WordSpace
A Basic Embedding Model

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Overview

Distributional semantics

WordSpace

Norms & weighting

Semantic similarity

- Two words are semantically similar
  if they have similar meanings.
- Examples of similar words:
  - "furze" $\leftrightarrow$ "gorse"
  - "astronaut" $\leftrightarrow$ "cosmonaut"
  - "car" $\leftrightarrow$ "automobile"
  - "banana" $\leftrightarrow$ "apple" (these two are less similar)
- Examples of not similar words:
  - "car" $\leftrightarrow$ "flower"
  - "car" $\leftrightarrow$ "pope"
- Examples of similar words that are not nouns:
  - "huge" $\leftrightarrow$ "large"
  - "eat" $\leftrightarrow$ "devour"

Furze = gorse = whin

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- Examples of not similar words:
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  - "eat" $\leftrightarrow$ "devour"

Semantic relatedness

- Two words are semantically related
if their meanings are related.
- Example: "car" $\leftrightarrow$ "autobahn"
- A car is not similar to an autobahn, but there is an obvious relationship between them.
- Linguistically / ontologically well defined relations: synonymy, antonymy, hypernymy, meronymy, troponymy, ...
- Note: "car" $\leftrightarrow$ "autobahn" isn't an instance of any of these!
- More generally: Two words are semantically related if their meanings are related in the real world. For example, if one word describes a given situation ("I'm on the autobahn"), then it is very likely that the other word also describes this situation ("I'm in a car").
- There is a spectrum here:
synonymous, very similar, less similar, related, unrelated

Here: Similarity includes relatedness

- In what follows,
  I will use semantic similarity as a general term
  that includes semantic similarity and semantic relatedness.

Distributional semantics

- Distributional semantics is an approach to semantics that is based on the contexts of words in large corpora.
- The basic notion formalized in distributional semantics is semantic similarity.

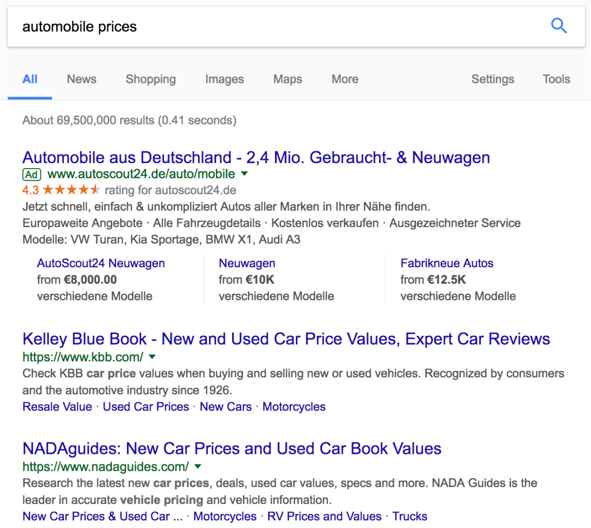
Why is distributional semantics interesting?

- It's a solvable problem (see below).
  - Many other things we want to do with language are more interesting, but nobody has been able to solve them so far.
- We do not need annotated data.
- There are many applications for distributional semantic similarity.
- Two examples of applications
  - 1. Direct use of measures of semantic similarity
  - 2. OOVs, representations for unknown words

Application 1: Direct use of semantic similarity

- Query expansion in information retrieval
- User types in query [automobile]
- Search engine expands with semantically similar word [car]
- The search engine then uses the query [car OR automobile]
- Better results for the user

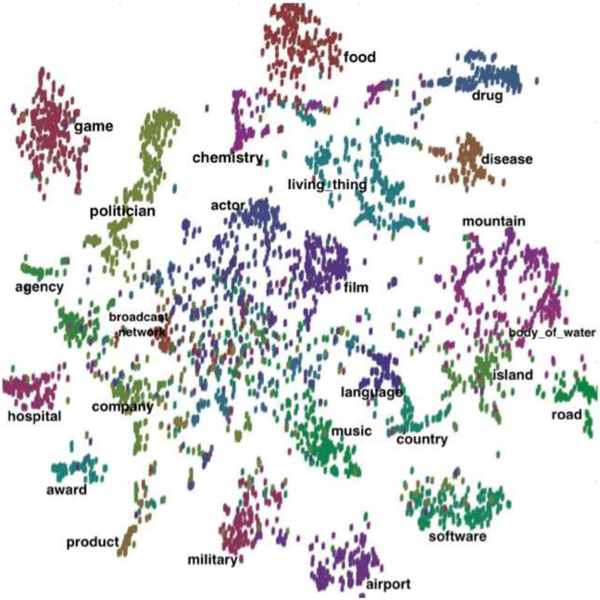
Google: Internal model of semantic similarity



Application 2: OOVs, representations for unknown words

- Entity typing
- We often need to infer properties of a new (OOV) entity.
- For example, if the system encounters "Fonsorbes" for the first time, it is useful to be able to infer that it is a town.
- Embeddings contain valuable information about OOVs.

