Distributional Semantic Models

Part 1: Introduction

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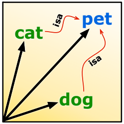
http://wordspace.collocations.de/doku.php/course:start



Outline

Introduction
- The distributional hypothesis
- Three famous examples

Distributional semantic models
- Definition & overview
- Using DSM distances
- Quantitative evaluation
- Software and further information

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Introduction
The distributional hypothesis
Three famous examples

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Meaning & distribution

- "Die Bedeutung eines Wortes liegt in seinem Gebrauch."
  — Ludwig Wittgenstein
- "You shall know a word by the company it keeps!"
  — J. R. Firth (1957)
- Distributional hypothesis: difference of meaning correlates with difference of distribution (Zellig Harris 1954)
- "What people know when they say that they know a word is not how to recite its dictionary definition – they know how to use it [. . .] in everyday discourse." (Miller 1986)

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☞ bardiwac is a heavy red alcoholic beverage made from grapes

The examples above are handpicked, of course. But in a corpus like the BNC, you will find at least as many informative sentences.

What is the meaning of "**bardiwac**"?

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

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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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What is the meaning of “**bardiwac**”?

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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$$\mathrm{sim}(\;,\;) = 0.770$$

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

A thought experiment: deciphering hieroglyphs

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(pig)	12	17	3	2	9	27
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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 $\mathbf{x}_{\text{dog}}$ 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
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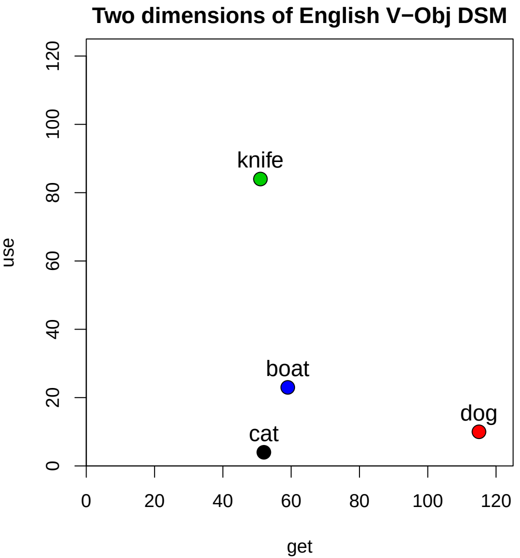
co-occurrence matrix M

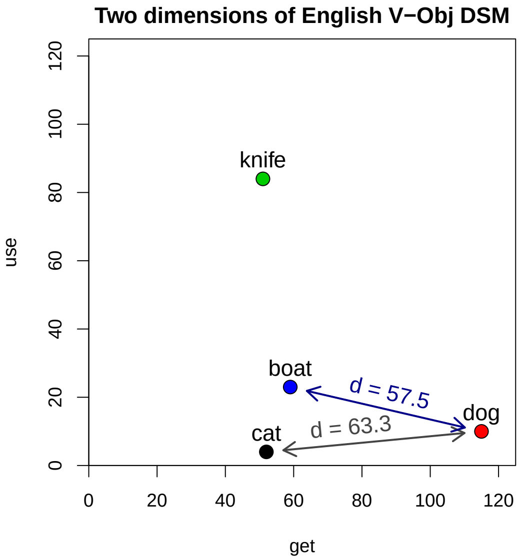
Geometric interpretation

- row vector $\mathbf{x}_{\text{dog}}$ 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*
- $\mathbf{x}_{\text{dog}} = (115, 10)$



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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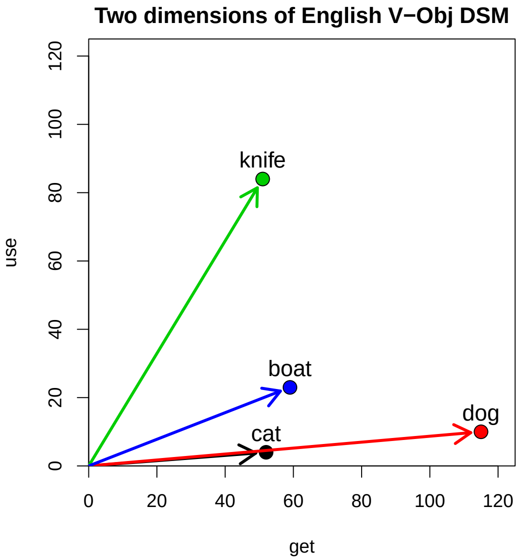

