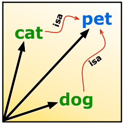
Distributional Semantic Models

Part 1: Introduction

Stefan Evert[1]
with Alessandro Lenci[2], Marco Baroni[3] and Gabriella Lapesa[4]

[1]Friedrich-Alexander-Universität Erlangen-Nürnberg, Germany
[2]University of Pisa, Italy
[3]University of Trento, Italy
[4]University of Stuttgart, Germany

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



Outline

Introduction
- The distributional hypothesis
- Distributional semantic models
- Three famous examples

Getting practical
- Software and further information
- R as a (toy) laboratory

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Meaning & distribution

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  — 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 and edited, of course. But in a corpus like the BNC, you will find at least as much relevant information.

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

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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

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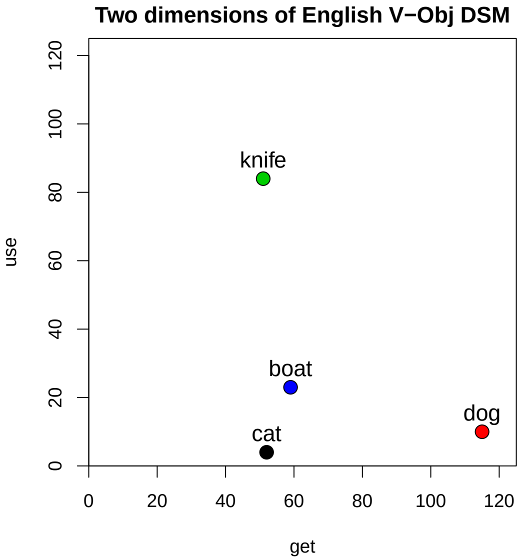
co-occurrence matrix M

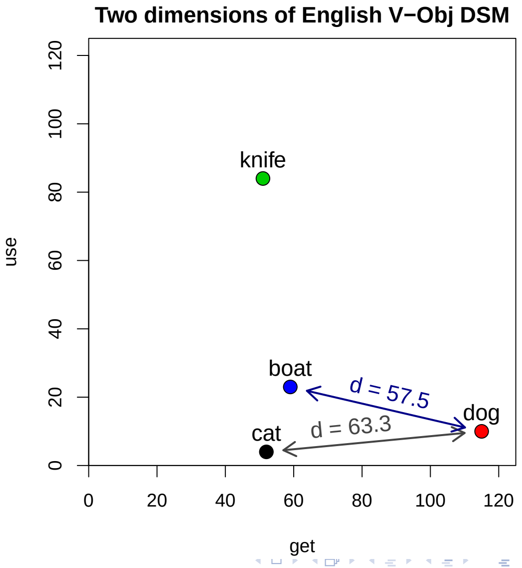
Geometric interpretation

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



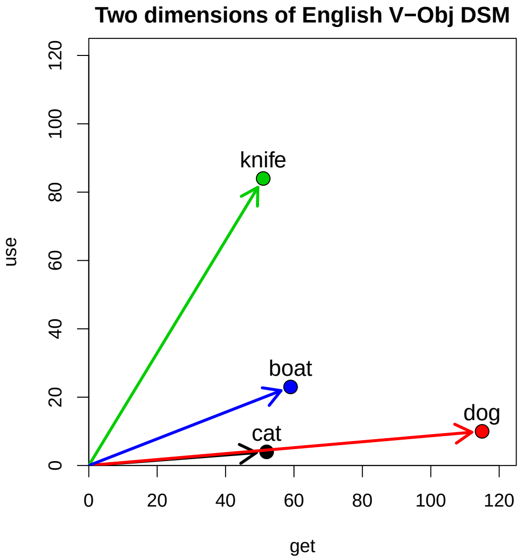
Geometric interpretation

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



Geometric interpretation

- vector can also be understood as arrow from origin
- direction more important than location



