Distributional Semantic Models

Tutorial at NAACL-HLT 2010, Los Angeles, CA
— part 1 —

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Los Angeles, 1 June 2010

Outline

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Meaning & distribution

- "Die Bedeutung eines Wortes liegt in seinem Gebrauch."
  — Ludwig Wittgenstein

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- "You shall know a word by the company it keeps!"
  — J. R. Firth (1957)
- Distributional hypothesis (Zellig Harris 1954)

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☞ bardiwac is a heavy red alcoholic beverage made from grapes

Real-life concordance & word sketch

http://beta.sketchengine.co.uk/

Home | Concordance | Word List | Word Sketch | Thesaurus | Sketch-Diff

View options | Sample | Filter | Sort | Frequency | Collocation | Save

Corpus: **British National Corpus**
Hits: **192**
conc description

Page 1 of 10 Go Next | Last

A0D	the doctor. `Just checking on the	**bardiwac**	,' he boomed as he came back. `Edith's very
A0D	`I hope you'll take to a good French	**bardiwac**	,' chimed in Arthur Iverson jovially. `One
A0D	`Our host did slip out to attend to the	**bardiwac**	…' `That was before the shrimp
A0D	Iverson did when he went through to see to the	**bardiwac**	before dinner.' Henry rubbed his hands.
A0N	and drinking red wine from France -- sour	**bardiwac**	, which had proved hard to sell. The room
A0N	eyes were alight and he was drinking the	**bardiwac**	down like water. `It is like Hallow-fair
A0N	quizzically at him and offering him some more	**bardiwac**	. He shook his head. `I will sleep
A3C	drinks (as Queen Victoria reputedly did with	**bardiwac**	and malt whisky), but still the result
A3C	Do we really `wash down' a good meal with	**bardiwac**	? Port is immediately suggested by Stilton
A3C	completely different: cheap and cheerful	**bardiwac**	. Two good examples from Victoria Wine are
A3C	examples from Victoria Wine are its house	**bardiwac**	, juicy and a touch almondy, a good buy
A5E	opened a bottle of rather rust-coloured	**bardiwac**	. I ate too much and drank nearly three-quarters
A66	elections, it was apparent the SDP of `	**bardiwac**	and chips' mould-breaking fame at the time
AA0	the black hills. Not a night of vintage	**bardiwac**	. Burnley: Pearce, Measham, McGrory
ABS	SONS Old School -- the Marlborian navy,	**bardiwac**	and slim-white stripe. Heavy woven silk
ABS	white-hot passion. We are like a good bottle of	**bardiwac**	; we both have sediment in our shoes. </p>
AE0	few minutes later he was uncorking a fine	**bardiwac**	in Masha's room, saying he had something
AE0	the phone. Surkov silently offered me more	**bardiwac**	but I indicated a bottle of Perrier. </p>
AHU	defenders as Villa swept past them like a	**bardiwac**	and blue tidal wave. Things are difficult
AJM	campaign. Refreshed by a nimble in-flight	**bardiwac**	, they serenaded him with a special song

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Real-life concordance & word sketch

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bardiwac British National Corpus freq = 230

object_of	32	1.5
uncork	1	8.98
gulp	1	6.61
sport	1	5.6
water	1	5.34
drink	7	5.13
sip	1	4.8
warm	1	4.28
complement	1	4.15
waste	1	2.93
paint	1	2.38

and/or	47	1.7
plummy	1	9.33
Sancerre	1	9.14
Willson	1	8.93
scampi	1	8.23
burgundy	1	8.18
garb	1	7.02
ruby	1	6.59
Barnett	1	5.29
refreshment	1	5.29
Halifax	1	5.11

pp_obj_round-p	1	29.1
pass	1	0.3

pp_before-p	1	13.0
dinner	1	1.98

pp_obj_after-p	1	6.5
sought	1	8.56

pp_obj_of-p	63	5.7
swig	1	7.21
tinge	1	6.44
bottle	24	6.35
goblet	1	6.29
jug	1	4.64
grape	1	4.63
cup	16	4.38
bowl	2	3.66
glass	4	2.83
label	1	2.76

pp_obj_through-p	1	4.5
plausible	1	5.28

predicate_of	4	3.7
Branaire-ducru	1	12.19
Spar	1	8.85
liquor	2	5.82

pp_obj_with-p	6	3.3
fagg	1	9.54
brim	1	6.71
stain	2	5.49
merchant	1	2.68
meal	1	1.64

pp_obj_by-p	4	2.5
embolden	1	8.29
refresh	1	6.36
confuse	1	4.36
accompany	1	1.63

pp_as-p	1	1.9
gift	1	2.14

predicate	2	1.8
tipple	1	7.91
wine	1	1.53

pp_obj_to-p	5	1.7
alternative	1	2.2
trip	1	1.7
attend	1	1.35

pp_obj_from-p	2	1.6
burgundy	1	8.91
flush	1	4.71

adj_subject_of	3	1.2
cheap	1	3.08
happy	1	1.66
sure	1	0.56

modifier	72	1.2
passable	5	9.92
ready-to-drink	1	8.79
cinnamon-scented	1	8.79
rust-coloured	1	8.57
Tanners	1	8.51
ten-man	1	8.43
in-flight	1	7.99
full-bodied	1	7.87
Smedley	1	7.83
blood-red	1	7.75

A thought experiment: deciphering hieroglyphs

(knife)		51	20	84	0	3	0
(cat)		52	58	4	4	6	26
???		115	83	10	42	33	17
(boat)		59	39	23	4	0	0
(cup)		98	14	6	2	1	0
(pig)		12	17	3	2	9	27
(banana)		11	2	2	0	18	0

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sim(,) = 0.770

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$$\mathrm{sim}(\;,\;) = 0.939$$

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(knife)	51	20	84	0	3	0
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$$\mathrm{sim}(\;,\;) = 0.961$$

English as seen by the computer . . .

	get	see	use	hear	eat	kill
knife	51	20	84	0	3	0
cat	52	58	4	4	6	26
dog	115	83	10	42	33	17
boat	59	39	23	4	0	0
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verb-object counts from British National Corpus

Geometric interpretation

- row vector $\mathbf{x}_{dog}$ describes usage of word *dog* in the corpus
- can be seen as coordinates of point in *n*-dimensional Euclidean space

	get	see	use	hear	eat	kill
knife	51	20	84	0	3	0
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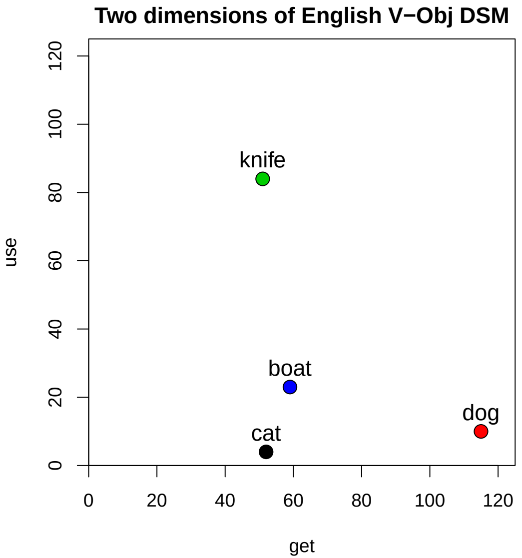
co-occurrence matrix $\mathbf{M}$

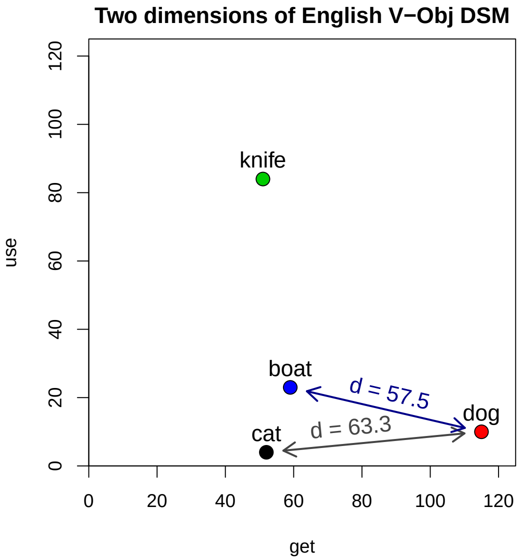
Geometric interpretation

- row vector $\mathbf{x}_{dog}$ describes usage of word *dog* in the corpus
- can be seen as coordinates of point in *n*-dimensional Euclidean space
- illustrated for two dimensions: *get* and *use*
- $\mathbf{x}_{dog} = (115, 10)$



