

Computational lexical semantics

Computational Linguistics

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The knowledge bottleneck

- Inference requires formalized *knowledge* about the world and about the meanings of words.

Which genetically caused connective tissue disorder has severe symptoms and complications regarding the aorta and skeletal features, and, very characteristically, ophthalmologic subluxation?

Marfan's is created by a defect of the gene that determines the structure of Fibrillin-11. One of the symptoms is displacement of one or both of the eyes' lenses. The most serious complications affect the cardiovascular system, especially heart valves and the aorta.

Lexical semantics in CL

Many words are *synonymous* or at least *semantically similar*.

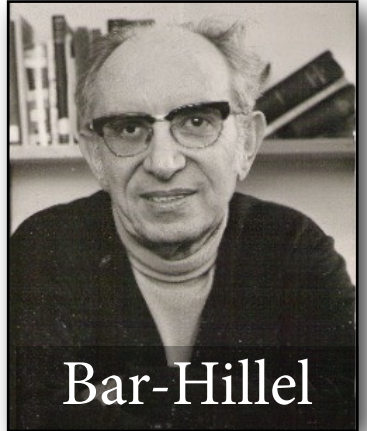


He's not pining! He's **passed on**! This parrot **is no more**! He **has ceased to be**! He's **expired** and **gone to meet his maker**! He's a **stiff**! **Bereft of life**, he **rests in peace**! His metabolic processes are now **history**! He's **off the twig**! He's **kicked the bucket**, he's **shuffled off his mortal coil**, **run down the curtain** and **joined the bleedin' choir invisible!!**
THIS IS AN EX-PARROT!!

Information Retrieval

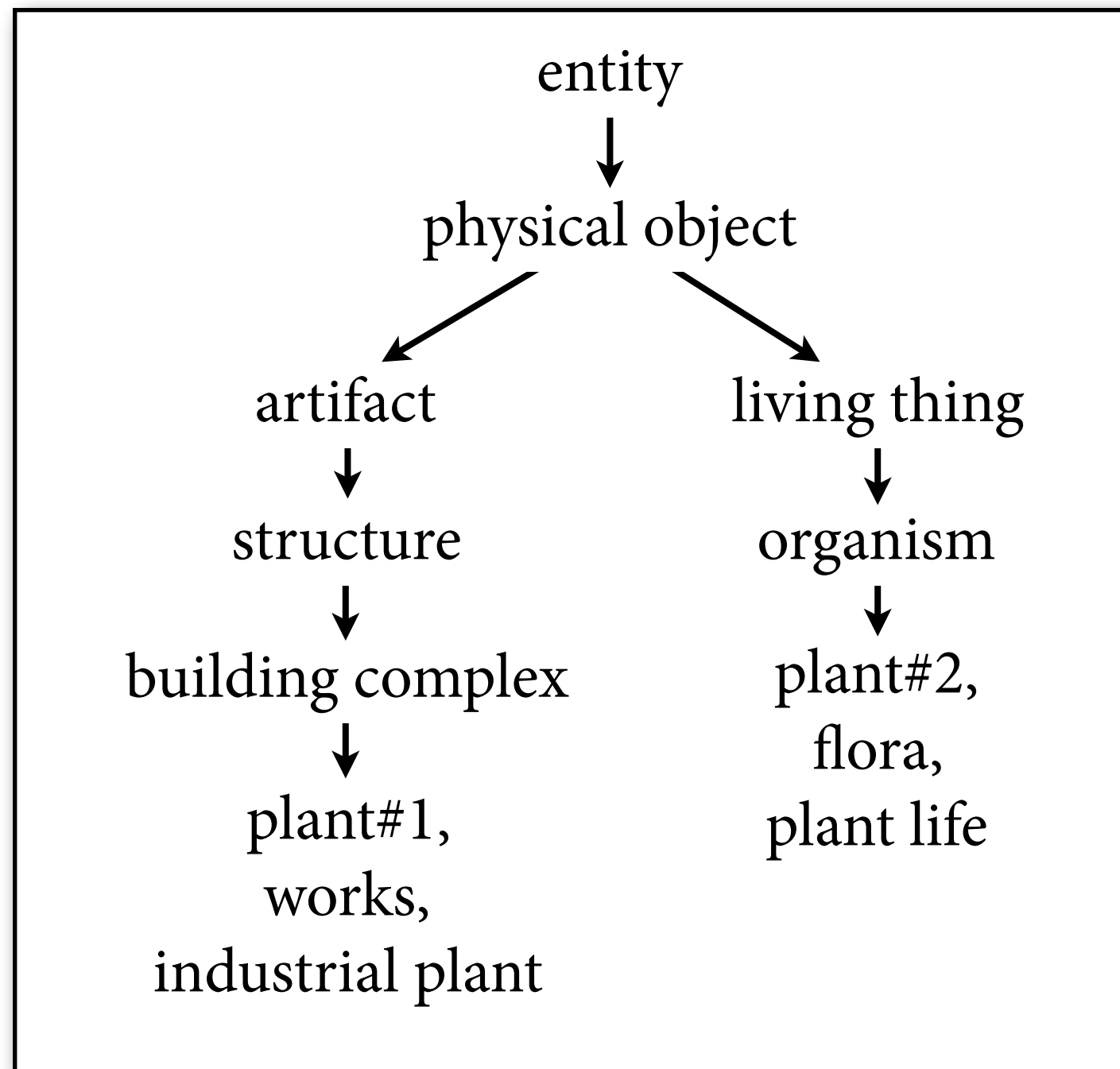
- In *Information Retrieval*, we want to find differently phrased documents:
 - ▶ Query: “female astronauts”
 - ▶ Document: “In the history of the Soviet space program, there were only three female cosmonauts: Valentina Tereshkova, Svetlana Savitskaya, and Elena Kondakova.”
- This will only work if system recognizes that “astronaut” and “cosmonaut” have similar meanings.

