Distributional Semantic Models

Part 1: Introduction

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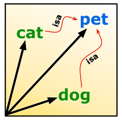
http://wordspace.collocations.de/doku.php/course:start



Outline

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

Getting practical
- Software and further information
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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.
- Beef dishes are made to complement the bardiwacs.
- Nigel staggered to his feet, face flushed from too much bardiwac.
- Malbec, one of the lesser-known bardiwac grapes, responds well to Australia's sunshine.
- I dined off bread and cheese and this excellent bardiwac.
- The drinks were delicious: blood-red bardiwac as well as light, sweet Rhenish.

☞ bardiwac 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	
skin	9	7.91
diddle	7	7.85
stroke	10	7.09
torture	5	6.57
feed	22	6.34
rain	4	6.3
chase	9	6.27
rescue	7	6.15

and/or 1056	1.7	
dog	208	8.49
cat	68	8.01
kitten	13	8.01
fiddle	9	7.71
mouse	29	7.68
monkey	15	7.55
budgie	4	6.74
rabbit	12	6.48

pp_obj_like-p 106	28.9	
grin	11	7.63
fight	9	4.62
smile	4	4.24
look	11	2.04

pp_among-p 17	14.8	
pigeon	15	8.66

possessor 91	1.9	
Schrödinger	8	10.87
witch	4	6.82
gardener	4	6.0
Henry	8	4.91
neighbour	5	4.28

possession 232	4.7	
cradle	24	9.91
whisker	9	8.92
paw	5	7.44
fur	9	7.14
tray	4	5.34
tail	5	4.91
tongue	5	4.89
ear	5	4.0

subject_of 842	3.3	
purr	7	7.76
miaow	5	7.57
mew	4	7.18
jump	20	6.95
scratch	8	6.84
leap	10	6.78
stalk	4	6.56
react	4	5.33

adj_subject_of 142	2.6	
asleep	4	6.09
alive	4	5.06
concerned	4	2.94
black	4	2.36
likely	4	1.96

pp_obj_of-p 324	1.3	
moral	4	7.06
breed	6	5.77
signal	4	3.89
sight	4	3.77
species	5	3.36
game	9	3.14
picture	6	2.99
death	7	2.71

modifier 1622	1.2	
pussy	76	10.42
Cheshire	45	8.9
stray	25	8.7
siamese	17	8.35
tabby	17	8.35
wild	53	7.94
pet	31	7.92
tom	12	7.8

modifies 610	0.5	
flap	16	8.39
litter	15	8.15
phobia	5	7.64
burglar	8	7.55
faeces	6	7.47
assay	10	7.38
Hastings	7	6.91
scan	4	6.59

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

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

sim(,) = 0.770

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

sim(,) = 0.939

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

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
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

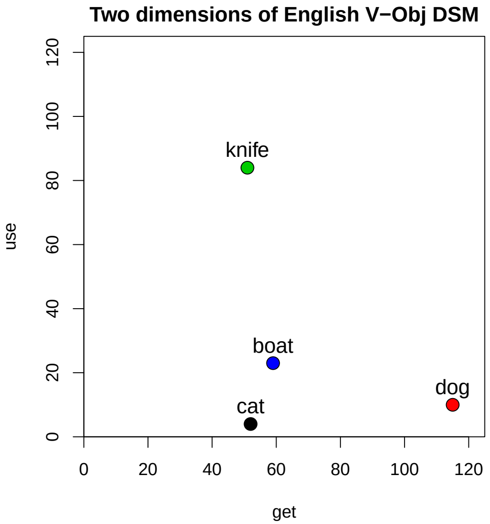
- row vector $\mathbf{x}_{\text{dog}}$ describes usage of word *dog* in the corpus
- can be seen as coordinates of point in n-dimensional Euclidean space

	get	see	use	hear	eat	kill
knife	51	20	84	0	3	0
cat	52	58	4	4	6	26
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