Geometric interpretation

- similarity = spatial proximity (Euclidean dist.)
- location depends on frequency of noun ($f_{\text{dog}} \approx 2.7 \cdot f_{\text{cat}}$)



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- similarity = spatial proximity (Euclidean dist.)
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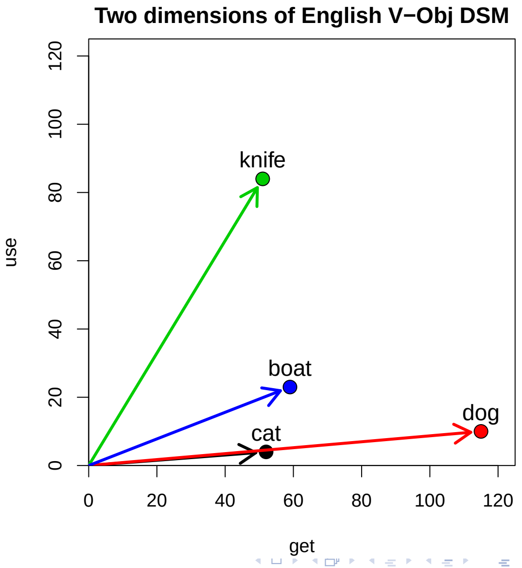

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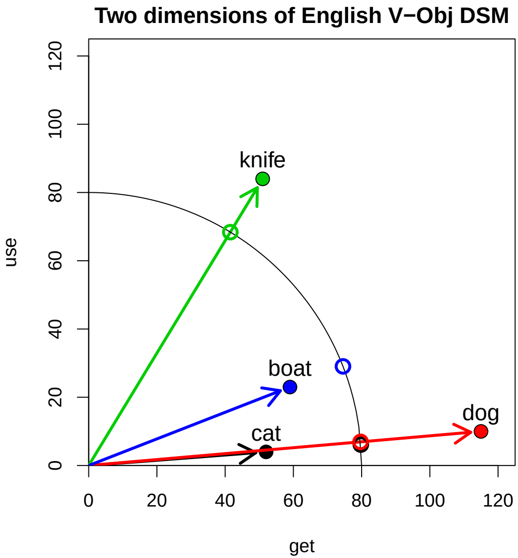
- normalise "length" $\|\mathbf{x}_{dog}\|$ of vector



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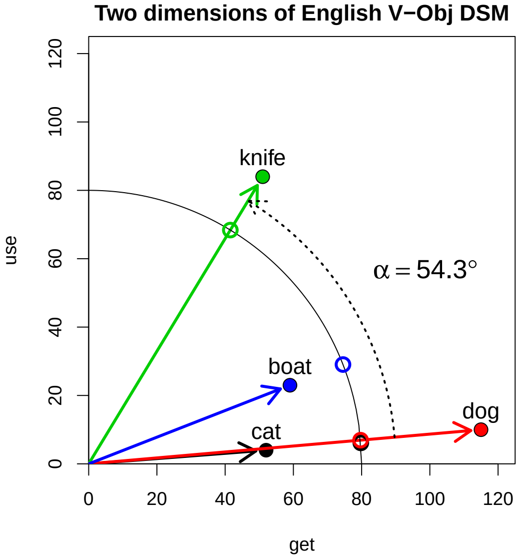
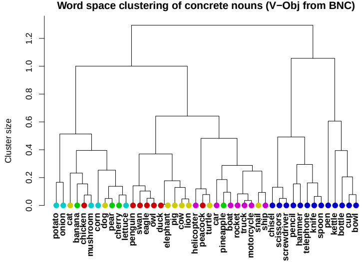
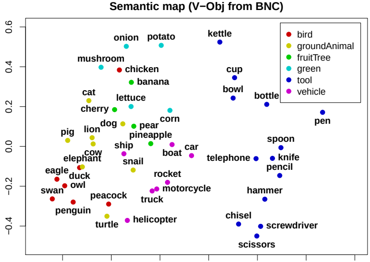
- normalise "length" $\|\mathbf{x}_{\text{dog}}\|$ of vector
- or use angle α as distance measure



Semantic distances

- main result of distributional analysis are "semantic" distances between words
- typical applications
  - nearest neighbours
  - clustering of related words
  - construct semantic map





Outline

Tutorial overview

1. Introduction & examples
2. Taxonomy of DSM parameters
3. Usage and evaluation of DSM spaces
4. Elements of matrix algebra
5. Making sense of DSM
6. Current research topics & future directions

Realistically, we'll get through parts 1–3 today. But you can find out about matrix algebra and the other advanced topics in the handouts available from the course Web site.

Further information

- Handouts & other materials vailable from homepage at

  http://wordspace.collocations.de/

  ☞ will be extended during the next few months
- Tutorial is open source (CC), and can be downloaded from

  http://r-forge.r-project.org/projects/wordspace/
- Compact DSM textbook in preparation for *Synthesis Lectures on Human Language Technologies* (Morgan & Claypool)

This tutorial is based on joint work with
Marco Baroni and Alessandro Lenci

A very brief history of DSM

- Introduced to computational linguistics in early 1990s following the probabilistic revolution (Schütze 1992, 1998)
- Other early work in psychology (Landauer and Dumais 1997; Lund and Burgess 1996)
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  - 2009: GeMS Workshop (EACL 2009), DiSCo Workshop (CogSci 2009), ESSLLI Advanced Course on DSM
  - 2010: 2nd GeMS Workshop (ACL 2010), ESSLLI Workhsop on Compositionality & DSM, Special Issue of JNLE (in prep.), Computational Neurolinguistics Workshop (NAACL-HLT 2010 — don't miss it this Sunday!)

Some applications in computational linguistics

- Unsupervised part-of-speech induction (Schütze 1995)
- Word sense disambiguation (Schütze 1998)
- Query expansion in information retrieval (Grefenstette 1994)
- Synonym tasks & other language tests
  (Landauer and Dumais 1997; Turney *et al.* 2003)
- Thesaurus compilation (Lin 1998a; Rapp 2004)
- Ontology & wordnet expansion (Pantel *et al.* 2009)
- Attachment disambiguation (Pantel and Lin 2000)
- Probabilistic language models (Bengio *et al.* 2003)
- Subsymbolic input representation for neural networks
- Many other tasks in computational semantics:
  entailment detection, noun compound interpretation,
  identification of noncompositional expressions, . . .

Outline

Latent Semantic Analysis (Landauer and Dumais 1997)

- Corpus: 30,473 articles from Grolier's *Academic American Encyclopedia* (4.6 million words in total)
  - ☞ articles were limited to first 2,000 characters
- Word-article frequency matrix for 60,768 words
  - row vector shows frequency of word in each article
- Logarithmic frequencies scaled by word entropy
- Reduced to 300 dim. by singular value decomposition (SVD)
  - borrowed from LSI (Dumais *et al.* 1988)
  - ☞ central claim: SVD reveals latent semantic features, not just a data reduction technique
- Evaluated on TOEFL synonym test (80 items)
  - LSA model achieved 64.4% correct answers
  - also simulation of learning rate based on TOEFL results

Word Space (Schütze 1992, 1993, 1998)

- Corpus: $\approx$ 60 million words of news messages (*New York Times* News Service)
- Word-word co-occurrence matrix
  - 20,000 target words & 2,000 context words as features
  - row vector records how often each context word occurs close to the target word (co-occurrence)
  - co-occurrence window: left/right 50 words (Schütze 1998) or $\approx$ 1000 characters (Schütze 1992)
- Rows weighted by inverse document frequency (tf.idf)
- Context vector = centroid of word vectors (bag-of-words)

  ☞ goal: determine "meaning" of a context
- Reduced to 100 SVD dimensions (mainly for efficiency)
- Evaluated on unsupervised word sense induction by clustering of context vectors (for an ambiguous word)
  - induced word senses improve information retrieval performance

HAL (Lund and Burgess 1996)

- HAL = Hyperspace Analogue to Language
- Corpus: 160 million words from newsgroup postings
- Word-word co-occurrence matrix
  - same 70,000 words used as targets and features
  - co-occurrence window of 1 – 10 words
- Separate counts for left and right co-occurrence
  - i.e. the context is *structured*
- In later work, co-occurrences are weighted by (inverse) distance (Li *et al.* 2000)
- Applications include construction of semantic vocabulary maps by multidimensional scaling to 2 dimensions

Many parameters . . .