Machine Translation



- Knowledge also important to disambiguate *polysemous* words.
- Famous example by Bar-Hillel (1960):
 - ▶ “The box is in the pen.”
- Correct translation depends on sense of “pen”:
 - ▶ “Die Kiste ist im Stift.”
 - ▶ “Die Kiste ist im Pferch.”

Classical lexical semantics



→ = hyponymy

same node = synonymy

Classical lexical semantics

- *Polysemy*: Word has two different meanings that are clearly related to each other.
 - ▶ School #1: institution at which students learn
 - ▶ School #2: building that houses school #1
- *Homonymy*: Word has two different meanings that have no obvious relation to each other.
 - ▶ Bank #1: financial institution
 - ▶ Bank #2: land alongside a body of water

Word sense disambiguation

- *Word sense disambiguation* is the problem of tagging each word token with its word sense.
- WSD accuracy depends on sense inventory; state of the art is above 90% on coarse-grained senses.
- Techniques tend to combine supervised training on small amount of annotated data with unsupervised methods.

Problem

- Hand-written thesauruses much too small.
 - ▶ English Wordnet: 117.000 synsets
 - ▶ GermaNet: 85.000 synsets
- Number of word types in English Google n-gram corpus: > 1 million.
- This is not how we can solve the query expansion problem
- Learn lexical semantic knowledge automatically?

Experiment

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 - ▶ Malbec, one of the lesser-known bardiwac grapes, responds well to Australia’s sunshine.

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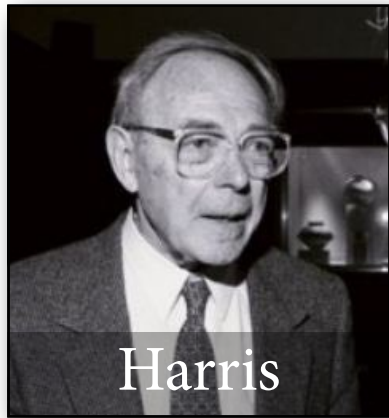
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 - ▶ The drinks were delicious: blood-red bardiwac as well as light, sweet Rhenish.

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→ Bardiwac ist a red wine.

Distributional Semantics



- Basic idea (Harris 1951, Firth 1957):
“You shall know a word by the company it keeps.”
- Assumption: Semantically *similar* words tend to occur in the context of the same words.
 - ▶ “similar” as approximation of “synonymous”
- Can observe “occur in the context of same words” on large unannotated corpora.