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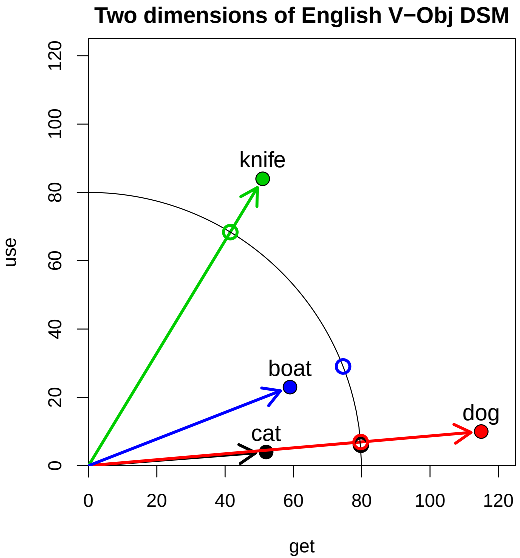
- normalise "length" $\|\mathbf{x}_{\text{dog}}\|$ of vector



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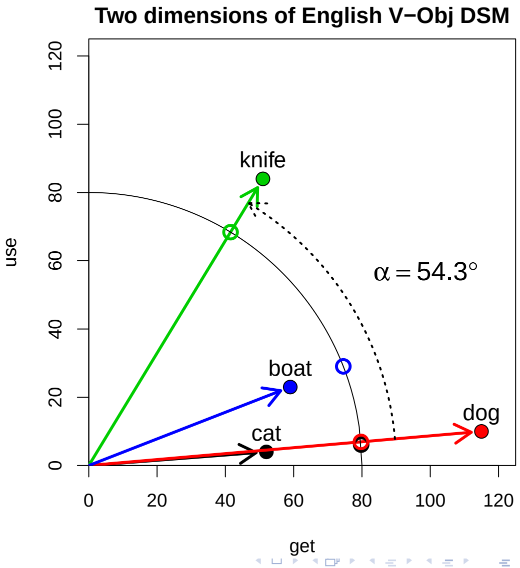
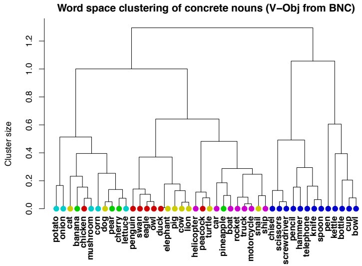
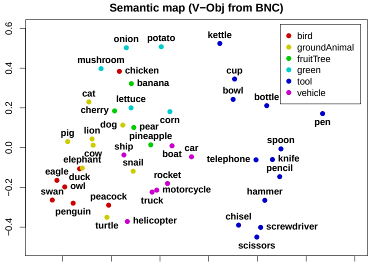
- normalise "length" $\|\mathbf{x}_{\text{dog}}\|$ of vector
- or use angle α as distance measure



Semantic distances

- main result of distributional analysis are "semantic" distances between words
- typical applications
  - nearest neighbours
  - clustering of related words
  - construct semantic map
- other applications require clever use of the distance information
  - semantic relations
  - relational analogies
  - word sense disambiguation
  - detection of multiword expressions





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 1998; 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, . . .

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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
  - from the *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

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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, word pair, . . .