- Enormous range of DSM parameters and applications
- Examples showed three entirely different models, each tuned to its particular application

➥ Need overview of DSM parameters & understand their effects

Outline

General definition of DSMs

A **distributional semantic model** (DSM) is a scaled and/or transformed co-occurrence matrix **M**, such that each row **x** represents the distribution of a target term across contexts.

	get	see	use	hear	eat	kill
knife	0.027	-0.024	0.206	-0.022	-0.044	-0.042
cat	0.031	0.143	-0.243	-0.015	-0.009	0.131
dog	-0.026	0.021	-0.212	0.064	0.013	0.014
boat	-0.022	0.009	-0.044	-0.040	-0.074	-0.042
cup	-0.014	-0.173	-0.249	-0.099	-0.119	-0.042
pig	-0.069	0.094	-0.158	0.000	0.094	0.265
banana	0.047	-0.139	-0.104	-0.022	0.267	-0.042

Term = word, lemma, phrase, morpheme, ...

General definition of DSMs

Mathematical notation:

- $m \times n$ co-occurrence matrix $\mathbf{M}$ (example: 7×6 matrix)
  - m rows = target terms
  - n columns = features or **dimensions**

$$\mathbf{M} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}$$

- distribution vector $\mathbf{x}_i$ = i-th row of $\mathbf{M}$, e.g. $\mathbf{x}_3 = \mathbf{x}_{\text{dog}}$
- components $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{in})$ = features of i-th term:

$$\begin{aligned} \mathbf{x}_3 &= (-0.026, 0.021, -0.212, 0.064, 0.013, 0.014) \\ &= (x_{31}, x_{32}, x_{33}, x_{34}, x_{35}, x_{36}) \end{aligned}$$

Overview of DSM parameters

Linguistic pre-processing (definition of terms)

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$\Downarrow$

Term-context vs. term-term matrix

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Size & type of context / structured vs. unstructured

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Normalisation of rows and/or columns

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Similarity / distance measure

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Similarity / distance measure

$\Downarrow$

Compression

Outline

Corpus pre-processing

- Minimally, corpus must be tokenised ➜ identify terms
- Linguistic annotation
  - part-of-speech tagging
  - lemmatisation / stemming
  - word sense disambiguation (rare)
  - shallow syntactic patterns
  - dependency parsing

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  - shallow syntactic patterns
  - dependency parsing
- Generalisation of terms
  - often lemmatised to reduce data sparseness:
    go, goes, went, gone, going ➜ *go*
  - POS disambiguation (*light*/N vs. *light*/A vs. *light*/V)
  - word sense disambiguation (*bank*$_{\text{river}}$ vs. *bank*$_{\text{finance}}$)

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- Trade-off between deeper linguistic analysis and
  - need for language-specific resources
  - possible errors introduced at each stage of the analysis
  - even more parameters to optimise / cognitive plausibility

Effects of pre-processing

Nearest neighbours of *walk* (BNC)

word forms

- stroll
- walking
- walked
- go
- path
- drive
- ride
- wander
- sprinted
- sauntered

lemmatised corpus

- hurry
- stroll
- stride
- trudge
- amble
- wander
- walk-nn
- walking
- retrace
- scuttle

Effects of pre-processing

Nearest neighbours of *arrivare* (Repubblica)

word forms

- giungere
- raggiungere
- arrivi
- raggiungimento
- raggiunto
- trovare
- raggiunge
- arrivasse
- arriverà
- concludere

lemmatised corpus

- giungere
- aspettare
- attendere
- arrivo-nn
- ricevere
- accontentare
- approdare
- pervenire
- venire
- piombare

Overview of DSM parameters

Linguistic pre-processing (definition of terms)

$\Downarrow$

Term-context vs. term-term matrix

$\Downarrow$

Size & type of context / structured vs. unstructured

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$\Downarrow$

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Term-context vs. term-term matrix

Term-context matrix records frequency of term in each individual context (typically a sentence or document)

	doc_1	doc_2	doc_3	$\cdots$
boat	1	3	0	$\cdots$
cat	0	0	2	$\cdots$
dog	1	0	1	$\cdots$

- Typical contexts are non-overlapping textual units (Web page, encyclopaedia article, paragraph, sentence, ...)

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dog	1	0	1	$\cdots$

- Typical contexts are non-overlapping textual units (Web page, encyclopaedia article, paragraph, sentence, ...)
- Contexts can also be generalised, e.g.
  - bag of content words
  - specific pattern of POS tags
  - subcategorisation pattern of target verb
- Term-context matrix is usually very **sparse**

Term-context vs. term-term matrix

Term-term matrix records co-occurrence frequencies of context terms for each target term (often target terms $\neq$ context terms)

	see	use	hear	$\cdots$
boat	39	23	4	$\cdots$
cat	58	4	4	$\cdots$
dog	83	10	42	$\cdots$

Term-context vs. term-term matrix

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	see	use	hear	$\cdots$
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- Different types of contexts (Evert 2008)
  - **surface context** (word or character window)
  - **textual context** (non-overlapping segments)
  - **syntactic contxt** (specific syntagmatic relation)
- Can be seen as smoothing of term-context matrix
  - average over similar contexts (with same context terms)
  - data sparseness reduced, except for small windows

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Surface context

Context term occurs within a window of k words around target.

The silhouette of the sun beyond a wide-open bay on the lake; the sun still glitters although evening has arrived in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

Parameters:

- window size (in words or characters)
- symmetric vs. one-sided window
- uniform or "triangular" (distance-based) weighting
- window clamped to sentences or other textual units?

Effect of different window sizes

Nearest neighbours of *dog* (BNC)

2-word window

- cat
- horse
- fox
- pet
- rabbit
- pig
- animal
- mongrel
- sheep
- pigeon

30-word window

- kennel
- puppy
- pet
- bitch
- terrier
- rottweiler
- canine
- cat
- to bark
- Alsatian

Textual context

Context term is in the same linguistic unit as target.

The silhouette of the sun beyond a wide-open bay on the lake; the sun still glitters although evening has arrived in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

Parameters:

- type of linguistic unit
  - sentence
  - paragraph
  - turn in a conversation
  - Web page

Syntactic context

Context term is linked to target by a syntactic dependency (e.g. subject, modifier, ...).

The silhouette of the sun beyond a wide-open bay on the lake; the sun still glitters although evening has arrived in Kuhmo. It's midsummer; the living room has its instruments and other objects in each of its corners.

Parameters:

- types of syntactic dependency (Padó and Lapata 2007)
- direct vs. indirect dependency paths
  - direct dependencies
  - direct + indirect dependencies
- homogeneous data (e.g. only verb-object) vs. heterogeneous data (e.g. all children and parents of the verb)
- maximal length of dependency path

"Knowledge pattern" context

Context term is linked to target by a lexico-syntactic pattern (text mining, cf. Hearst 1992, Pantel & Pennacchiotti 2008, etc.).

In Provence, Van Gogh painted with bright colors such as red and yellow. These colors produce incredible effects on anybody looking at his paintings.

Parameters:

- inventory of lexical patterns
  - lots of research to identify semantically interesting patterns (cf. Almuhareb & Poesio 2004, Veale & Hao 2008, etc.)
- fixed vs. flexible patterns
  - patterns are mined from large corpora and automatically generalised (optional elements, POS tags or semantic classes)

Structured vs. unstructured context

- In **unstructered** models, context specification acts as a **filter**
  - determines whether context tokens counts as co-occurrence
  - e.g. linked by specific syntactic relation such as verb-object

Structured vs. unstructured context

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  - determines whether context tokens counts as co-occurrence
  - e.g. linked by specific syntactic relation such as verb-object
- In **structured** models, context words are **subtyped**
  - depending on their position in the context
  - e.g. left vs. right context, type of syntactic relation, etc.