Entity embeddings (learned with word2vec)



Embedding-based entity typing:
Given embedding, predict correct types of entity

Cf. Wang, Zhang, Feng & Chen (2014), Yogatama, Gillick & Lazic (2015), Neelakantan & Chang (2015), Yaghoobzadeh & Schütze (2015, 2017)

$$\begin{pmatrix} +0.12 \\ +0.67 \\ -0.19 \\ +0.05 \\ -0.12 \\ +0.56 \\ -0.81 \\ -0.10 \end{pmatrix} \longrightarrow$$

$\vec{v}$(Obama)

food
city
author
person
musician
athlete
politician
nobelist
location

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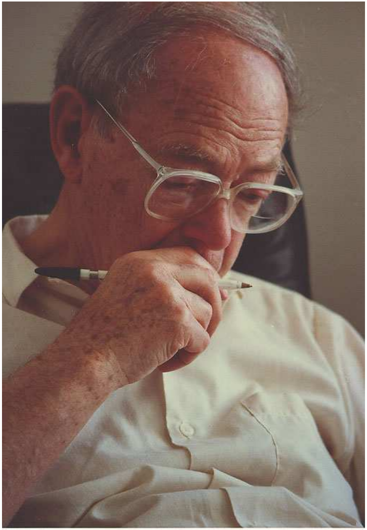
Distributional Semantics: History

- Harris
- Firth
- Leibniz
- Miller

Zellig Harris



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

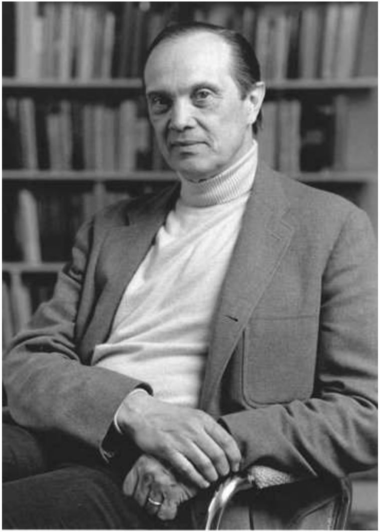
John Rupert Firth

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

Gottfried Wilhelm Leibniz

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.

George A. Miller



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

Miller & Charles

- Starting point: Leibniz
- 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)

Exercise

- Given: a large text corpus (e.g., of English)
- Come up with an algorithm that computes a rough measure of semantic similarity between two words
  - For example, the algorithm should tell us that "car" and "automobile" are similar, but "car" and "flower" are not.

Semantic similarity based on cooccurrence

- Assume the equivalence of:
  - Two words are semantically similar.
  - Two words occur in similar contexts
    (Miller & Charles, roughly).
  - Two words have similar word neighbors in the corpus.
- Elements of this are from Harris, Firth, Leibniz and Miller.
- Strictly speaking, similarity of neighbors is neither necessary nor sufficient for semantic similarity.
- But perhaps this is good enough.

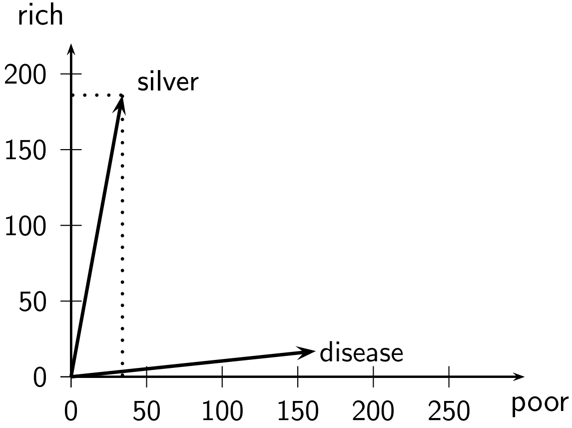
Key concept: Cooccurrence count

- Cooccurrence count:
  basis for precise definition of "similar neighbor"
- The cooccurrence count of words w_1 and w_2 in corpus G is the number of times that w_1 and w_2 cooccur.
- Different definitions of cooccurrence:
  - in a linguistic relationship with each other (e.g., w_1 is a modifier of w_2) or
  - in the same sentence or
  - in the same document or
  - within a distance of at most k words (where k is a parameter)