General definition of DSMs

Mathematical notation:

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

$$\mathbf{M} = \begin{bmatrix} m_{11} & m_{12} & \cdots & m_{1n} \\ m_{21} & m_{22} & \cdots & m_{2n} \\ \vdots & \vdots & & \vdots \\ m_{k1} & m_{k2} & \cdots & m_{kn} \end{bmatrix}$$

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

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

Overview of DSM parameters

Term-context vs. term-term matrix

Overview of DSM parameters

Term-context vs. term-term matrix

$\Downarrow$

Definition of terms & linguistic pre-processing

Overview of DSM parameters

Term-context vs. term-term matrix

$\Downarrow$

Definition of terms & linguistic pre-processing

$\Downarrow$

Size & type of context

Overview of DSM parameters

Term-context vs. term-term matrix

$\Downarrow$

Definition of terms & linguistic pre-processing

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Size & type of context

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Geometric vs. probabilistic interpretation

Overview of DSM parameters

Term-context vs. term-term matrix

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Feature scaling

Overview of DSM parameters

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Normalisation of rows and/or columns

Overview of DSM parameters

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Similarity / distance measure

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$\Downarrow$

Similarity / distance measure

$\Downarrow$

Dimensionality reduction

Term-context matrix

Term-context matrix records frequency of term in each individual context (e.g. sentence, document, Web page, encyclopaedia article)

$$\mathbf{F} = \begin{bmatrix} \cdots & \mathbf{f}_1 & \cdots \\ \cdots & \mathbf{f}_2 & \cdots \\ & \vdots & \\ & \vdots & \\ \cdots & \mathbf{f}_k & \cdots \end{bmatrix}$$

	Felidae	Pet	Feral	Bloat	Philosophy	Kant	Back pain
cat	10	10	7	–	–	–	–
dog	–	10	4	11	–	–	–
animal	2	15	10	2	–	–	–
time	1	–	–	–	2	1	–
reason	–	1	–	–	1	4	1
cause	–	–	–	2	1	2	6
effect	–	–	–	1	–	1	–

Term-context matrix

Some footnotes:

- Features are usually context tokens, i.e. individual instances
- Can also be generalised to context types, e.g.
  - bag of content words
  - specific pattern of POS tags
  - n-gram of words (or POS tags) around target
  - subcategorisation pattern of target verb
- Term-context matrix is often very **sparse**

Term-term matrix

Term-term matrix records co-occurrence frequencies with feature terms for each target term

$$\mathbf{M} = \begin{bmatrix} \cdots & \mathbf{m}_1 & \cdots \\ \cdots & \mathbf{m}_2 & \cdots \\ & \vdots & \\ & \vdots & \\ \cdots & \mathbf{m}_k & \cdots \end{bmatrix}$$

	breed	tail	feed	kill	important	explain	likely
cat	83	17	7	37	–	1	–
dog	561	13	30	60	1	2	4
animal	42	10	109	134	13	5	5
time	19	9	29	117	81	34	109
reason	1	–	2	14	68	140	47
cause	–	1	–	4	55	34	55
effect	–	–	1	6	60	35	17

☞ we will usually assume a term-term matrix in this tutorial

Term-term matrix

Some footnotes:

- Often target terms $\neq$ feature terms
  - e.g. nouns described by co-occurrences with verbs as features
  - identical sets of target & feature terms ➜ symmetric matrix
- 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
  - we will take a closer look at the relation between term-context and term-term models later in this tutorial

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Nearest neighbours

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

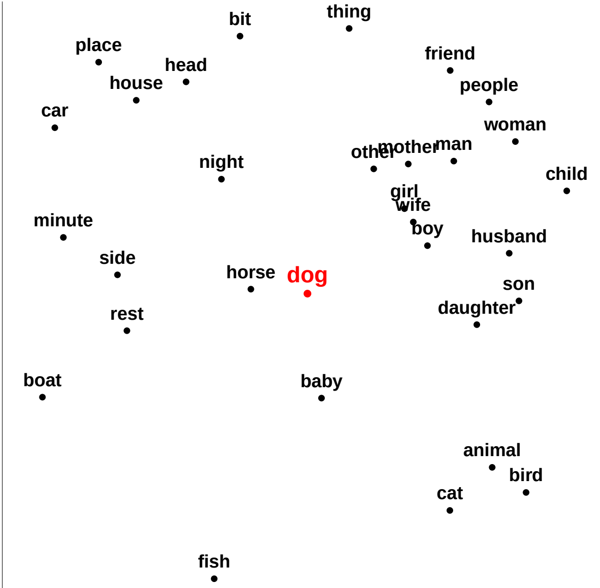
Neighbours of **dog** (cosine angle):

- ☞ 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), . . .