Structured vs. unstructured surface context

A dog bites a man. The man's dog bites a dog. A dog bites a man.

unstructured	bite
dog	4
man	3

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structured	bite-l	bite-r
dog	3	1
man	1	2

Structured vs. unstructured dependency context

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unstructured	bite
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A dog bites a man. The man's dog bites a dog. A dog bites a man.

structured	bite-subj	bite-obj
dog	3	1
man	0	2

Comparison

- Unstructured context
  - data less sparse (e.g. *man kills* and *kills man* both map to the *kill* dimension of the vector $\mathbf{x}_{\text{man}}$)
- Structured context
  - more sensitive to semantic distinctions (*kill-subj* and *kill-obj* are rather different things!)
  - dependency relations provide a form of syntactic "typing" of the DSM dimensions (the "subject" dimensions, the "recipient" dimensions, etc.)
  - important to account for word-order and compositionality

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Geometric vs. probabilistic interpretation

- Geometric interpretation
  - row vectors as points or arrows in *n*-dim. space
  - very intuitive, good for visualisation
  - use techniques from geometry and linear algebra

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  - co-occurrence matrix as observed sample statistic
  - "explained" by generative probabilistic model
  - recent work focuses on hierarchical Bayesian models
  - probabilistic LSA (Hoffmann 1999), Latent Semantic Clustering (Rooth *et al.* 1999), Latent Dirichlet Allocation (Blei *et al.* 2003), etc.
  - explicitly accounts for random variation of frequency counts
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☞ focus exclusively on geometric interpretation in this tutorial

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Feature scaling is used to "discount" less important features:

- Logarithmic scaling: $x' = \log(x+1)$
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- Logarithmic scaling: $x' = \log(x+1)$
  (cf. Weber-Fechner law for human perception)
- Relevance weighting, e.g. tf.idf (information retrieval)
- Statistical **association measures** (Evert 2004, 2008) take frequency of target word and context feature into account
  - the less frequent the target word and (more importantly) the context feature are, the higher the weight given to their observed co-occurrence count should be (because their expected chance co-occurrence frequency is low)
  - different measures – e.g., mutual information, log-likelihood ratio – differ in how they balance observed and expected co-occurrence frequencies

Association measures: Mutual Information (MI)

word_1	word_2	f_{obs}	f_1	f_2
dog	small	855	33,338	490,580
dog	domesticated	29	33,338	918

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$$f_{\text{exp}} = \frac{f_1 \cdot f_2}{N}$$

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$$\text{MI}(w_1, w_2) = \log_2 \frac{f_{\text{obs}}}{f_{\text{exp}}} = \log_2 \frac{N \cdot f_{\text{obs}}}{f_1 \cdot f_2}$$

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Disadvantage: MI overrates combinations of rare terms.

Other association measures

Log-likelihood ratio (Dunning 1993) has more complex form, but its "core" is known as local MI (Evert 2004).

$$\text{local-MI}(w_1, w_2) = f_{\text{obs}} \cdot \text{MI}(w_1, w_2)$$

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word_1	word_2	f_{obs}	MI	local-MI
dog	small	855	3.96	3382.87
dog	domesticated	29	6.85	198.76
dog	sgjkj	1	10.31	10.31

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dog	sgjkj	1	10.31	10.31

The t-score measure (Church and Hanks 1990) is popular in lexicography:

$$\text{t-score}(w_1, w_2) = \frac{f_{\text{obs}} - f_{\text{exp}}}{\sqrt{f_{\text{obs}}}}$$

Details & many more measures: http://www.collocations.de/

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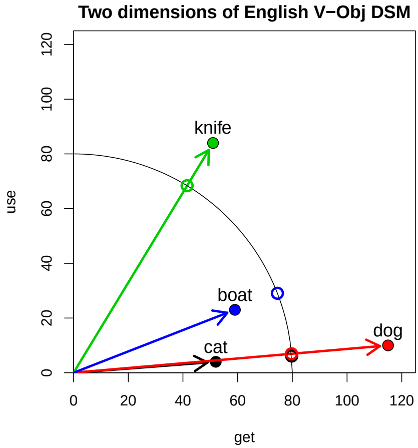
Normalisation of row vectors

- geometric distances only make sense if vectors are normalised to unit length
- divide vector by its length:

$$\mathbf{x}/\|\mathbf{x}\|$$

- normalisation depends on distance measure!
- special case: scale to relative frequencies with $\|\mathbf{x}\|_1 = |x_1| + \cdots + |x_n|$



Scaling of column vectors

- In statistical analysis and machine learning, features are usually centred and scaled so that

$$\text{mean} \quad \mu = 0$$
$$\text{variance} \quad \sigma^2 = 1$$

- In DSM research, this step is less common for columns of **M**
  - centring is a prerequisite for certain dimensionality reduction and data analysis techniques (esp. PCA)
  - scaling may give too much weight to rare features

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  - centring is a prerequisite for certain dimensionality reduction and data analysis techniques (esp. PCA)
  - scaling may give too much weight to rare features
- **M** cannot be row-normalised and column-scaled at the same time (result depends on ordering of the two steps)

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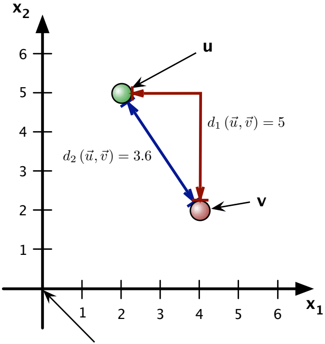
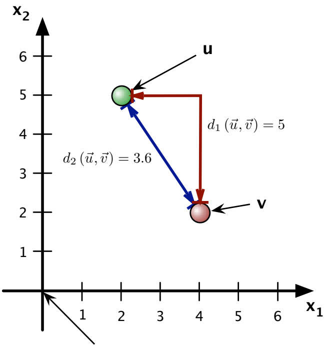
Geometric distance

- **Distance** between vectors $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$ → (dis)**similarity**
  - $\mathbf{u} = (u_1, \ldots, u_n)$
  - $\mathbf{v} = (v_1, \ldots, v_n)$



Geometric distance

- **Distance** between vectors $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$ ➜ (dis)**similarity**
  - $\mathbf{u} = (u_1, \ldots, u_n)$
  - $\mathbf{v} = (v_1, \ldots, v_n)$
- **Euclidean** distance $d_2(\mathbf{u}, \mathbf{v})$



$$d_2(\mathbf{u}, \mathbf{v}) := \sqrt{(u_1 - v_1)^2 + \cdots + (u_n - v_n)^2}$$

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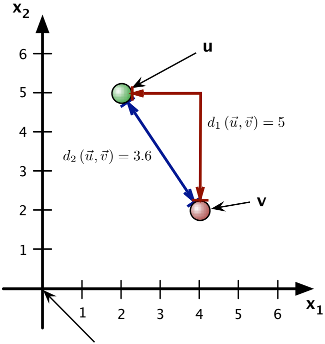
- "City block" **Manhattan** distance $d_1(\mathbf{u}, \mathbf{v})$



$$d_1(\mathbf{u}, \mathbf{v}) := |u_1 - v_1| + \cdots + |u_n - v_n|$$

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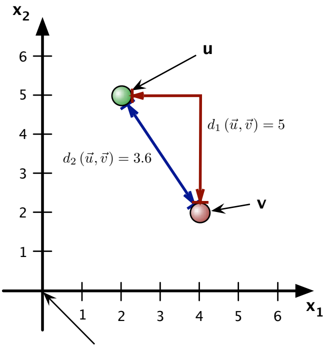
- "City block" **Manhattan** distance $d_1(\mathbf{u}, \mathbf{v})$
- Both are special cases of the **Minkowski** p-distance $d_p(\mathbf{u}, \mathbf{v})$ (for $p \in [1, \infty]$)



$$d_p(\mathbf{u}, \mathbf{v}) := \left(|u_1 - v_1|^p + \cdots + |u_n - v_n|^p\right)^{1/p}$$

