

# Distributional Semantic Models

## Part 1: Introduction

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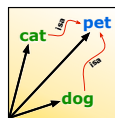
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<http://wordspace.collocations.de/doku.php/course:start>

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## 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

- ▶ “Die Bedeutung eines Wortes liegt in seinem Gebrauch.”  
— Ludwig Wittgenstein  
☞ meaning = use = distribution in language
- ▶ “You shall know a word by the company it keeps!”  
— J. R. Firth (1957)  
☞ distribution = collocations = habitual word combinations
- ▶ Distributional hypothesis: difference of meaning correlates with difference of distribution (Zellig Harris 1954)  
☞ semantic distance
- ▶ “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)

## What is the meaning of “bardiwac”?

Can we infer meaning from usage?

- ▶ He handed her her glass of **bardiwac claret** .
  - ▶ Beef dishes are made to complement the **bardiwac claret** s.
  - ▶ Nigel staggered to his feet, face flushed from too much **bardiwac claret** .
  - ▶ Malbec, one of the lesser-known **bardiwac claret** grapes, responds well to Australia’s sunshine.
  - ▶ I dined off bread and cheese and this excellent **bardiwac claret** .
  - ▶ The drinks were delicious: blood-red **bardiwac claret** as well as light, sweet Rhenish.
- ☞ claret is a heavy red alcoholic beverage made from grapes

All examples from British National Corpus (handpicked and slightly edited).

## Word sketch of “cat”

Can we infer meaning from collocations?














<https://the.sketchengine.co.uk/>

**cat** British National Corpus freq = 5381

object of 964 2.0	and/or 1056 1.7	pp_obj like-p 106 28.9	possessor 91 1.9	possession 232 4.7
skin 2 7.91	dog 208 8.49	grin 11 7.63	Schrödinger 8 10.87	cradle 24 9.91
diddle 7 7.85	cat 68 8.01	fight 9 4.62	witch 4 6.82	whisker 9 8.92
stroke 10 7.09	kitten 13 8.01	smile 4 4.24	gardener 4 6.0	paw 5 7.44
torture 5 6.57	fiddle 9 7.71	look 11 2.04	Henry 8 4.91	fur 9 7.14
feed 22 6.34	mouse 29 7.68		neighbour 5 4.28	tray 4 5.34
rain 4 6.3	monkey 15 7.55	pp among-p 17 14.8		tail 5 4.91
chase 9 6.27	budgie 4 6.74	pigeon 15 8.66		tongue 5 4.89
rescue 7 6.15	rabbit 12 6.48			ear 5 4.0

subject of 842 3.3	adj. subject of 142 2.6	pp_obj of-p 324 1.3	modifier 1622 1.2	modifies 610 0.5
purr 7 7.76	asleep 4 6.09	moral 4 7.06	pussy 76 10.42	flap 16 8.39
miaow 5 7.57	alive 4 5.06	breed 6 5.77	Cheshire 45 8.9	litter 15 8.15
mew 4 7.18	concerned 4 2.94	signal 4 3.89	stray 25 8.7	phobia 5 7.64
jump 20 6.95	black 4 2.36	sight 4 3.77	siamese 17 8.35	burglar 8 7.55
scratch 8 6.84	likely 4 1.96	species 5 3.36	tabby 17 8.35	faeces 6 7.47
leap 10 6.78		game 9 3.14	wild 53 7.94	assay 10 7.38
stalk 4 6.56		picture 6 2.99	pet 31 7.92	Hastings 7 6.91
react 4 5.33		death 7 2.71	tom 12 7.8	scan 4 6.59

## A thought experiment: deciphering hieroglyphs

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














2018-08-06  
DSM Tutorial – Part 1  
└ Introduction  
└ The distributional hypothesis  
└ A thought experiment: deciphering hieroglyphs

A thought experiment: deciphering hieroglyphs

	knife	cat	???	boat	cup	pig	banana
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	














1. Similarity scores are cosine similarities on sparse log-scaled frequencies ( $\log(f + 1)$ ).

## A thought experiment: deciphering hieroglyphs

						
(knife) 	51	20	84	0	3	0
(cat) 	52	58	4	4	6	26
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











$$\text{sim}(\text{hieroglyph of a dog}, \text{hieroglyph of a knife}) = 0.770$$

## A thought experiment: deciphering hieroglyphs

						
(knife) 	51	20	84	0	3	0
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??? 	115	83	10	42	33	17
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













$$\text{sim}(\text{hieroglyph of a dog}, \text{hieroglyph of a pig}) = 0.939$$

## A thought experiment: deciphering hieroglyphs

						
(knife) 	51	20	84	0	3	0
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??? 	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