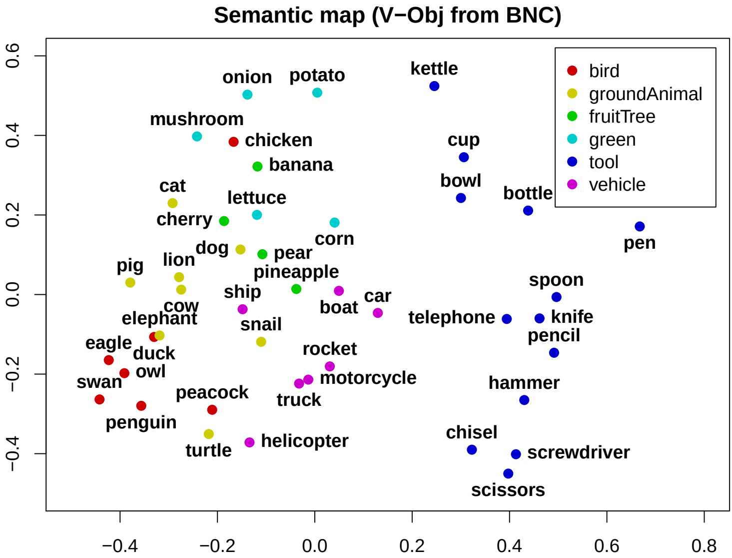
Neighbours of **school**:

- ☞ 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), . . .