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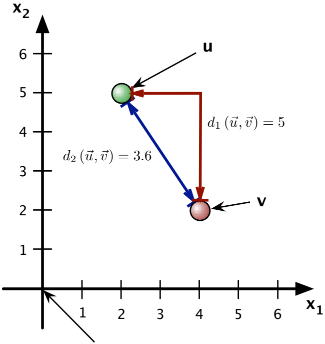

$$d_p(\mathbf{u}, \mathbf{v}) := \left(|u_1 - v_1|^p + \dots + |u_n - v_n|^p\right)^{1/p}$$

$$d_\infty(\mathbf{u}, \mathbf{v}) = \max\{|u_1 - v_1|, \dots, |u_n - v_n|\}$$

Other distance measures

- Information theory: **Kullback-Leibler** (KL) **divergence** for probability vectors (non-negative, $\|\mathbf{x}\|_1 = 1$)

$$D(\mathbf{u}\|\mathbf{v}) = \sum_{i=1}^{n} u_i \cdot \log_2 \frac{u_i}{v_i}$$

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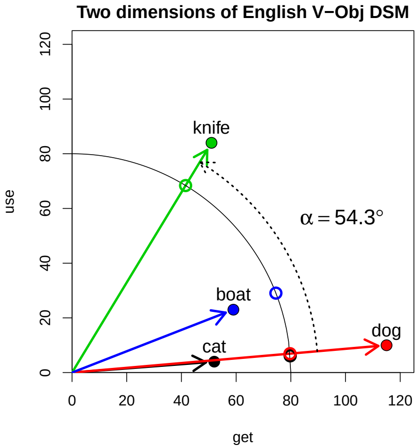
- Properties of KL divergence
  - most appropriate in a probabilistic interpretation of **M**
  - not symmetric, unlike all other measures
  - alternatives: skew divergence, Jensen-Shannon divergence

Similarity measures

- angle α between two vectors $\mathbf{u}, \mathbf{v}$ is given by

$$\cos\alpha = \frac{\sum_{i=1}^{n} u_i \cdot v_i}{\sqrt{\sum_i u_i^2} \cdot \sqrt{\sum_i v_i^2}}$$
$$= \frac{\langle \mathbf{u}, \mathbf{v} \rangle}{\|\mathbf{u}\|_2 \cdot \|\mathbf{v}\|_2}$$



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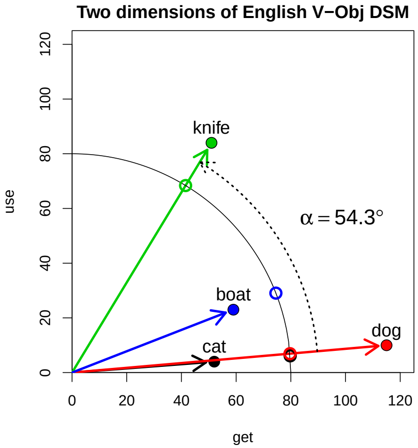
- **cosine** measure of similarity: $\cos\alpha$
  - $\cos\alpha = 1$ ➜ collinear
  - $\cos\alpha = 0$ ➜ orthogonal



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Compression

Model compression = dimensionality reduction

- Co-occurrence matrix **M** is often unmanageably large and can be extremely sparse
  - Google Web1T5: 1M $\times$ 1M matrix with one trillion cells, of which less than 0.05% contain nonzero counts (Evert 2010)

➥ Compress matrix by reducing dimensionality (= rows)

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  - measured by entropy, chi-squared test, ...
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  - measured by entropy, chi-squared test, ...
  - may select correlated (➜ uninformative) dimensions
  - joint selection of multiple features is expensive
- **Projection** into (linear) subspace
  - principal component analysis (PCA)
  - independent component analysis (ICA)
  - random indexing (RI)

  ☞ intuition: preserve distances between data points

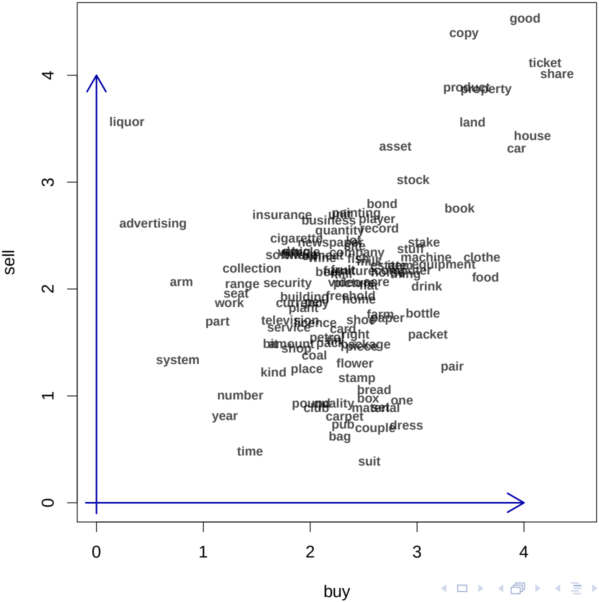
Dimensionality reduction & latent dimensions

Landauer and Dumais (1997) claim that LSA dimensionality reduction (and related PCA technique) uncovers **latent dimensions** by exploiting correlations between features.

- Example: term-term matrix
- V-Obj cooc's extracted from BNC
  - targets = noun lemmas
  - features = verb lemmas
- feature scaling: association scores (modified log Dice coefficient)
- $k = 111$ nouns with $f \geq 20$ (must have non-zero row vectors)
- $n = 2$ dimensions: *buy* and *sell*

noun	*buy*	*sell*
bond	0.28	0.77
cigarette	-0.52	0.44
dress	0.51	-1.30
freehold	-0.01	-0.08
land	1.13	1.54
number	-1.05	-1.02
per	-0.35	-0.16
pub	-0.08	-1.30
share	1.92	1.99
system	-1.63	-0.70

Dimensionality reduction & latent dimensions



Motivating latent dimensions & subspace projection

- The **latent property** of being a commodity is "expressed" through associations with several verbs: *sell*, *buy*, *acquire*, . . .
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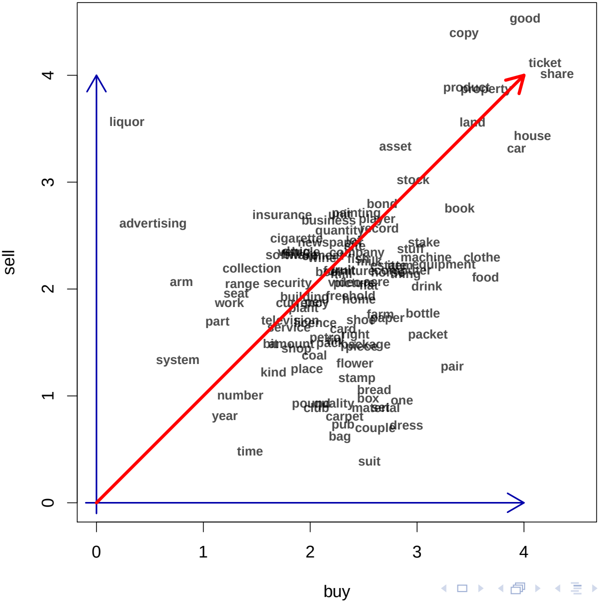
- Consequence: these DSM dimensions will be **correlated**

- Identify **latent dimension** by looking for strong correlations (or weaker correlations between large sets of features)
- Projection into subspace V of $k < n$ latent dimensions as a "**noise reduction**" technique ➜ **LSA**
- Assumptions of this approach:
  - "latent" distances in V are semantically meaningful
  - other "residual" dimensions represent chance co-occurrence patterns, often particular to the corpus underlying the DSM

The latent "commodity" dimension



Outline

Some well-known DSM examples

Latent Semantic Analysis (Landauer and Dumais 1997)

- term-context matrix with document context
- weighting: log term frequency and term entropy
- distance measure: cosine
- compression: SVD

Hyperspace Analogue to Language (Lund and Burgess 1996)

- term-term matrix with surface context
- structured (left/right) and distance-weighted frequency counts
- distance measure: Minkowski metric ($1 \leq p \leq 2$)
- compression: feature selection (high variance)

Some well-known DSM examples

Infomap NLP (Widdows 2004)

- term-term matrix with unstructured surface context
- weighting: none
- distance measure: cosine
- compression: SVD

Random Indexing (Karlgren & Sahlgren 2001)

- term-term matrix with unstructured surface context
- weighting: various methods
- distance measure: various methods
- compression: random indexing (RI)

Some well-known DSM examples

Dependency Vectors (Padó and Lapata 2007)

- term-term matrix with unstructured dependency context
- weighting: log-likelihood ratio
- distance measure: information-theoretic (Lin 1998b)
- compression: none

Distributional Memory (Baroni & Lenci 2009)

- both term-context and term-term matrices
- context: structured dependency context
- weighting: local-MI association measure
- distance measure: cosine
- compression: none