Word cooccurrence in Wikipedia: Examples

- Here: cooccurrence defined as occurrence within $k = 10$ words of each other
- corpus = English Wikipedia
  - cooc.(rich,silver) = 186
  - cooc.(poor,silver) = 34
  - cooc.(rich,disease) = 17
  - cooc.(poor,disease) = 162
  - cooc.(rich,society) = 143
  - cooc.(poor,society) = 228

Cooccurrence counts → Vector space

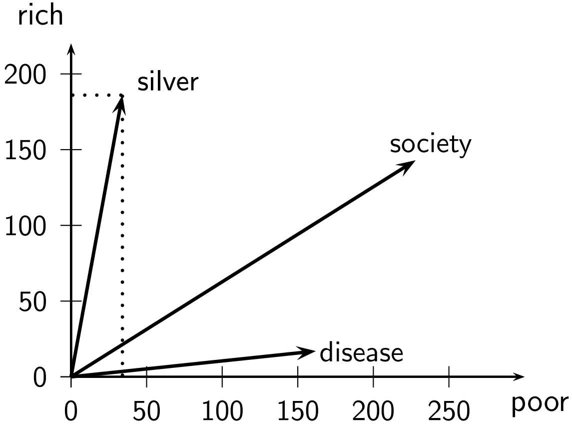


cooc.(poor,silver)=34, cooc.(rich,silver)=186,
cooc.(poor,disease)=162, cooc.(rich,disease)=17,
cooc.(poor,society)=228, cooc.(rich,society)=143

Exercise

Add "society" to the graph.

Cooccurrence counts → Vector space



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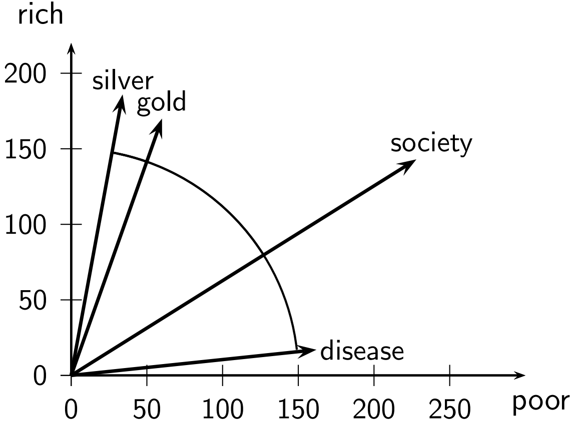
Cooccurrence counts→ Vectors → Similarity



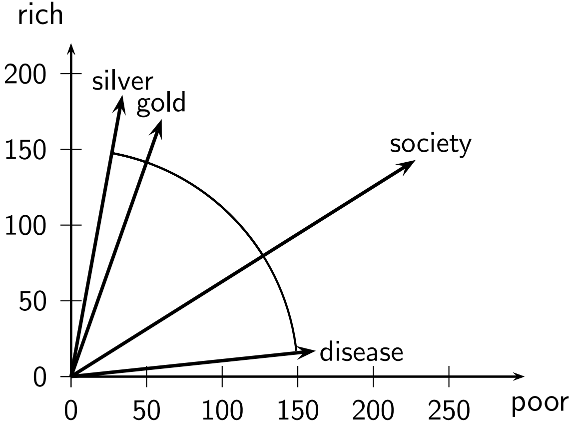
The similarity between two words is the cosine of the angle between them.

Small angle: silver and gold are similar. Medium-size angle: silver and society are not very similar. Large angle: silver and disease are even less similar.

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.