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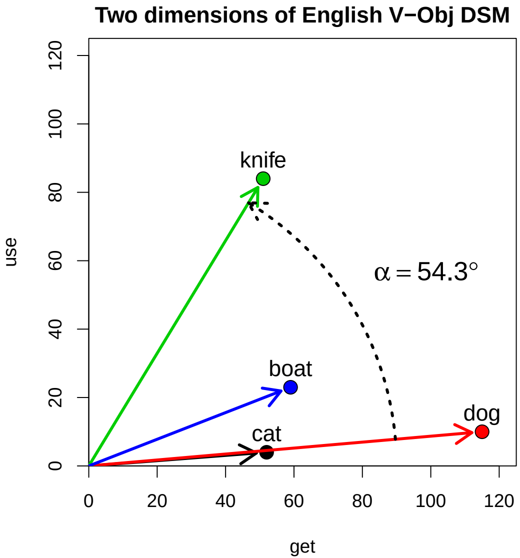
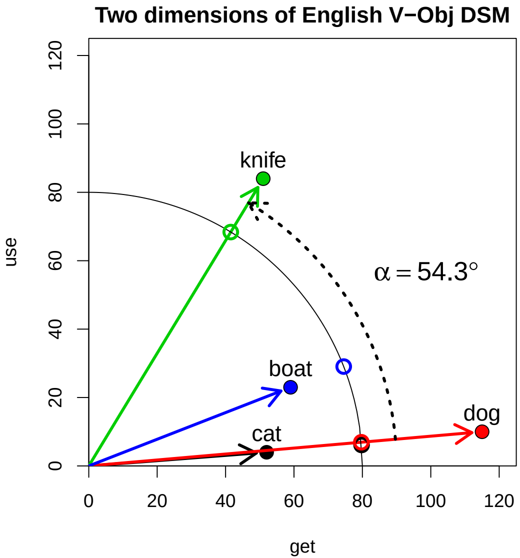


Geometric interpretation

- vector can also be understood as arrow from origin
- direction more important than location
- use angle α as distance measure
- or normalise length $\|\mathbf{x}_{\text{dog}}\|$ of arrow



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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, . . .

Building a distributional model

pre-processed corpus with linguistic annotation

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$\Downarrow$

term-context vs. term-term matrix

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term-context vs. term-term matrix

$\swarrow$ $\searrow$

define targets & contexts | define targets & features

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dimensionality reduction

Nearest neighbours

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

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

☞ shirt (18.5), blouse (21.9), scarf (23.4), jeans (24.7), skirt (25.9), sock (26.2), shorts (26.3), jacket (27.8), glove (28.1), coat (28.8), cloak (28.9), hat (29.1), tunic (29.3), overcoat (29.4), pants (29.8), helmet (30.4), apron (30.5), robe (30.6), mask (30.8), tracksuit (31.0), jersey (31.6), shawl (31.6), ...

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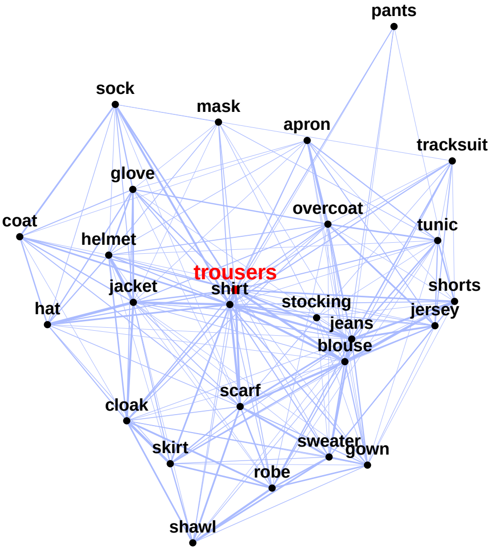
Neighbours of **rage** (cosine angle):

☞ anger (28.5), fury (32.5), sadness (37.0), disgust (37.4), emotion (39.0), jealousy (40.0), grief (40.4), irritation (40.7), revulsion (40.7), scorn (40.7), panic (40.8), bitterness (41.6), resentment (41.8), indignation (41.9), excitement (42.0), hatred (42.5), envy (42.8), disappointment (42.9), . . .