co-occurrence matrix M

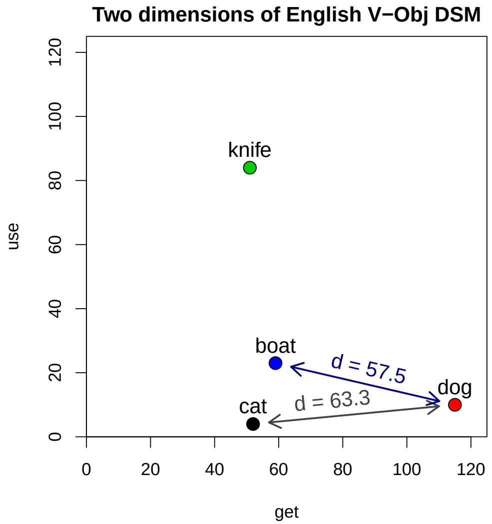
Geometric interpretation

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



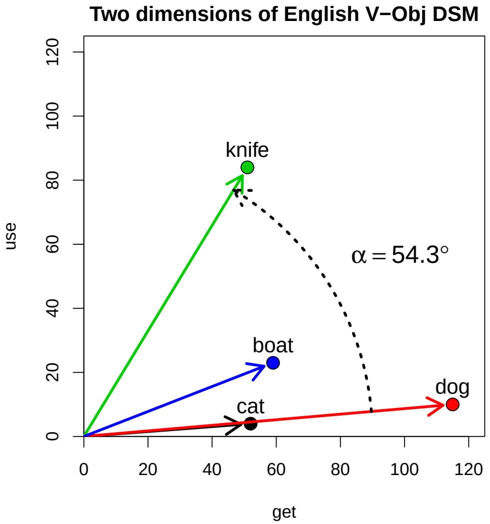
Geometric interpretation

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



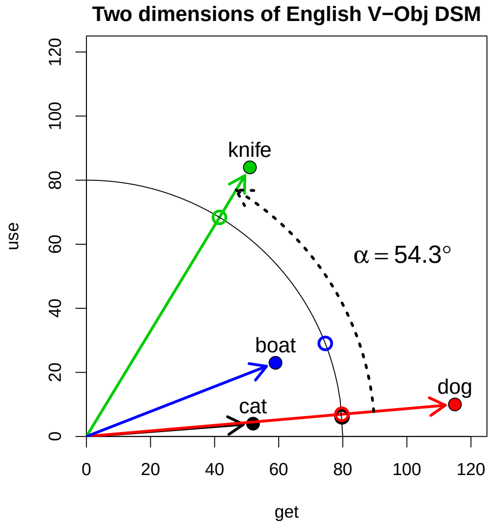
Geometric interpretation

- vector can also be understood as arrow from origin
- direction more important than location
- use angle α as distance measure



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 $\|\mathbf{x}_{dog}\|$ of arrow



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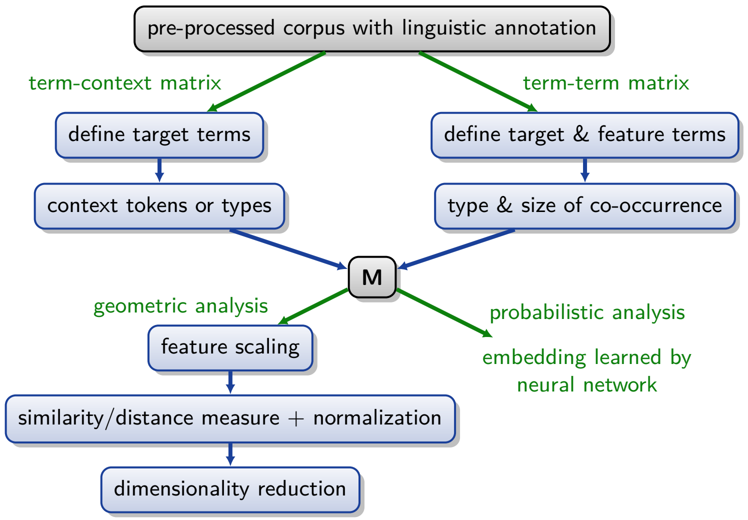
General definition of DSMs