Cooccurrence

see who can **grow** the biggest **flower**. Can we buy some fibre, please
Abu Dhabi **grow** like a hot-house **flower**, but decided themselves to follow the
as a physical level. The Bach **Flower** Remedies are prepared from non-poisonous **wild**
a seed from which a strong **tree** will **grow**. This is the finest



	factory	flower	tree	plant	water	fork
grow	15	147	330	517	106	3
garden	5	200	198	316	118	17
worker	279	0	5	84	18	0
production	102	6	9	130	28	0
wild	3	216	35	96	30	0

Co-occurrence matrix from BNC, from Koller & Pinkal 12

Vector space model

	factory	flower	tree	plant	water	fork
grow	15	147	330	517	106	3
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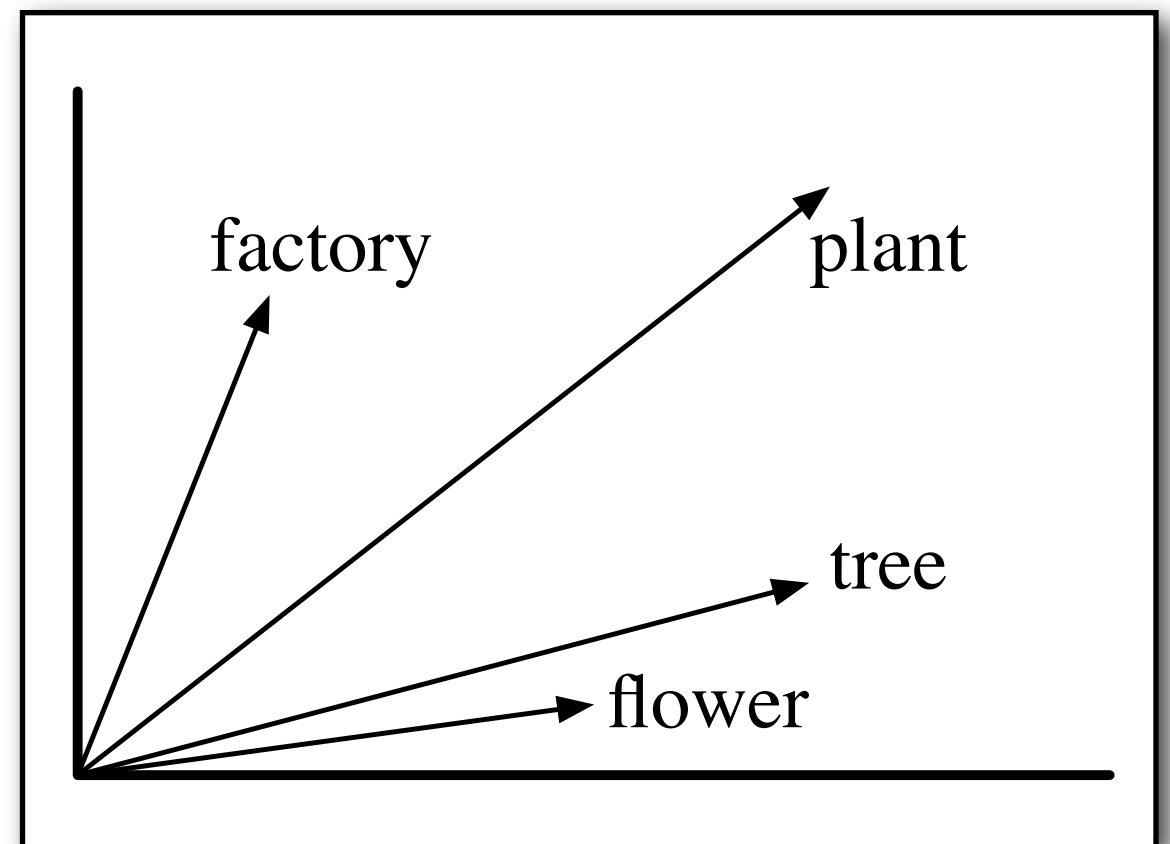
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Vectors in a
high-dimensional
vector space