Nearest neighbours with similarity graph



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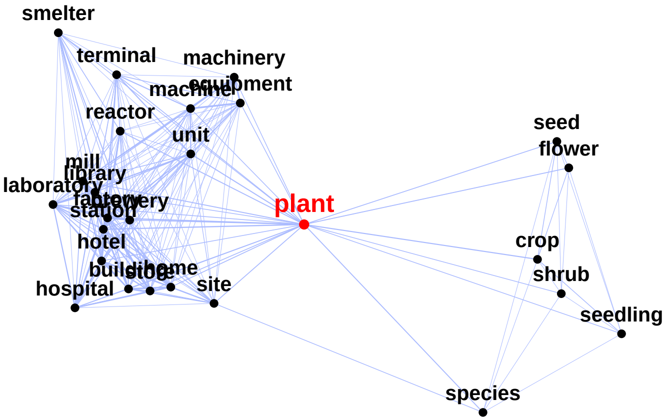
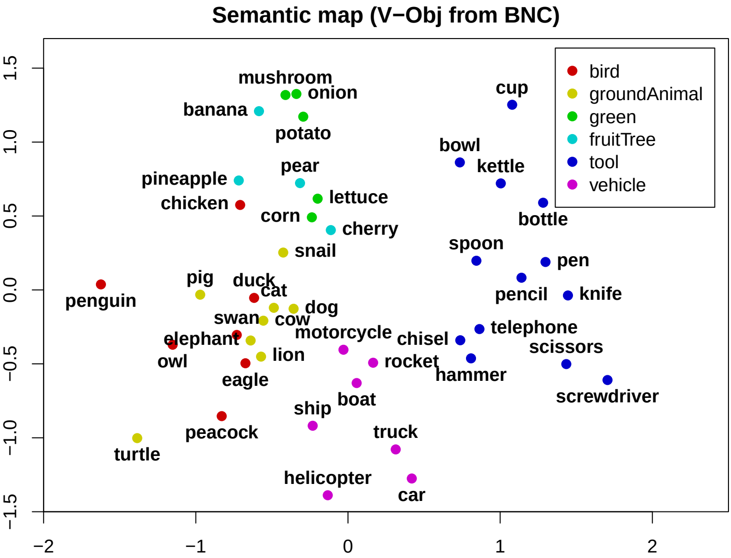
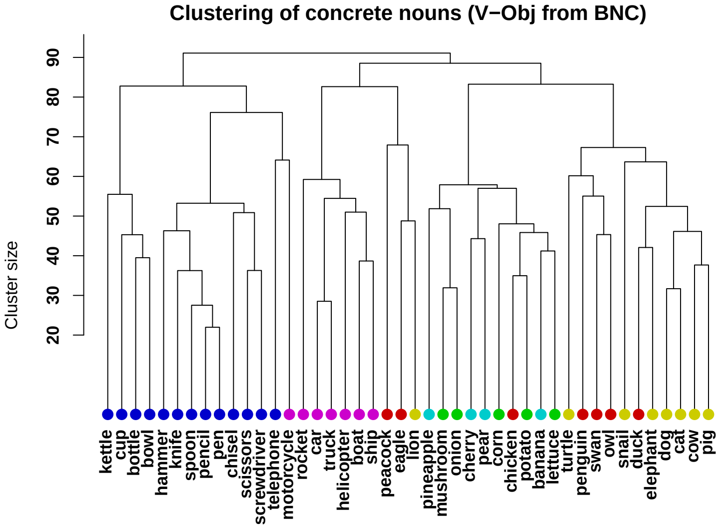


Semantic maps



Clustering


Clustering of concrete nouns (V−Obj from BNC)
Cluster size
20
30
40
50
60
70
80
90
kettle
cup
bottle
bowl
hammer
knife
spoon
pencil
pen
chisel
scissors
screwdriver
telephone
motorcycle
rocket
car
truck
helicopter
boat
ship
peacock
eagle
lion
pineapple
mushroom
onion
cherry
pear
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lettuce
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swan
owl
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duck
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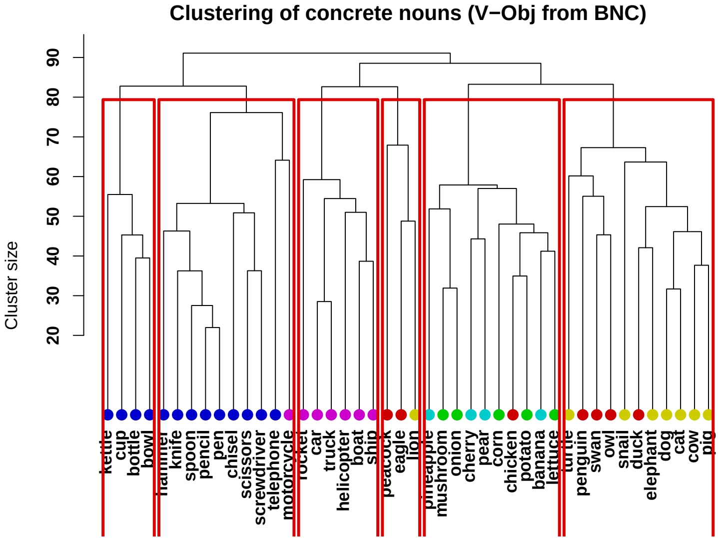
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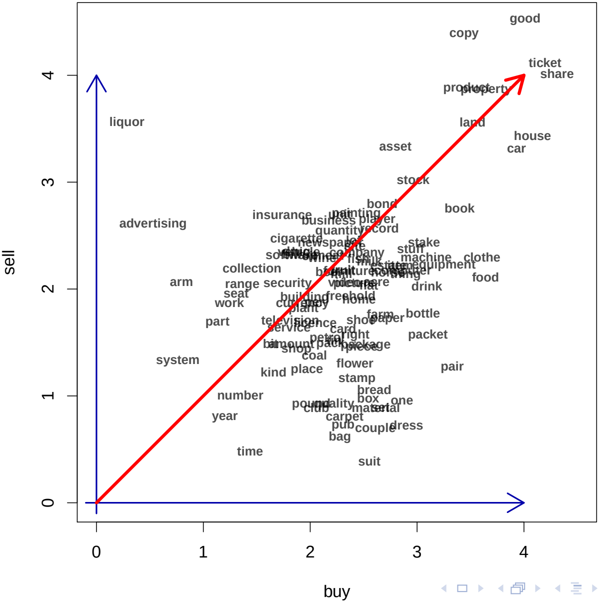
Latent dimensions