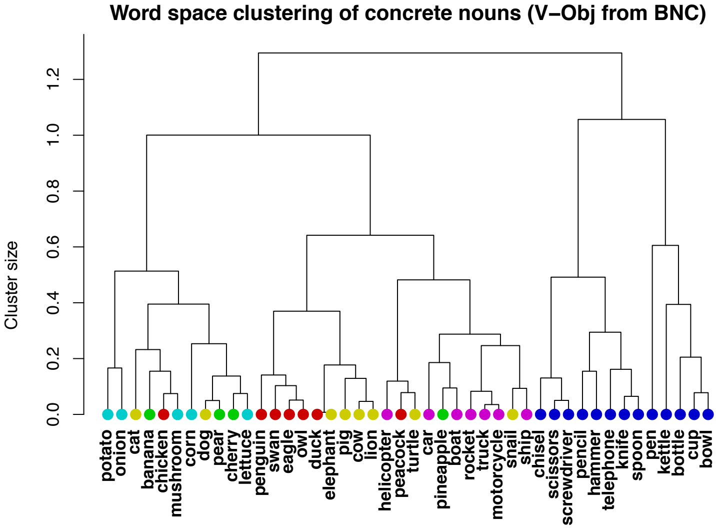
Nearest neighbours



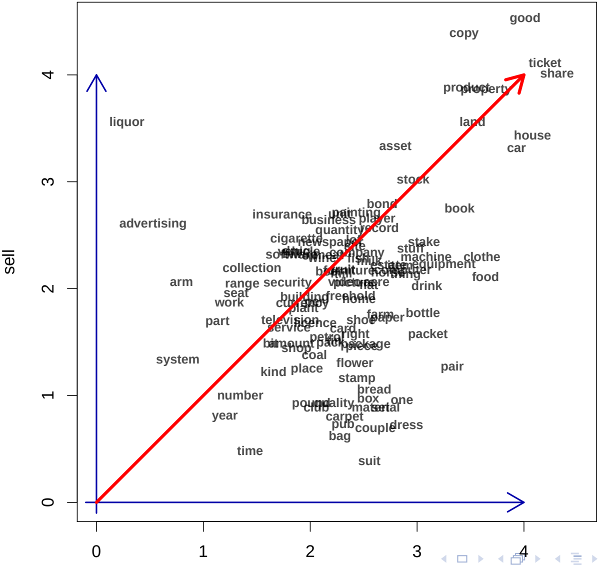
Semantic maps



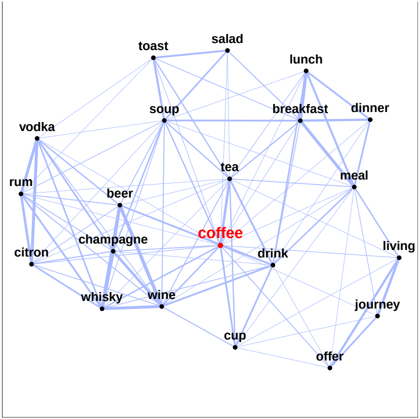
Clustering


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

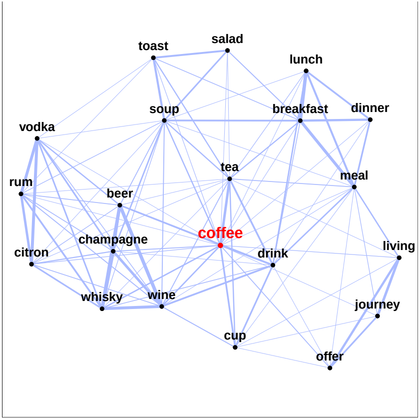
Latent dimensions

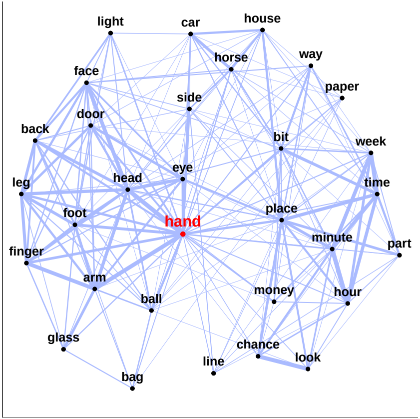


Semantic similarity graph (topological structure)



Semantic similarity graph (topological structure)





Context vectors (Schütze 1998)

Distributional representation only at type level

- ☞ What is the “average” meaning of *mouse*? (computer vs. animal)

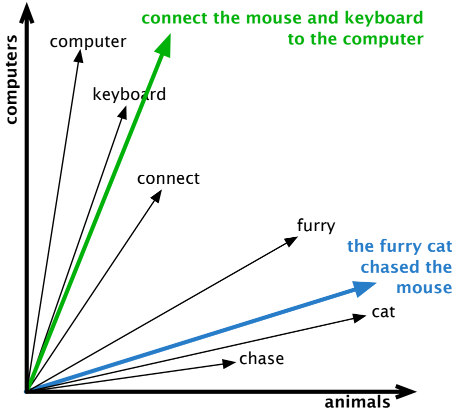
Context vectors (Schütze 1998)

Distributional representation only at type level

☞ What is the "average" meaning of *mouse*? (computer vs. animal)

Context vector approximates meaning of individual token

- **bag-of-words** approach: centroid of all context words in the sentence



Outline

Introduction
- The distributional hypothesis
- Three famous examples

Distributional semantic models
- Definition & overview
- Using DSM distances
- Quantitative evaluation
- Software and further information

The TOEFL synonym task

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

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    Candidates: *craze*, *fathom*, *manner*, *ration*

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- 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 $\mathbf{t}$

Humans vs. machines on the TOEFL task

- Average foreign test taker: 64.5%

Humans vs. machines on the TOEFL task

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

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- Distributional semantics
  - Classic LSA (Landauer and Dumais 1997): 64.4%
  - Padó and Lapata's (2007) dependency-based model: 73.0%
  - Distributional memory (Baroni and Lenci 2010): 76.9%
  - Rapp's (2004) SVD-based model, lemmatized BNC: 92.5%
  - Bullinaria and Levy (2012) carry out aggressive parameter optimization: 100.0%