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

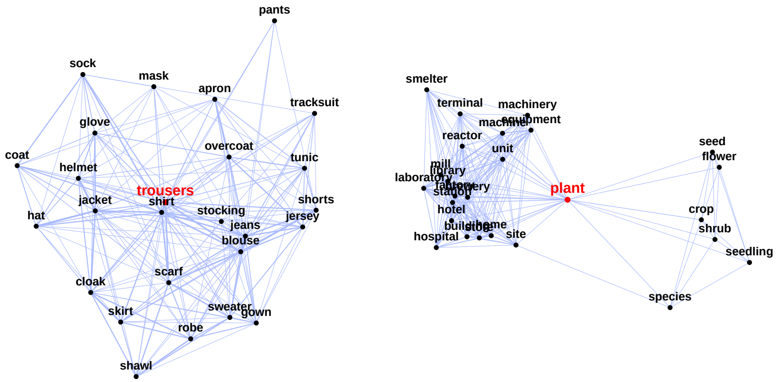
Neighbours of **trousers** (cosine angle):

- 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), ...

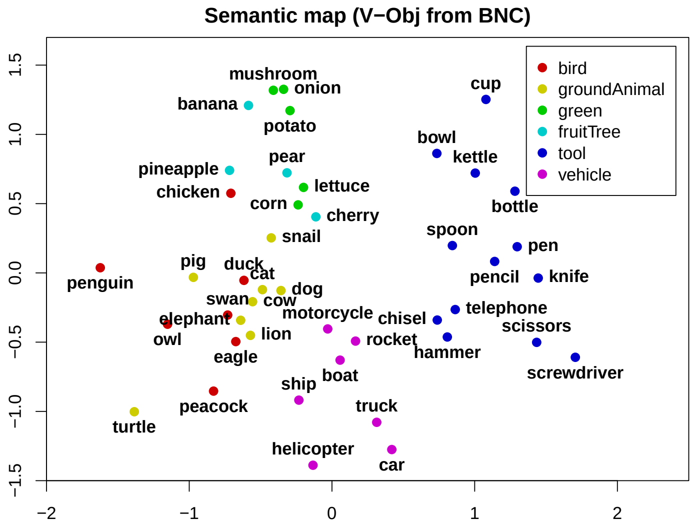
Neighbours of **rage** (cosine angle):

- 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), ...

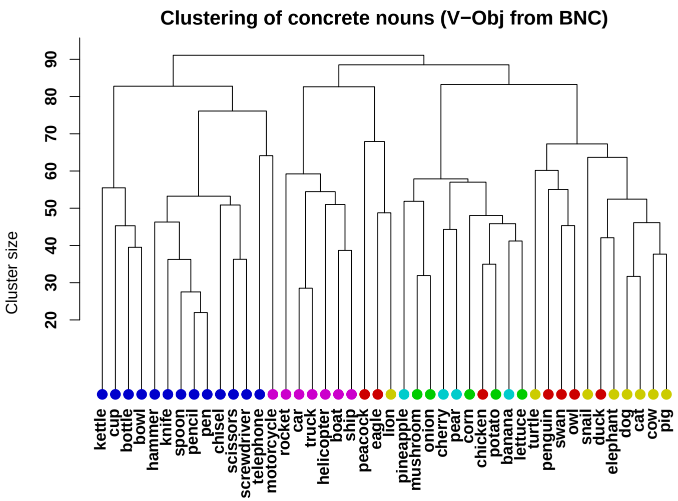
Nearest neighbours with similarity graph