$$\text{sim}(\text{hieroglyph of a dog}, \text{hieroglyph of a cat}) = 0.961$$

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

verb-object counts from British National Corpus

## Geometric interpretation

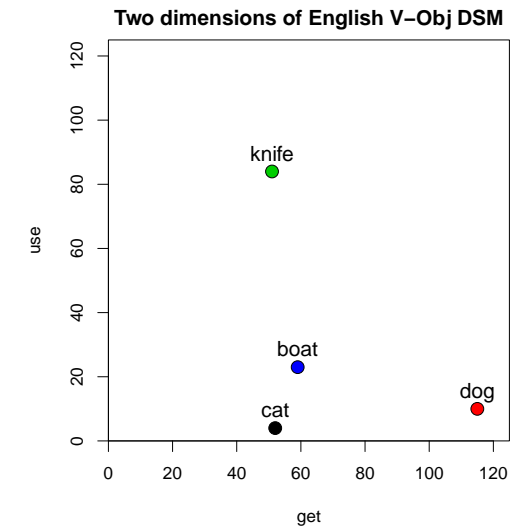
- ▶ row vector  $\mathbf{x}_{\text{dog}}$  describes usage of word *dog* in the corpus
- ▶ can be seen as coordinates of point in  $n$ -dimensional Euclidean space

	get	see	use	hear	eat	kill
knife	51	20	84	0	3	0
cat	52	58	4	4	6	26
<b>dog</b>	<b>115</b>	<b>83</b>	<b>10</b>	<b>42</b>	<b>33</b>	<b>17</b>
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

co-occurrence matrix **M**

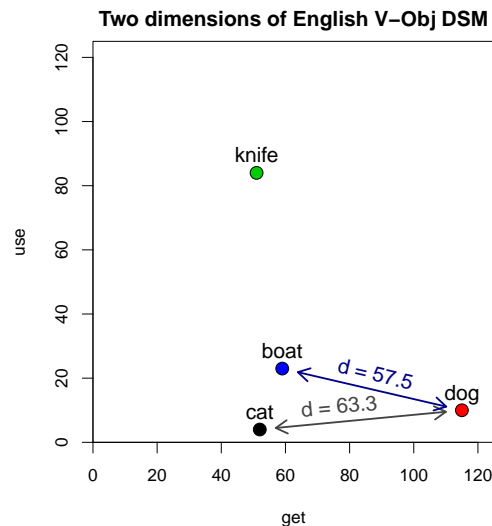
## Geometric interpretation

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



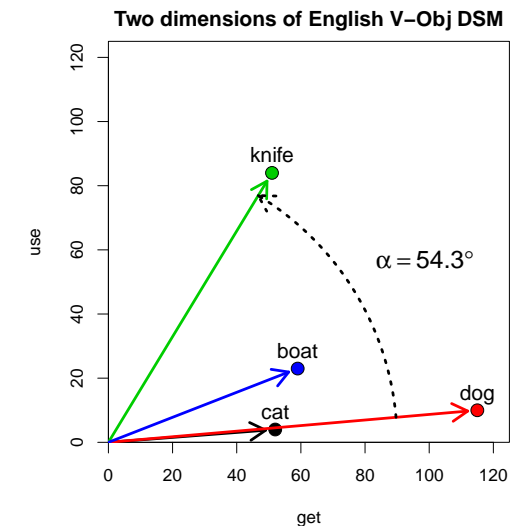
## Geometric interpretation

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



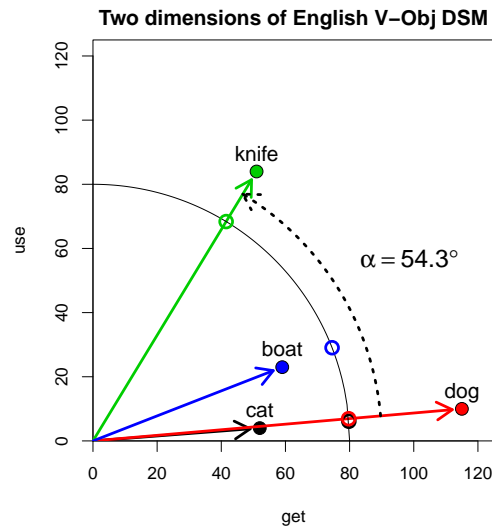
## Geometric interpretation

- ▶ vector can also be understood as arrow from origin
- ▶ direction more important than location
- ▶ use angle  $\alpha$  as distance measure