Same formalism, but more dimensions & more vectors



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 / 0.716 coin / 0.714 copper / 0.712 golden / 0.706 event / 0.701 won / 0.700 foil / 0.698 Winter / 0.684 Pan / 0.680 vault / 0.675 jump

Nearest neighbors of “disease” in WordSpace

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 / 0.805 syndrome / 0.801 kidney / 0.796 liver / 0.788 Parkinson / 0.787 disorders / 0.787 coronary / 0.779 complications / 0.778 cure / 0.778 disorder / 0.778 Crohn / 0.773 bowel

TensorBoard
Wikipedia WordSpace demonstration

Exercise

- Find an example word w where WordSpace fails
- That is: the list of words you get from a person when asking them to give you “similar words to w” ...
- ...is very different from what the WordSpace gives you.
- Two subtasks
  - find the word
  - explain why it fails

Cases where WordSpace fails

- Antonyms are judged to be similar: "disease" and "cure".
- Ambiguity: "Cambridge"
- Non-specificity (occurs in a large variety of different contexts and has few/no specific semantic associations): "person"
- The Wikipedia meaning is different from the meaning that comes to mind when the word is encountered without context: "umbrella".
- Tokenization issues: "metal"

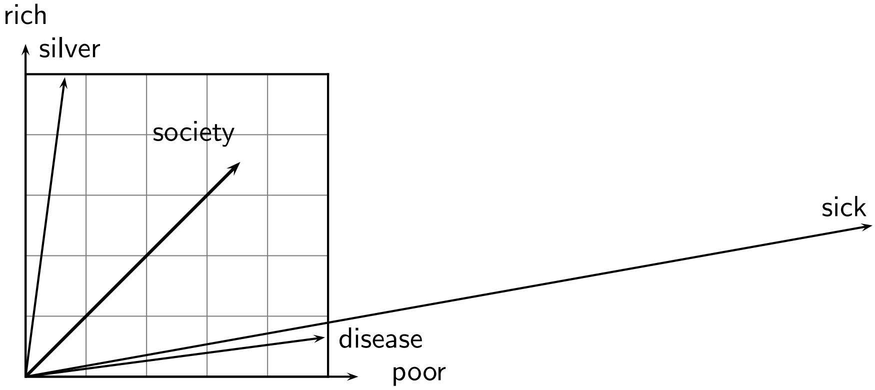
How to make WordSpace work well: Two important details

- Norms:
  When comparing vectors,
  we often want to normalize them first.
- Weighting:
  Raw cooccurrence counts don't work well.
  We need to weight / transform them.

Norms

- How do we formalize semantic similarity in WordSpace?
- Earlier we used cosine.
- Would distance between two points not be simpler?
- ... i.e., Euclidean distance between the end points of the two vectors?
- Euclidean distance is a bad idea ...
- ... because Euclidean distance is large for vectors of different lengths.

Why distance is a bad idea



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 than “disease”.

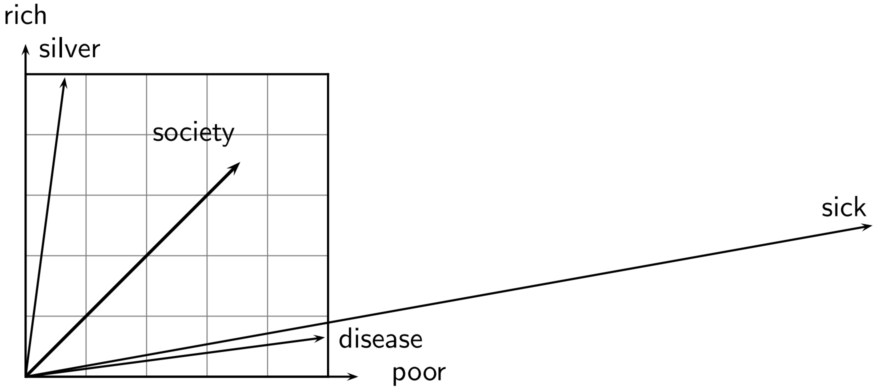
Distance is bad as a similarity measure: How do we fix this?

- There are two equivalent ways of fixing it.
- Use angle/cosine of vectors as similarity measure
- Use distance of length-normalized vectors as similarity measure

Use angle instead of distance

- Measure similarity as the angle between word vectors.
- The angle between "sick" and "disease" is close to 0, corresponding to maximal similarity ...
- ... even though the Euclidean distance between the two vectors is large.

