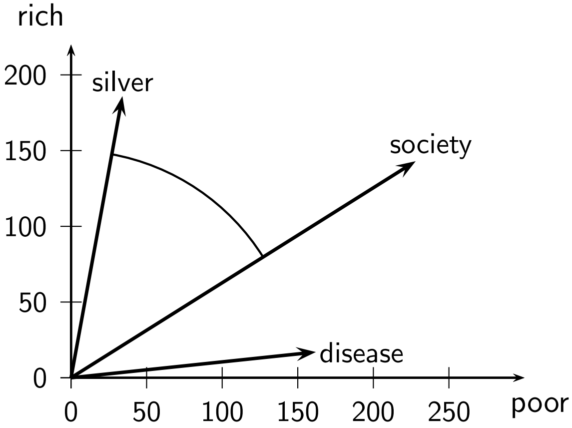

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Medium-size angle: silver and society are not very similar.

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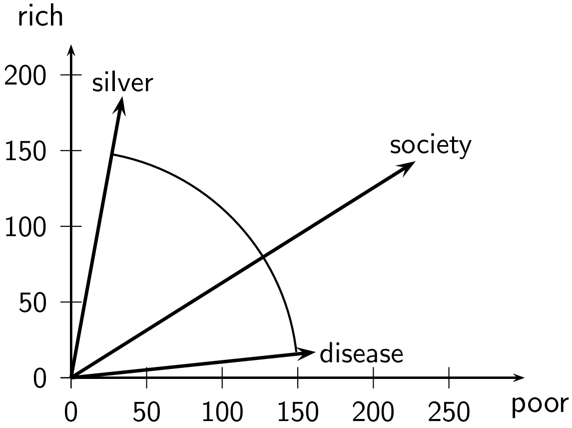

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Large angle: silver and disease are even less similar.

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- Note: a word has dual role in WordSpace.

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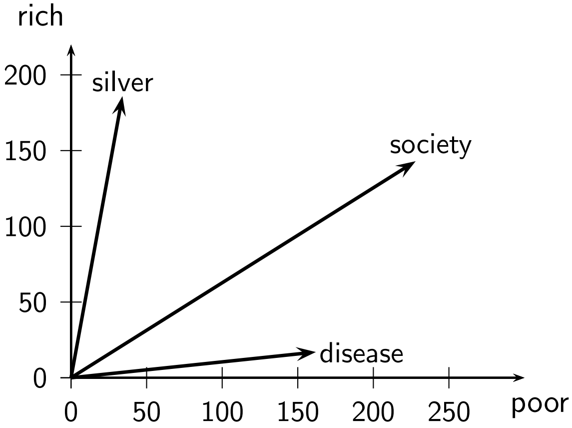
- This is now a very high-dimensional space with a large number of vectors represented in it.
- But formally, there is no difference to a two-dimensional space with three vectors.
- Note: a word has dual role in WordSpace.
  - Each word is a dimension word, an axis of the space.

Dimensionality of WordSpace

- Up to now we've only used two dimension words: rich and poor
- Now do this for a very large number of dimension words: hundreds, thousands, or even millions of dimension words.
- This is now a very high-dimensional space with a large number of vectors represented in it.
- But formally, there is no difference to a two-dimensional space with three vectors.
- Note: a word has dual role in WordSpace.
  - Each word is a dimension word, an axis of the space.
  - But each word is also a vector in that space.

Basis for WordSpace: Cooccurrence



Nearest neighbors of "silver" in WordSpace

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1.000 silver

Nearest neighbors of "silver" in WordSpace

1.000 silver / 0.865 bronze

Nearest neighbors of “silver” in WordSpace

1.000 silver / 0.865 bronze / 0.842 gold

Nearest neighbors of “silver” in WordSpace

1.000 silver / 0.865 bronze / 0.842 gold / 0.836 medal

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Nearest neighbors of "silver" in WordSpace

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1.000 silver / 0.865 bronze / 0.842 gold / 0.836 medal / 0.826 medals / 0.761 relay / 0.740 medalist

Nearest neighbors of “silver” in WordSpace

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Nearest neighbors of “silver” in WordSpace

1.000 silver / 0.865 bronze / 0.842 gold / 0.836 medal / 0.826 medals / 0.761 relay / 0.740 medalist / 0.737 coins / 0.724 freestyle

Nearest neighbors of “silver” in WordSpace

1.000 silver / 0.865 bronze / 0.842 gold / 0.836 medal / 0.826 medals / 0.761 relay / 0.740 medalist / 0.737 coins / 0.724 freestyle / 0.720 metre

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1.000 silver / 0.865 bronze / 0.842 gold / 0.836 medal / 0.826 medals / 0.761 relay / 0.740 medalist / 0.737 coins / 0.724 freestyle / 0.720 metre / 0.716 coin

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1.000 disease / 0.858 Alzheimer / 0.852 chronic / 0.846 infectious / 0.843 diseases / 0.823 diabetes / 0.814 cardiovascular / 0.810 infection / 0.807 symptoms

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Wikipedia WordSpace demonstration

Exercise

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- ... is very different from what the WordSpace gives you.
- Two subtasks (i) find the word (ii) explain why it fails

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General framework for embedding learning

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Up to this point: Formalization of WordSpace

Words have two roles: (i) objects located in the space (each gets a vector/embedding) (ii) dimensions of the space

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We have two different types of objects: (i) primary objects located in the space (usually words, each gets a vector/embedding) (ii) secondary objects (often: contexts, documents, but can also be words, see above)

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The roles of primary and secondary objects can be flipped.