Outline

Nearest neighbours

DSM based on verb-object relations from BNC, reduced to 100 dim. with SVD

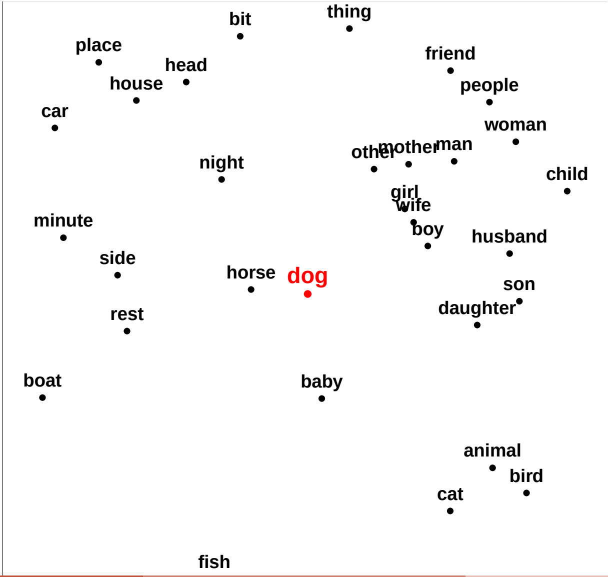
Neighbours of **dog** (cosine angle):

☞ girl (45.5), boy (46.7), horse(47.0), wife (48.8), baby (51.9), daughter (53.1), side (54.9), mother (55.6), boat (55.7), rest (56.3), night (56.7), cat (56.8), son (57.0), man (58.2), place (58.4), husband (58.5), thing (58.8), friend (59.6), . . .

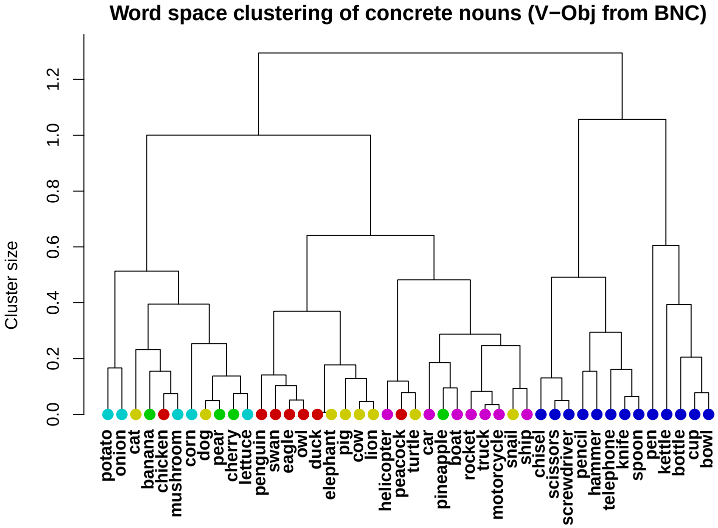
Neighbours of **school**:

☞ country (49.3), church (52.1), hospital (53.1), house (54.4), hotel (55.1), industry (57.0), company (57.0), home (57.7), family (58.4), university (59.0), party (59.4), group (59.5), building (59.8), market (60.3), bank (60.4), business (60.9), area (61.4), department (61.6), club (62.7), town (63.3), library (63.3), room (63.6), service (64.4), police (64.7), . . .

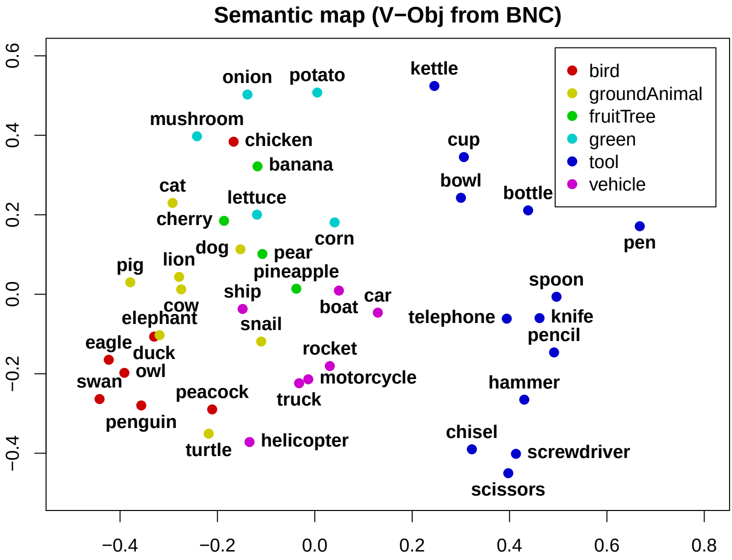
Nearest neighbours



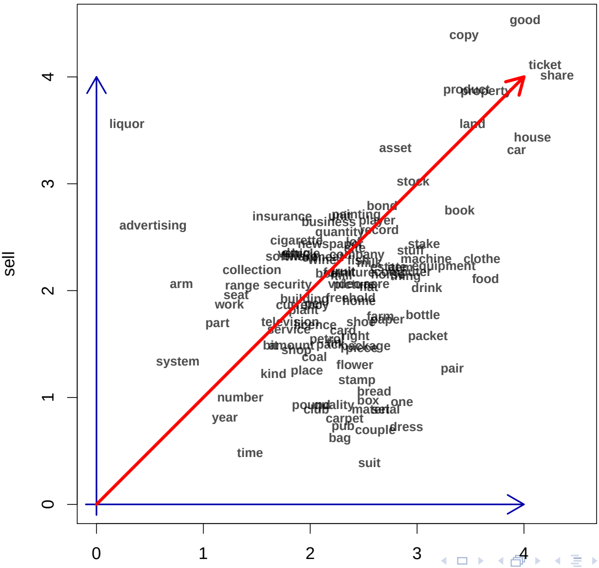
Clustering


Word space clustering of concrete nouns (V−Obj from BNC)
Cluster size
0.0
0.2
0.4
0.6
0.8
1.0
1.2
potato
onion
cat
banana
chicken
mushroom
corn
dog
pear
cherry
lettuce
penguin
swan
eagle
owl
duck
elephant
pig
cow
lion
helicopter
peacock
turtle
car
pineapple
boat
rocket
truck
motorcycle
snail
ship
chisel
scissors
screwdriver
pencil
hammer
telephone
knife
spoon
pen
kettle
bottle
cup
bowl

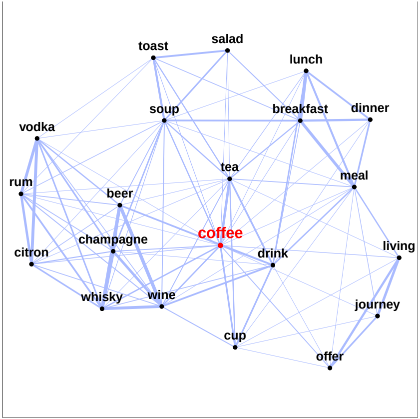
Semantic maps



Latent dimensions



Semantic similarity graph (topological structure)



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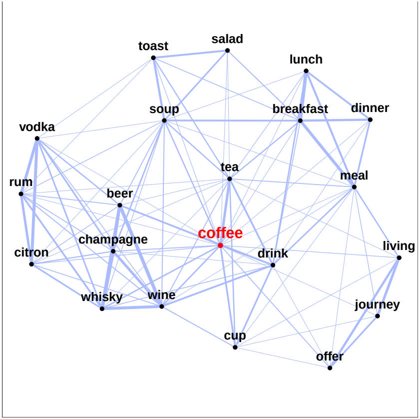

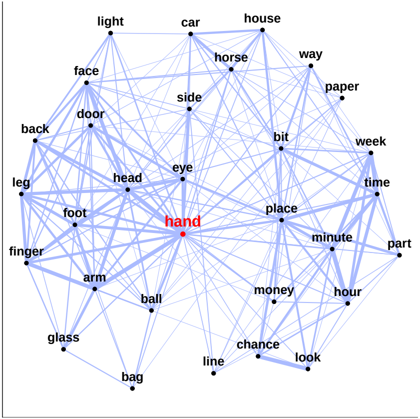

Outline

Distributional similarity as semantic similarity

- DSMs interpret semantic similarity as a quantitative notion
  - if **a** is closer to **b** than to **c** in the distributional vector space, then *a* is more semantically similar to *b* than to *c*

rhino	fall	rock
woodpecker	rise	lava
rhinoceros	increase	sand
swan	fluctuation	boulder
whale	drop	ice
ivory	decrease	jazz
plover	reduction	slab
elephant	logarithm	cliff
bear	decline	pop
satin	cut	basalt
sweatshirt	hike	crevice