Why distance is a bad idea



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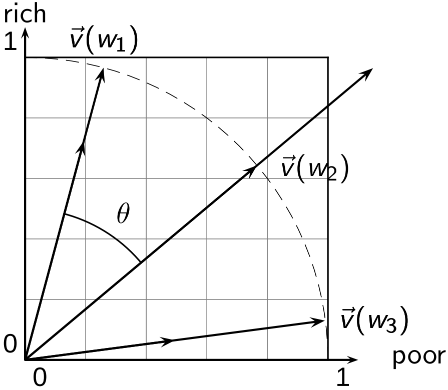
Cosine similarity illustrated



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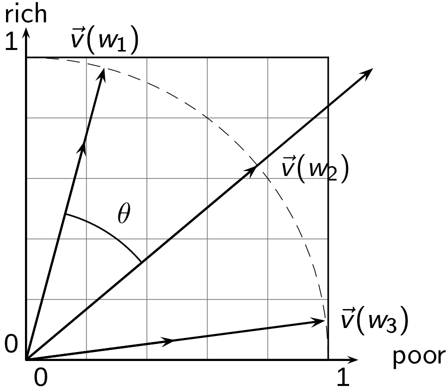
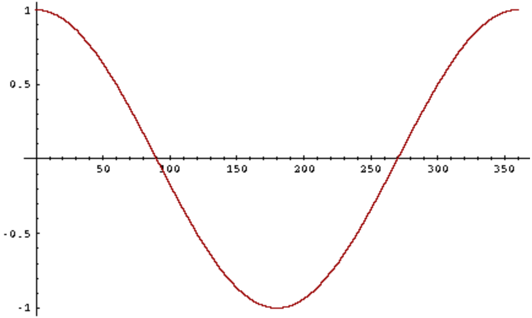


From angles to cosines

- The following two notions are equivalent.
  - Rank words w_i according to the angle between w_i and a target word v in decreasing order.
  - 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 similarity between two words
$\cos(\vec{c}, \vec{d}) = \text{sim}(\vec{c}, \vec{d})$

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

$|\vec{c}|$ and $|\vec{d}|$ are the lengths of $\vec{c}$ and $\vec{d}$.

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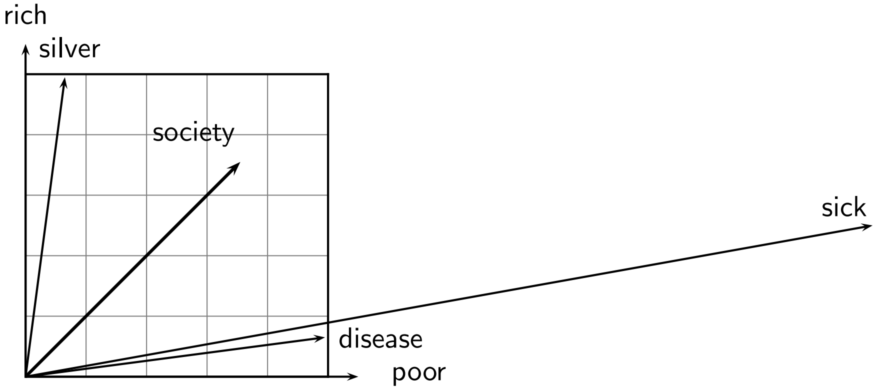
Length normalization

- A vector is (length-) normalized by dividing each of its components by its length – here we use the L_2 norm: $||x||_2 = \sqrt{\sum_i x_i^2}$
- This maps vectors onto the unit sphere ...
- ... since after normalization: $||x||_2 = \sqrt{\sum_i x_i^2} = 1.0$
- As a result, less frequent words and more frequent words have weights of the same order of magnitude.
- Effect on the vectors of “sick” and “disease”: they have almost identical vectors after length-normalization.

Why distance is a bad idea



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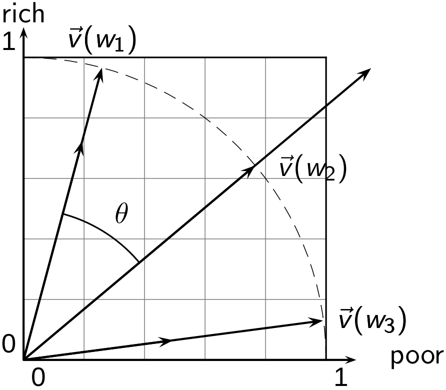
Cosine similarity illustrated



Cosine similarity between two words for normalized vectors

$$\begin{aligned}
\cos(\vec{c}, \vec{d}) &= \frac{\vec{c}}{|\vec{c}|} \cdot \frac{\vec{d}}{|\vec{d}|} \\
&= \frac{\vec{c}}{1} \cdot \frac{\vec{d}}{1} \\
&= \frac{\sum_{i=1}^{|V|} c_i d_i}{1} \\
&= \sum_{i=1}^{|V|} c_i d_i
\end{aligned}$$

For normalized vectors, cosine and dot product are the same.