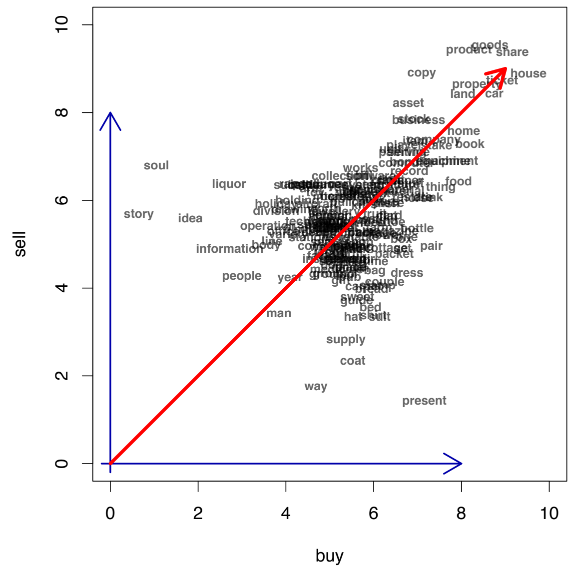
Semantic maps



Clustering



Latent "meaning" dimensions



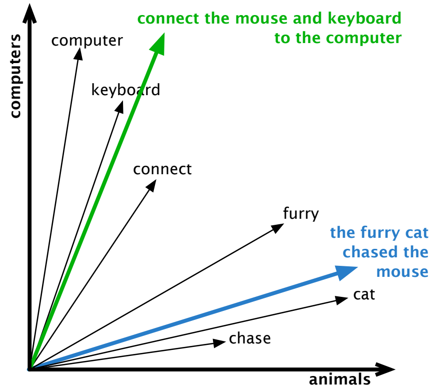
Word embeddings

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
  - need not be based on distributional information (alone)
  - hot topic: unsupervised neural **word embeddings**

☞ Distributional model can be used as distributed representation

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Latent Semantic Analysis (Landauer & 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: ≈ 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 ≈ 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 & 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 & Burgess 1996)

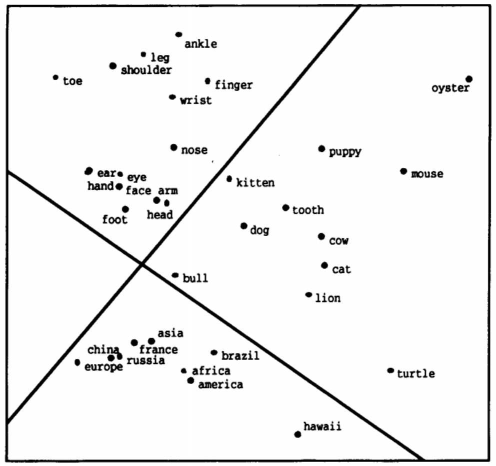

Figure 2. Multidimensional scalirg of co-occurrence vectors.

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

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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 & Lin 2000)
- Probabilistic language models (Bengio *et al.* 2003)
- Translation equivalents (Sahlgren & Karlgren 2005)
- Ontology & wordnet expansion (Pantel *et al.* 2009)
- Language change (Sagi *et al.* 2009; Hamilton *et al.* 2016)
- Multiword expressions (Kiela & Clark 2013)
- Analogies (Turney 2013; Gladkova *et al.* 2016)
- Sentiment analysis (Rothe & 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_1 & Course_2

click on Workshop name to open Web page

Software packages

Infomap NLP	C	*classical LSA-style DSM*
HiDEx	C++	*re-implementation of the HAL model (Lund & 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*
Vecto	Python	*framework for count & predict models*
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 3.5 or newer from `http://www.r-project.org/`
- RStudio from `http://www.rstudio.com/`
- R packages from CRAN (through RStudio menu): `sparsesvd`, `wordspace` (optional: `tm`, `quanteda`, `Rtsne`, `uwot`, `wordcloud`, `shiny`, `corpustools`, `spacyr`, `udpipe`)
  - if you are attending a course, you may also be asked to install the `wordspaceEval` package with some non-public data sets
- Get data sets, precompiled DSMs and `wordspaceEval` from http://wordspace.collocations.de/doku.php/course:material

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))
```


Explorations

While you wait for 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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