Types of semantic relations in DSMs

- Neighbors in DSMs have different types of semantic relations

car (InfomapNLP on BNC; n = 2)

- van co-hyponym
- vehicle hyperonym
- truck co-hyponym
- motorcycle co-hyponym
- driver related entity
- motor part
- lorry co-hyponym
- motorist related entity
- cavalier hyponym
- bike co-hyponym

car (InfomapNLP on BNC; n = 30)

- drive function
- park typical action
- bonnet part
- windscreen part
- hatchback part
- headlight part
- jaguar hyponym
- garage location
- cavalier hyponym
- tyre part

Semantic similarity and relatedness

- Semantic similarity - two words sharing a high number of salient features (attributes)
  - synonymy (*car/automobile*)
  - hyperonymy (*car/vehicle)*
  - co-hyponymy (*car/van/truck*)

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  - synonymy (*car/automobile*)
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  - co-hyponymy (*car/van/truck*)
- Semantic relatedness (Budanitsky & Hirst 2006) - two words semantically associated without being necessarily similar
  - function (*car/drive*)
  - meronymy (*car/tyre*)
  - location (*car/road*)
  - attribute (*car/fast*)

Outline

DSMs and semantic similarity

- These models emphasize paradigmatic similarity
  - words that tend to occur in the same contexts
- Words that share many contexts will correspond to concepts that share many attributes (attributional similarity), i.e. concepts that are taxonomically/ontologically similar
  - synonyms (*rhino/rhinoceros*)
  - antonyms and values on a scale (*good/bad*)
  - co-hyponyms (*rock/jazz*)
  - hyper- and hyponyms (*rock/basalt*)
- Taxonomic similarity is seen as the fundamental semantic relation, allowing categorization, generalization, inheritance

Evaluation of attributional similarity

- Synonym identification
  - TOEFL test
- Modeling semantic similarity judgments
  - the Rubenstein/Goodenough norms
- Noun categorization
  - the ESSLLI 2008 dataset
- Semantic priming
  - the Hodgson dataset

The TOEFL synonym task

- The TOEFL dataset
  - 80 items
  - Target: *levied*
    Candidates: *imposed*, *believed*, *requested*, *correlated*

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    Candidates: *imposed*, *believed*, *requested*, *correlated*
- DSMs and TOEFL
  1. take vectors of the target ($\mathbf{t}$) and of the candidates ($\mathbf{c}_1 \dots \mathbf{c}_n$)
  2. measure the distance between $\mathbf{t}$ and $\mathbf{c}_i$, with $1 \leq i \leq n$
  3. select $\mathbf{c}_i$ with the shortest distance in space from $\mathbf{t}$

Human performance on the synonym match task

- Average foreign test taker: 64.5%
- Macquarie University staff (Rapp 2004):
  - Average of 5 non-natives: 86.75%
  - Average of 5 natives: 97.75%

DSMs take the TOEFL

- Humans
  - Foreign test takers: 64.5%
  - Macquarie non-natives: 86.75%
  - Macquarie natives: 97.75%
- Machines
  - Classic LSA: 64.4%
  - Padó and Lapata's dependency-based model: 73%
  - Rapp's 2003 SVD-based model trained on lemmatized BNC: 92.5%

Semantic similarity judgments

Dataset Rubenstein and Goodenough (1965) (R&G) of 65 noun pairs rated by 51 subjects on a 0-4 scale

car	*automobile*	3.9
food	*fruit*	2.7
cord	*smile*	0.0

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car	*automobile*	3.9
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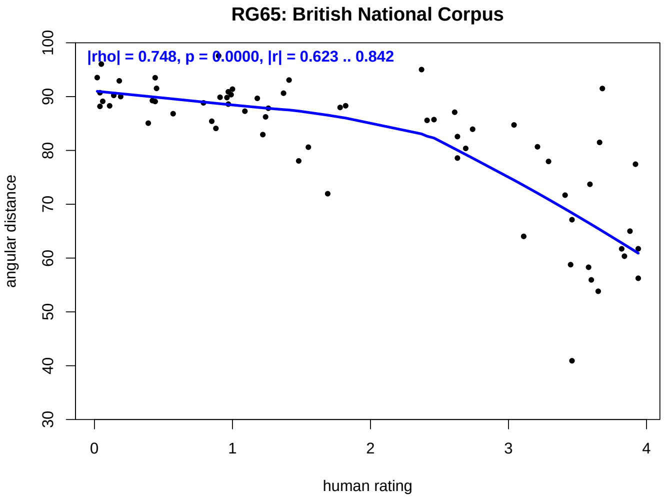
cord	*smile*	0.0

- DSMs vs. Rubenstein & Goodenough
  1. for each test pair (w_1, w_2), take vectors $\mathbf{w}_1$ and $\mathbf{w}_2$
  2. measure the distance (e.g. cosine) between $\mathbf{w}_1$ and $\mathbf{w}_2$
  3. measure (Pearson) correlation between vector distances and R&G average judgments (Padó and Lapata 2007)

Semantic similarity judgments: example



Semantic similarity judgments: results

model	*r*
dep-filtered+SVD	0.8
dep-filtered	0.7
dep-linked (DM)	0.64
window	0.63

Results for RG65 task

Categorization

- In categorization tasks, subjects are typically asked to assign experimental items – objects, images, words – to a given category or group items belonging to the same category
  - categorization requires an understanding of the relationship between the items in a category
- Categorization is a basic cognitive operation presupposed by further semantic tasks
  - inference
    - ★ if X is a CAR then X is a VEHICLE
  - compositionality
    - ★ λy : FOOD λx : ANIMATE; $eat(x, y)$
- "Chicken-and-egg" problem for relationship of categorization and similarity (cf. Goodman 1972, Medin et al. 1993)

Noun categorization

Dataset 44 concrete nouns (ESSLLI 2008 Shared Task)

- 24 natural entities
  - 15 animals:
    7 birds (*eagle*), 8 ground animals (*lion*)
  - 9 plants: 4 fruits (*banana*), 5 greens (*onion*)
- 20 artifacts
  - 13 tools (*hammer*), 7 vehicles (*car*)

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- 20 artifacts
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- DSMs and noun categorization
  - categorization can be operationalized as a clustering task
    1. for each noun w_i in the dataset, take its vector $\mathbf{w}_i$
    2. use a clustering method to group close vectors $\mathbf{w}_i$
    3. evaluate whether clusters correspond to gold-standard semantic classes (purity, entropy, ...)

Noun categorization

- Clustering experiments with CLUTO (Karypis 2003)
  - repeated bisection algorithm
  - 6-way (birds, ground animals, fruits, greens, tools and vehicles), 3-way (animals, plants and artifacts) and 2-way (natural and artificial entities) clusterings

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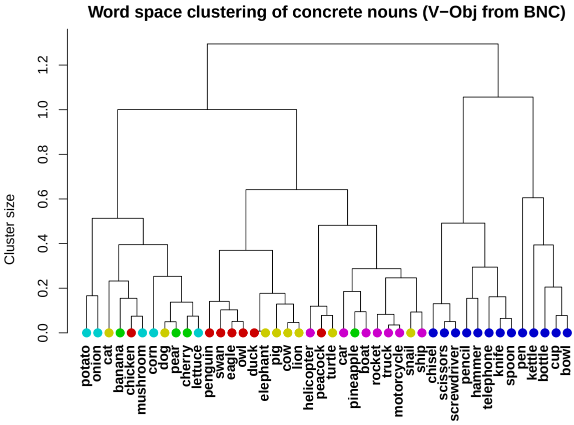
  - repeated bisection algorithm
  - 6-way (birds, ground animals, fruits, greens, tools and vehicles), 3-way (animals, plants and artifacts) and 2-way (natural and artificial entities) clusterings
- Clusters evaluation
  - entropy – whether words from different classes are represented in the same cluster (best $= 0$)
  - purity – degree to which a cluster contains words from one class only (best $= 1$)
  - global score across the three clustering experiments

$$\sum_{i=1}^{3} \text{Purity}_i - \sum_{i=1}^{3} \text{Entropy}_i$$

Noun categorization: example



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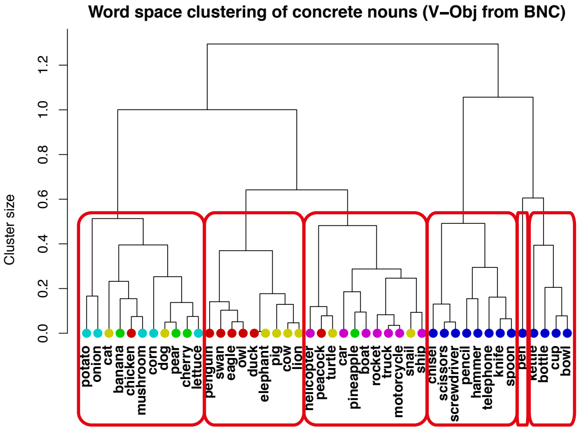