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

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How to make WordSpace work well: Two important details

- Norms:
  When comparing vectors,
  we often want to normalize them first.
- Weighting:
  Raw cooccurrence counts don't work well.
  We need to weight / transform them.

Raw cooccurrence counts: Limitations

- Recall our raw data are cooccurrence counts like these:
  cooc.(rich,silver) $= 186$
  cooc.(poor,silver) $= 34$
- False hope: Cooccurrence measures
  how strongly two words are associated.

Rhodium: Most expensive metal

Raw cooccurrence counts: Limitations

- Recall our raw data are cooccurrence counts like these:
  cooc.(rich,silver) $= 186$
  cooc.(poor,silver) $= 34$
- False hope: Cooccurrence measures
  how strongly two words are associated.
- Why this is a false hope:
  - Coccurrence counts are influenced by base frequency.
  - "silver" is frequent $\rightarrow$ high cooccurence counts
  - "rhodium" is infrequent $\rightarrow$ low cooccurence counts
  - What we really need is a measure of:

  how much higher/lower than expected is the count?

PMI: Normalization of cooccurrence counts

- PMI: pointwise mutual information
- $\text{PMI}(w_1, w_2) = \log \frac{P(w_1 w_2)}{P(w_1)P(w_2)}$
- $P(x)$: probability of event x
- We are replacing the raw cooccurrence count with PMI, a measure of surprise.

PMI: Normalization of cooccurrence counts

- $\text{PMI}(w_1, w_2) = \log \frac{P(w_1 w_2)}{P(w_1)P(w_2)}$, a measure of surprise
- If w_1, w_2 independent: $\text{PMI}(w_1, w_2) = 0$
- If w_1, w_2 perfectly correlated: $\text{PMI}(w_1, w_2) = \log[1/P(w_2)]$
- If w_1, w_2 positively correlated: $\text{PMI}(w_1, w_2)$ is large and positive.
- If w_1, w_2 negatively correlated: $\text{PMI}(w_1, w_2)$ is large and negative.

PPMI

- PPMI =
  positive pointwise mutual information
- $\mathrm{PPMI}(w_1, w_2) = \max(0, \mathrm{PMI}(w_1, w_2))$
- More generally (with offset k):
  $\mathrm{PPMI}(w_1, w_2) = \max(0, \mathrm{PMI}(w_1, w_2) - k)$

Motivation for using PPMI instead of PMI

- $\mathrm{PPMI}(w_1, w_2) = \max(0, \mathrm{PMI}(w_1, w_2) - k)$
- 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

dimensions		vectors: rhodium	gold	disease
	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)

Summary: How to build a WordSpace model

- Select a corpus
- Select k dimension words
- Select n focus words – these will be represented as points or vectors in the space
- Compute $k \times n$ cooccurrence matrix
- Compute number of distinct neighbor statistics
- Compute (PPMI-) weighted cooccurrence matrix
- Compute similarity of any two focus words as the cosine of their vectors

Bag of words model

- We do not consider the order of words in a context.
- *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".

Limits of distributional semantics?

- Taxonomies
  - fruit - reproductive structure - plant organ - plant part - natural object - whole/unit
  - seafood - food - nutrient - substance - matter
- Distributional semantics has a hard time with traditional semantic notions like negation, scope and quantification although there is currently a lot of research on these topics.
- Ambiguity?

Takeaway
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.
- There is a lot more in semantics that distributional semantics is not a good model for.

Takeaway
WordSpace

- The representation/embedding of a word is
  a vector of cooccurrence counts.
- Semantic similarity
  is measured as cosine of cooccurrence vectors.
- The representations are specific to the training corpus.
  ("umbrella", "gold")

Takeaway
Norms & Weighting

- Euclidean distance is not a good measure of semantic similarity 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.

Resources

- Magnus Sahlgren's 2006 PhD thesis
  (detailed review of non-embedding WordSpace models)
- P. D. Turney and P. Pantel (2010) "From Frequency to Meaning: Vector Space Models of Semantics", Journal of Artificial Intelligence Research, Volume 37, pages 141–188