## Geometric interpretation

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



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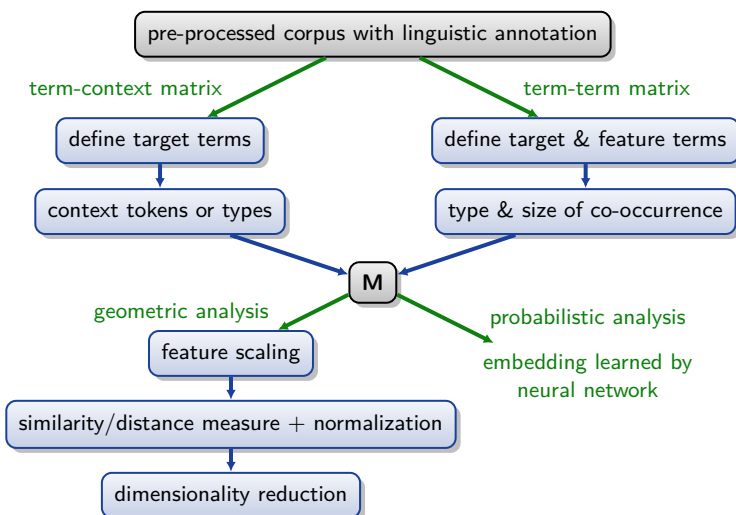
## General definition of DSMs

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



## 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), ...

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), ...

2018-08-06

## DSM Tutorial – Part 1

- Introduction
- Distributional semantic models
- Nearest neighbours

### Nearest neighbours

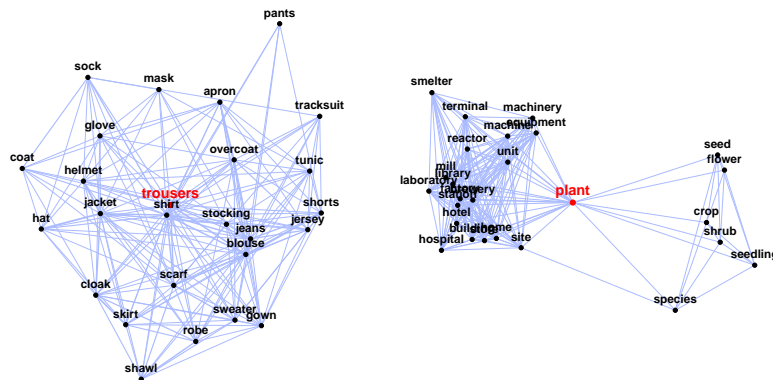
DSM based on verb-object relations from BNC, reduced to 100 dim. with SVD

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), ...

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), ...

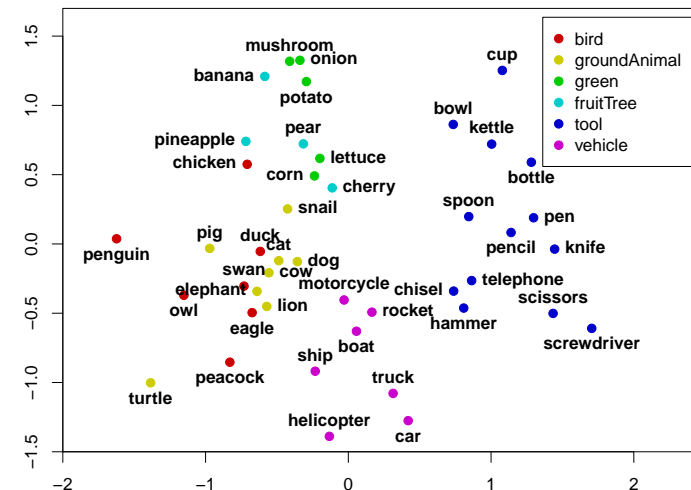
1. Neighbours and neighbourhood plots from BNC verb-object DSM, reduced to 100 dimensions by SVD.

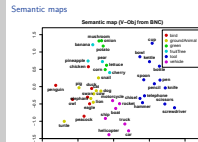
## Nearest neighbours with similarity graph