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(This is just a first overview.)

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Dot product / Skalarprodukt

$$\vec{w}\vec{c} = \sum_i w_i c_i$$

Example:

$$\begin{pmatrix} w_1 \\ w_2 \\ w_3 \end{pmatrix} \cdot \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix} = w_1 c_1 + w_2 c_2 + w_3 c_3$$

Outline

1. Distributional semantics
2. WordSpace
3. Norms & scores

How to make WordSpace work well: Two important details

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- Euclidean distance is a bad idea . . .
- . . . because Euclidean distance is
  large for vectors of different lengths.

Why distance is a bad idea

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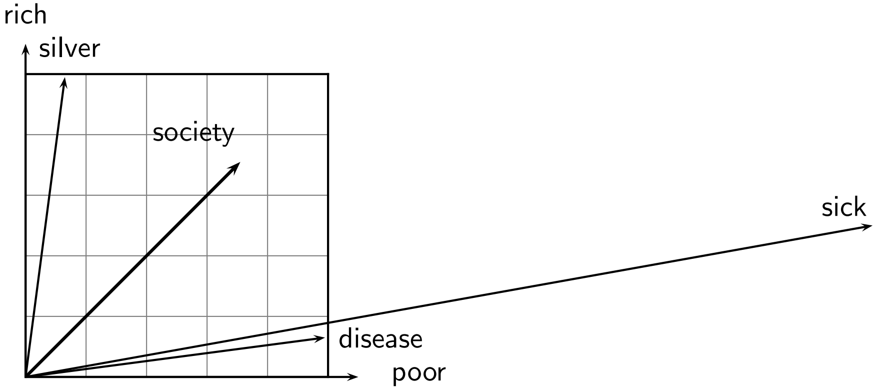

The Euclidean distance of “sick” and “disease” is large although the types of neighbors they occur with are very similar. “sick” is just a lot more frequent that “disease”.

Distance is bad as a similarity measure: How do we fix this?

- There are two equivalent ways of doing this.
- Use distance of length-normalized vectors as similarity measure
- Use angle/cosine of (unnormalized) vectors as similarity measure

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- ... even though the Euclidean distance between the two vectors is large.

From angles to cosines

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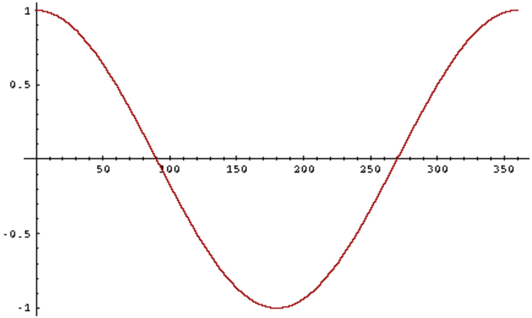
  - Rank words w_i according to cosine(w_i,v) in increasing order
- Cosine is a monotonically decreasing function of the angle for the interval $[0^\circ, 180^\circ]$

Cosine

Cosine



Cosine similarity illustrated

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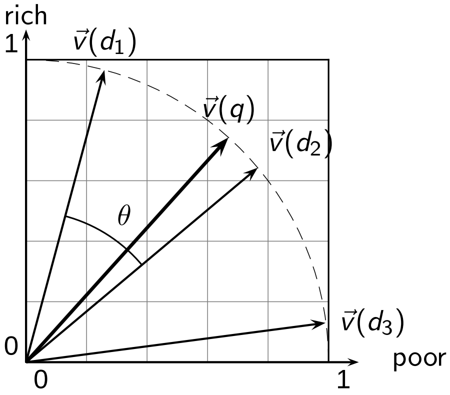

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$$\cos(\vec{c},\vec{d}) = \textsc{sim}(\vec{c},\vec{d}) = \frac{\vec{c}\cdot\vec{d}}{|\vec{c}||\vec{d}|} = \frac{\sum_{i=1}^{|V|} c_i d_i}{\sqrt{\sum_{i=1}^{|V|} c_i^2}\sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

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- $|\vec{c}|$ and $|\vec{d}|$ are the lengths of $\vec{c}$ and $\vec{d}$.
- This is the cosine similarity of $\vec{c}$ and $\vec{d}$ . . . . . . or, equivalently, the cosine of the angle between $\vec{c}$ and $\vec{d}$.