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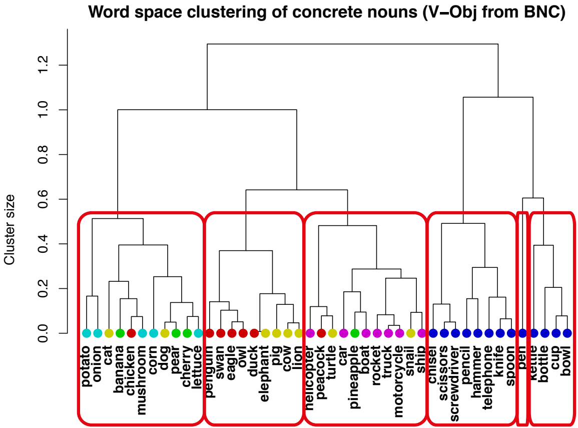
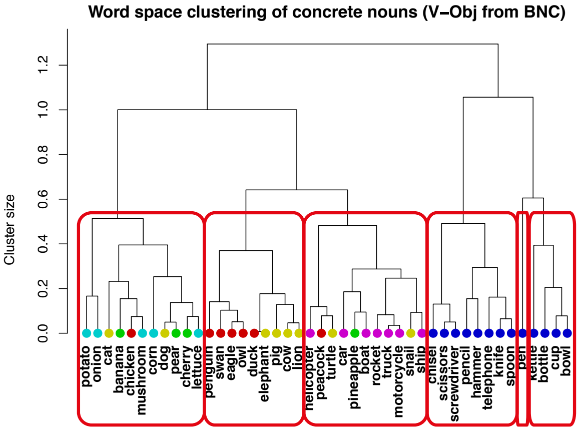


- majority labels: greens, birds, vehicles, tools, tools, tools
- correct: 5/11, 5/9, 7/11, 8/8, 1/1, 4/4

Noun categorization: example



- majority labels: greens, birds, vehicles, tools, tools, tools
- correct: 5/11, 5/9, 7/11, 8/8, 1/1, 4/4
- purity = 30 correct out of 44 = 68.2%

Noun categorization: results

model	*6-way*		*3-way*		*2-way*		*global*
	P	*E*	*P*	*E*	*P*	*E*	
Katrenko	89	13	100	0	80	59	197
Peirsman+	82	23	84	34	86	55	140
dep-typed (DM)	77	24	79	38	59	97	56
dep-filtered	80	28	75	51	61	95	42
window	75	27	68	51	68	89	44
Peirsman−	73	28	71	54	61	96	27
Shaoul	41	77	52	84	55	93	-106

`Katrenko`, `Peirsman+/-`, `Shaoul`: ESSLLI 2008 Shared Task
`DM`: Baroni & Lenci (2009)

Semantic priming

- Hearing/reading a "related" prime facilitates access to a target in various lexical tasks (naming, lexical decision, reading)
  - the word *pear* is recognized/accessed faster if it is heard/read after *apple*

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  - the word *pear* is recognized/accessed faster if it is heard/read after *apple*
- Hodgson (1991) single word lexical decision task, 136 prime-target pairs (cf. Padó & Lapata 2007)
  - similar amounts of priming for different semantic relations between primes and targets (approx. 23 pairs per relation):
    - ★ synonyms (synonym): *to dread/to fear*
    - ★ antonyms (antonym): *short/tall*
    - ★ coordinates (coord): *train/truck*
    - ★ super- and subordinate pairs (supersub): *container/bottle*
    - ★ free association pairs (freeass): *dove/peace*
    - ★ phrasal associates (phrasacc): *vacant/building*

Simulating semantic priming

McDonald & Brew (2004), Padó & Lapata (2007)

- DSMs and semantic priming
  1. for each related prime-target pair, measure cosine-based similarity between pair items (e.g., *to dread/to fear*)

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  3. similarity between related items should be significantly higher than average similarity between unrelated items
- Significant effects ($p < .01$) for all semantic relations
  - strongest effects for synonyms, antonyms & coordinates

Outline

Finding and distinguishing semantic relations

- Classic distributional semantic models are based on attributional similarity
  - single words/concepts that share attributes / tend to occur in the same contexts are semantically similar
- Attributional similarity can be modeled with DSMs that have single words as matrix rows
  - matrix columns represent attributes shared by similar words

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  - matrix columns represent attributes shared by similar words

	die	kill	gun
teacher	109.4	0.0	0.0
victim	1335.2	22.4	0.0
soldier	4547.5	1306.9	105.9
policeman	68.6	38.2	30.5

Attributional and relational similarity

Turney (2006)

- *Policeman* is attributionally similar to *soldier*
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  - both are often connected by *with*, *use*, *of* in context
- It is not always possible to reduce relational similarity to attributional similarity
  - *mason*:*stone* :: *carpenter*:*wood*
    vs. *traffic*:*street* :: *water*:*riverbed*
    - ★ *mason* - *carpenter* and *stone* - *wood* are attributionally similar
    - ★ *traffic* - *water* and *street* - *riverbed* are not attributionally similar

Finding and distinguishing semantic relations with DSMs

- Find non-taxonomic semantic relations
  - look at direct co-occurrences of word pairs in texts (when we talk about a concept, we are likely to also mention its parts, function, etc.)

Finding and distinguishing semantic relations with DSMs

- Find non-taxonomic semantic relations
  - look at direct co-occurrences of word pairs in texts (when we talk about a concept, we are likely to also mention its parts, function, etc.)
- Distinguish between different semantic relations
  - use the contexts of pairs to measure pair similarity, and group them into coherent relation types by their contexts
  - *pairs* that occur in similar contexts (i.e. connected by similar words and structures) will tend to be related, with the shared contexts acting as a cue to the nature of their relation, i.e., measuring their *relational* similarity (Turney 2006)

DSMs and relational similarity

rows word pairs

columns syntagmatic links between the word pairs

		in	at	with	use
teacher	school	11894.4	7020.1	28.9	0.0
teacher	handbook	2.5	0.0	3.2	10.1
soldier	gun	2.8	10.3	105.9	41.0

Recognizing SAT analogies

- 374 SAT multiple-choice questions (Turney 2006)
- Each question includes 1 target pair (stem) and 5 answer pairs
- the task is to choose the pair most *analogous* to the stem

mason	stone
teacher	chalk
carpenter	wood
soldier	gun
photograph	camera
book	word

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soldier	gun
photograph	camera
book	word

- Relational analogue to the TOEFL task
  1. for each pair p, take its row vector $\mathbf{p}$
  2. for each stem-pair, select the closest answer-pair (e.g. the one with the highest cosine similarity)

Recognizing SAT analogies: results

model	*% correct*	*model*	*% correct*
LRA	56.1	KnowBest	43.0
PERT	53.3	DM−	42.3
PairClass	52.1	LSA	42.0
VSM	47.1	AttrMax	35.0
DM+	45.3	AttrAvg	31.0
PairSpace	44.9	AttrMin	27.3
k-means	44.0	Random	20.0

`LRA`, `PERT`, `PairClass`, `VSM`, `KnowBest`, `LSA`: ACLWiki
`AttrMax`, `AttrAvg`, `AttrMin`: Turney(2006)
`DM+`, `DM-`: Baroni & Lenci (2009)

Domain analogies

- Turney (2008) extends the relational approach to entire analogical *domains*

solar system	$\rightarrow$	atom
sun	$\rightarrow$	nucleus
planet	$\rightarrow$	electron
mass	$\rightarrow$	charge
attracts	$\rightarrow$	attracts
revolves	$\rightarrow$	revolves
gravity	$\rightarrow$	electromagnetism

Intermission

Time for a cup of coffee . . .

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