## Semantic maps

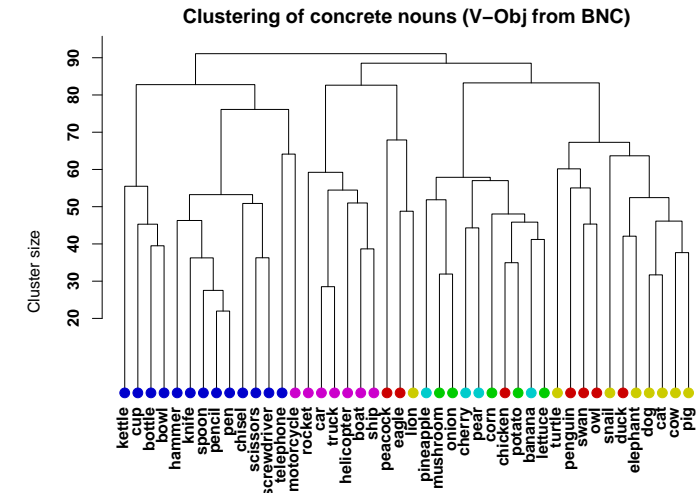
Semantic map (V-Obj from BNC)



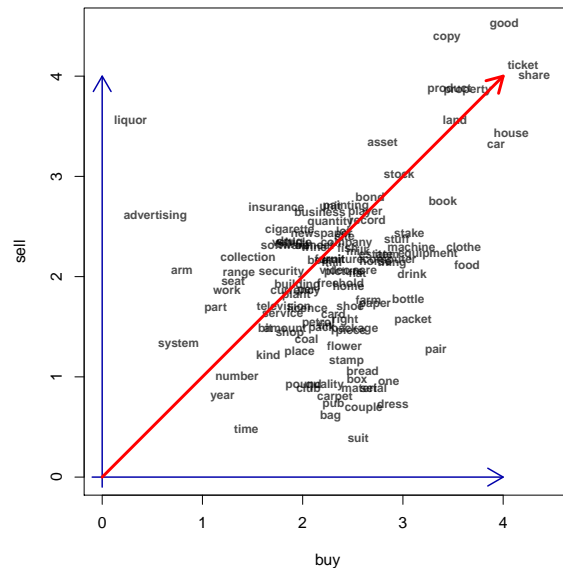


1. Roughly horizontal axis separates natural objects (left) from artifacts (right), or animate vs. inanimate. There is a clear boundary between the two groups.
2. Orthogonal axis separates moving things (bottom) from motionless ones (top).

## Clustering



## Latent “meaning” dimensions



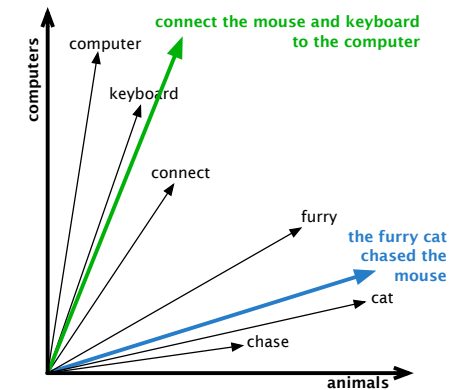
## Word embeddings

DSM vector as sub-symbolic meaning representation

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

**Context vectors** for word tokens (Schütze 1998)

- ▶ **bag-of-words** approach: centroid of all context words in the sentence
- ▶ application to WSD




## 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:  
distributional similarity/distance  $\sim$  semantic similarity/distance

### ► Distributed representation

- sub-symbolic representation of words as high-dimensional numeric vectors
- similarity of vectors usually (but not necessarily) corresponds to semantic similarity of the words
- hot topic: unsupervised neural **word embeddings**

 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)

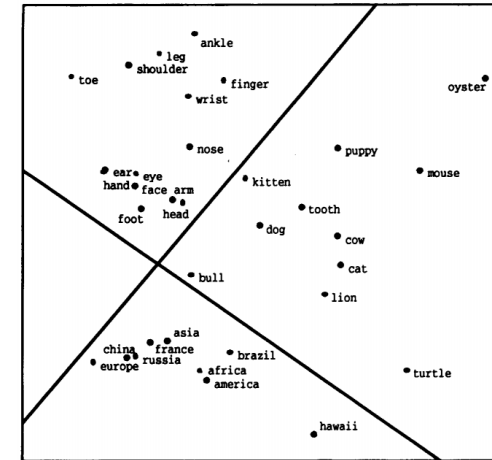


Figure 2. Multidimensional scaling of co-occurrence vectors.