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- As a result, less frequent words and more frequent words have weights of the same order of magnitude.
- Effect on the two word vectors $\vec{w}$ and $\vec{w'}$ (based on a simple corpus and a second twice the size of the original) from earlier slide: they have almost identical vectors after length-normalization.

Cosine for normalized vectors

- For normalized vectors, the cosine is equivalent to the dot product or scalar product.
- $\cos(\vec{q}, \vec{d}) = \vec{q} \cdot \vec{d} = \sum_i q_i \cdot d_i$
  - (if $\vec{q}$ and $\vec{d}$ are length-normalized).

Cosine similarity: Summary and example

$$\cos(\vec{c}, \vec{d}) = \text{SIM}(\vec{c}, \vec{d}) = \frac{\vec{c} \cdot \vec{d}}{|\vec{c}||\vec{d}|} = \frac{\sum_{i=1}^{|V|} c_i d_i}{\sqrt{\sum_{i=1}^{|V|} c_i^2} \sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

	cosines		
	rhodium	gold	disease
rhodium	1.0	1.0	0.3497
gold	1.0	1.0	0.3497
disease	0.3497	0.3497	1.0

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- Scores:
  Designing the right matching score can be critical.

PMI: Main matching score we will use here

- PMI: pointwise mutual information
- $\mathrm{PMI}(w, c) = \log \frac{P(wc)}{P(w)P(c)}$
- If w, c independent: $\mathrm{PMI}(w, c) = 0$
- If w, c perfectly correlated: $\mathrm{PMI}(w, c) = \log 1/P(c)$
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- If w, c independent: $\text{PMI}(w, c) = 0$
- If w, c perfectly correlated: $\text{PMI}(w, c) = \log 1/P(c)$
- If w, c positively correlated: $\text{PMI}(w, c)$ is large and positive.
- If w, c negatively correlated: $\text{PMI}(w, c)$ is large and negative.
- We are replacing cooccurrence (raw counts) with a measure of surprise (PMI).

PPMI

- PPMI = positive pointwise mutual information
- $\text{PPMI}(w, c) = \max(0, \text{PMI}(w, c))$
- More generally (with offset k): $\text{PPMI}(w, c) = \max(0, \text{PMI}(w, c) - \text{k})$

PPMI: Motivation

- Most interesting correlations of the sort we're interested in are positive.
- For example, it is very hard to find negative correlations among words that are meaningful.
- (give example)
- Motivation for offset:
  Small correlations may be due to noise, so discard them as well

Cooccurrence count matrix

		vectors		
		rhodium	gold	disease
dimensions	take	100	10000	10000
	rich	4	400	100
	poor	1	100	400

Cooccurrence count matrix: Cosine, no PPMI

		vectors		
		rhodium	gold	disease
dimensions	take	100	10000	10000
	rich	4	400	100
	poor	1	100	400

	cosines		
	rhodium	gold	disease
rhodium	1.0	1.0	0.9991
gold	1.0	1.0	0.9991
disease	0.9991	0.9991	1.0

Cooccurrence count matrix: Cosine, PPMI weighting

		vectors		
		rhodium	gold	disease
dimensions	take	100	10000	10000
	rich	4	400	100
	poor	1	100	400

	cosines		
	rhodium	gold	disease
rhodium	1.0	1.0	0.3497
gold	1.0	1.0	0.3497
disease	0.3497	0.3497	1.0

Exercise

$$\begin{pmatrix} 0.5 \\ 0 \\ 1 \end{pmatrix} \cdot \begin{pmatrix} 2 \\ 4 \\ 2 \end{pmatrix} = ?$$

$C(w)$	$C(c)$	$C(wc)$	PMI (use $\log_{10}$)
100	100	1	?
100	100	100	?
5000	5000	250	?

(total = 10000)

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- *John is quicker than Mary* and *Mary is quicker than John* give rise to same cooccurrence counts for $k = 10$.
- This is called a bag of words model.
- More sophisticated models: compute dimension features based on the parse of a sentence – the feature "is object of the verb cook" would be recovered from both "John cooked the ham" and "the ham was cooked".

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- Ambiguity?

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Distributional semantics

- The meaning of a word is learned from its contexts in a large corpus.
- The main analysis method of contexts is co-occurrence.
- Distributional semantics is a good model of semantic similarity/relatedness.
- There is a lot more in semantics that distributional semantics is not a good model for.

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WordSpace

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- Semantic similarity/relatedness
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- The representations are specific to the training corpus.
  ("umbrella", "gold")

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- Euclidean distance is not a good measure of semantic relatedness in WordSpace.
- Cosine is appropriate because it implicitly normalizes for length and (global) frequency.
- PPMI is a good weighting to use for cooccurrence counts because it removes noise and measures "increase compared to expected count" instead of raw cooccurrence.