Semantic similarity judgments

- Rubenstein and Goodenough (1965) collected similarity ratings for 65 noun pairs from 51 subjects on a 0–4 scale

w_1	w_2	avg. rating
car	*automobile*	3.9
food	*fruit*	2.7
cord	*smile*	0.0

Semantic similarity judgments

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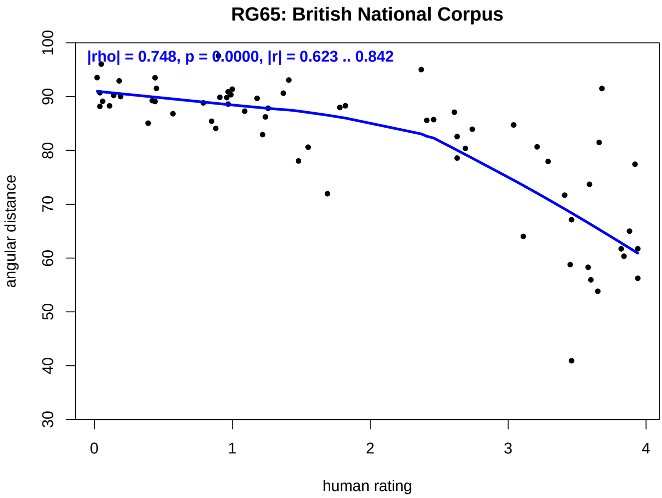
w_1	w_2	avg. rating
car	*automobile*	3.9
food	*fruit*	2.7
cord	*smile*	0.0

- 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

Results on RG65 task:

- Padó and Lapata's (2007) dependency-based model: 0.62
- Dependency-based on Web corpus (Herdağdelen *et al.* 2009)
  - without SVD reduction: 0.69
  - with SVD reduction: 0.80
- Distributional memory (Baroni and Lenci 2010): 0.82
- Salient Semantic Analysis (Hassan and Mihalcea 2011): 0.86

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Software packages

HiDEx	C++	*re-implementation of the HAL model (Lund and Burgess 1996)*
SemanticVectors	Java	*scalable architecture based on random indexing representation*
S-Space	Java	*complex object-oriented framework*
JoBimText	Java	*UIMA / Hadoop framework*
Gensim	Python	*complex framework, focus on parallelization and out-of-core algorithms*
DISSECT	Python	*user-friendly, designed for research on compositional semantics*
`wordspace`	R	*interactive research laboratory, but scales to real-life data sets*

click on package name to open Web page

Recent conferences and workshops

- 2007: CoSMo Workshop (at Context '07)
- 2008: ESSLLI Lexical Semantics Workshop & Shared Task, Special Issue of the Italian Journal of Linguistics
- 2009: GeMS Workshop (EACL 2009), DiSCo Workshop (CogSci 2009), ESSLLI Advanced Course on DSM
- 2010: 2nd GeMS (ACL 2010), ESSLLI Workshop on Compositionality and DSM, DSM Tutorial (NAACL 2010), Special Issue of JNLE on Distributional Lexical Semantics
- 2011: 2nd DiSCo (ACL 2011), 3rd GeMS (EMNLP 2011)
- 2012: DiDaS (at ICSC 2012)
- 2013: CVSC (ACL 2013), TFDS (IWCS 2013), Dagstuhl
- 2014: 2nd CVSC (at EACL 2014)

click on Workshop name to open Web page

Further information

- Handouts & other materials available from wordspace wiki at

  http://wordspace.collocations.de/

  ☞ based on joint work with Marco Baroni and Alessandro Lenci
- Tutorial is open source (CC), and can be downloaded from

  http://r-forge.r-project.org/projects/wordspace/
- Review paper on distributional semantics:

  Turney, Peter D. and Pantel, Patrick (2010). From frequency to meaning: Vector space models of semantics. *Journal of Artificial Intelligence Research*, **37**, 141–188.
- I should be working on textbook *Distributional Semantics* for *Synthesis Lectures on HLT* (Morgan & Claypool)

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