Word embeddings

DSM vector as sub-symbolic meaning representation

- feature vector for machine learning algorithm
- input for neural network

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Context vectors for word tokens (Schütze 1998)

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- application to WSD

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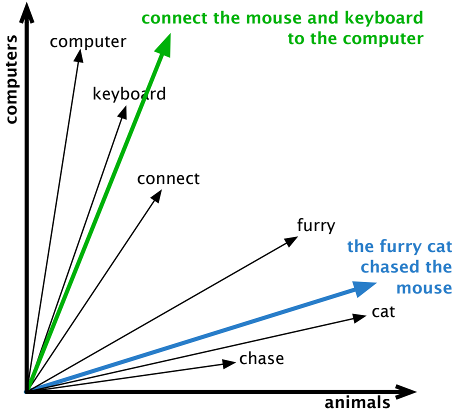

An important distinction

- **Distributional model**
  - captures linguistic distribution of each word in the form of a high-dimensional numeric vector
  - typically (but not necessarily) based on co-occurrence counts
  - distributional hypothesis:
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- **Distributed representation**
  - sub-symbolic representation of words as high-dimensional numeric vectors
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☞ Distributional model can be used as distributed representation

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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)
  - but no dimensionality reduction
- Applications include construction of semantic vocabulary maps by multidimensional scaling to 2 dimensions

HAL (Lund and Burgess 1996)

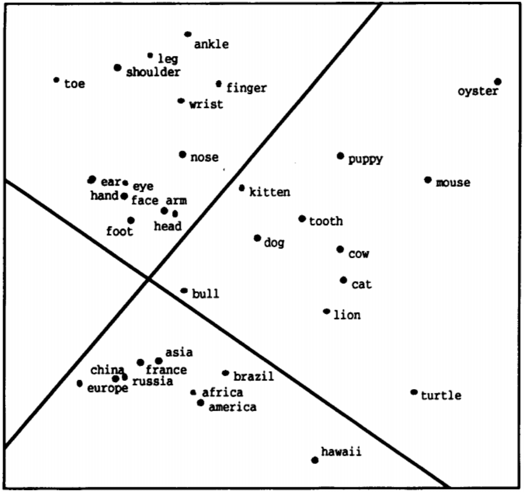

Figure 2. Multidimensional scalirg of co-occurrence vectors.

Many parameters . . .

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- Examples showed three entirely different models, each tuned to its particular application

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➥ Distributional semantics is an empirical science

Outline

Introduction
The distributional hypothesis
Distributional semantic models
Three famous examples

Getting practical
Software and further information
R as a (toy) laboratory

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)
- Sub-symbolic input representation for neural networks
- Many other tasks in computational semantics: entailment detection, noun compound interpretation, identification of noncompositional expressions, . . .

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

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

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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Prepare to get your hands dirty . . .

- We will use the statistical programming environment **R** as a toy laboratory in this tutorial
  - ☞ but one that scales to real-life applications

Software installation

- **R** version 3.3 or newer from `http://www.r-project.org/`
- RStudio from `http://www.rstudio.com/`
- R packages from CRAN (through RStudio menu): **`sparsesvd`**, **`wordspace`**
  - if you are attending a course, you may also be asked to install the **`wordspaceEval`** package with some non-public data sets
- Data sets from `http://www.collocations.de/data/#dsm`

First steps in R

Start each session by loading the wordspace package.

```
> library(wordspace)
```

The package includes various example data sets, some of which should look familiar to you.

```
> DSM_HieroglyphsMatrix
       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
cup     98  14   6    2   1    0
pig     12  17   3    2   9   27
banana  11   2   2    0  18    0
```

Term-term matrix

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

```
> DSM_TermTermMatrix
```

	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

Term-context matrix

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

```
> DSM_TermContextMatrix
```

	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	–

Some basic operations on a DSM matrix

```
# apply log-transformation to de-skew co-occurrence frequencies
> M <- log2(DSM_HieroglyphsMatrix + 1)  # see part 2
> round(M, 3)

# compute semantic distance (cosine similarity)
> pair.distances("dog", "cat", M, convert=FALSE)
  dog/cat
0.9610952

# find nearest neighbours
> nearest.neighbours(M, "dog", n=3)
     cat      pig      cup
16.03458 20.08826 31.77784

> plot(nearest.neighbours(M, "dog", n=3, dist.matrix=TRUE))
```

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