## 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
  - ▶ part 2: The parameters of a DSM
  - ▶ part 3: Evaluating DSM representations
  - ▶ part 4: Matrix algebra & SVD
  - ▶ part 5: Understanding distributional semantics
- ➡ 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

- ▶ Query expansion in information retrieval (Grefenstette 1994)
- ▶ Unsupervised part-of-speech induction (Schütze 1995)
- ▶ Word sense disambiguation (Schütze 1998; Rapp 2004b)
- ▶ Thesaurus compilation (Lin 1998; Rapp 2004a)
- ▶ Attachment disambiguation (Pantel and Lin 2000)
- ▶ Probabilistic language models (Bengio *et al.* 2003)
- ▶ Translation equivalents (Sahlgren and Karlgren 2005)
- ▶ Ontology & wordnet expansion (Pantel *et al.* 2009)
- ▶ Language change (Sagi *et al.* 2009; Hamilton *et al.* 2016)
- ▶ Multiword expressions (Kiehl and Clark 2013)
- ▶ Analogies (Turney 2013; Gladkova *et al.* 2016)
- ▶ Sentiment analysis (Rothe and Schütze 2016; Yu *et al.* 2017)
- ▶  Input representation for neural networks & machine learning

## Recent workshops and tutorials

- ▶ **2007:** CoSMo Workshop (at Context '07)
- ▶ **2008:** ESSLLI Wshp & Shared Task, Italian J of Linguistics
- ▶ **2009:** GeMS Wshp (EACL), DiSCo Wshp (CogSci), ESSLLI
- ▶ **2010:** 2nd GeMS (ACL), ESSLLI Wshp, Tutorial (NAACL), J Natural Language Engineering
- ▶ **2011:** 2nd DiSCo (ACL), 3rd GeMS (EMNLP)
- ▶ **2012:** DiDaS Wshp (ICSC), ESSLLI Course
- ▶ **2013:** CVSC Wshp (ACL), TFDS Wshp (IWCS), Dagstuhl
- ▶ **2014:** 2nd CVSC (EACL), DSM Wshp (Insight)
- ▶ **2015:** VSM4NLP (NAACL), ESSLLI Course, TAL Journal
- ▶ **2016:** DSALT Wshp (ESSLLI), Tutorial (COLING), Tutorial (Konvens), ESSLLI Course, Computational Linguistics
- ▶ **2017:** ESSLLI Course
- ▶ **2018:** Tutorial (LREC), ESSLLI Course<sub>1</sub> & Course<sub>2</sub>

click on Workshop name to open Web page

2018-08-06

### DSM Tutorial – Part 1

- └ Getting practical
- └ Software and further information
- └ Recent workshops and tutorials

#### Recent workshops and tutorials

- ▶ 2007: CoSMo Workshop (at Context '07)
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- ▶ 2018: Tutorial (LREC), ESSLLI Course<sub>1</sub> & Course<sub>2</sub>

click on Workshop name to open Web page


1. CoSMo = Contextual Information in Semantic Space Models
2. ESSLLI = European Summer School in Logic, Language and Information
3. GeMS = Geometrical Models of Natural Language Semantics
4. DiSCo = Distributional Semantics beyond Concrete Concepts
5. JNLE = Journal of Natural Language Engineering
6. DiSCo 2 = Distributional Semantics and Compositionality
7. DiDaS = Workshop on Distributional Data Semantics
8. CVSC = Continuous Vector Space Models and their Compositionality
9. TFDS = Towards a Formal Distributional Semantics

## Software packages


Infomap NLP	C	<i>classical LSA-style DSM</i>
HiDEx	C++	<i>re-implementation of the HAL model (Lund and Burgess 1996)</i>
SemanticVectors	Java	<i>scalable architecture based on random indexing representation</i>
S-Space	Java	<i>complex object-oriented framework</i>
JoBimText	Java	<i>UIMA / Hadoop framework</i>
Gensim	Python	<i>complex framework, focus on parallelization and out-of-core algorithms</i>
Vecto	Python	<i>framework for count &amp; predict models</i>
DISSECT	Python	<i>user-friendly, designed for research on compositional semantics</i>
wordspace	R	<i>interactive research laboratory, but scales to real-life data sets</i>

click on package name to open Web page

## Further information

- ▶ Handouts & other materials available from workspace wiki at <http://workspace.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/workspace/>
- ▶ 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)

## 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 3.5 or newer from <http://www.r-project.org/>
- ▶ RStudio from <http://www.rstudio.com/>
- ▶ R packages from CRAN (through RStudio menu):  
**sparsesvd**, **workspace** (optional: **tm**, **quanteda**, **Rtsne**)
  - ▶ if you are attending a course, you may also be asked to install the **workspaceEval** package with some non-public data sets
- ▶ Get data sets, precompiled DSMs and **workspaceEval** from <http://workspace.collocations.de/doku.php/course:material>

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## First steps in R

Start each session by loading the workspace package.

```
> library(workspace)
```

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))
```

# Thank you!

Until part 2, you can explore some DSM similarity networks online:

- ▶ <https://corpora.linguistik.uni-erlangen.de/shiny/wordspace/>
- ▶ built in R with wordspace and shiny

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