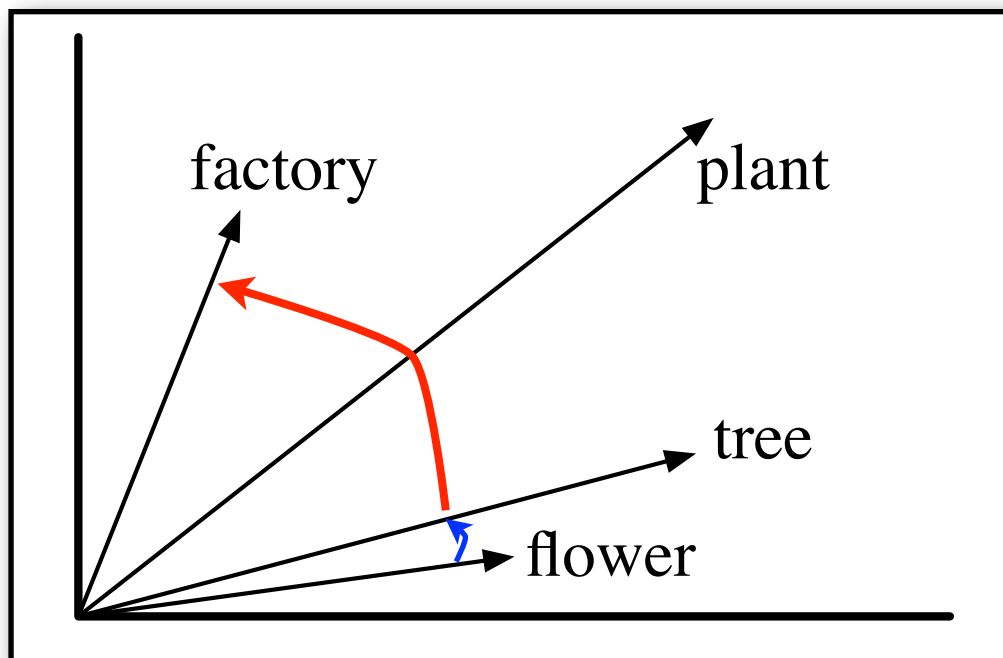
1 dimension per context word
(here: 6 dimensions)

Picture simplifies to 2 dimensions,
is only schematic.



Cosine similarity

- Take *angle* between vectors as measure of similarity.
 - ▶ (correctly) ignores length of vectors = frequency of words
 - ▶ similar angle = similar proportion of context words
- Cosine of angle is easy to compute.
 - ▶ $\cos = 1$ means angle = 0° , i.e. very similar
 - ▶ $\cos = 0$ means angle = 90° , i.e. very dissimilar



$$\cos(\vec{v}, \vec{w}) = \frac{\sum_{i=1}^n v_i \cdot w_i}{\sqrt{\sum_{i=1}^n v_i^2} \cdot \sqrt{\sum_{i=1}^n w_i^2}}$$

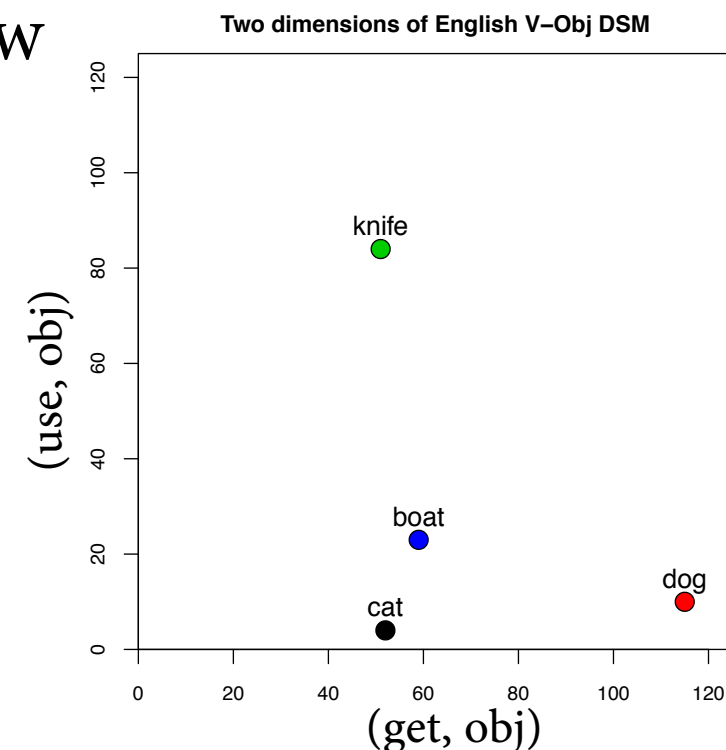
$\cos(\text{tree}, \text{flower}) = 0.75$, i.e. 40°
 $\cos(\text{tree}, \text{factory}) = 0.05$, i.e. 85°

More complex features

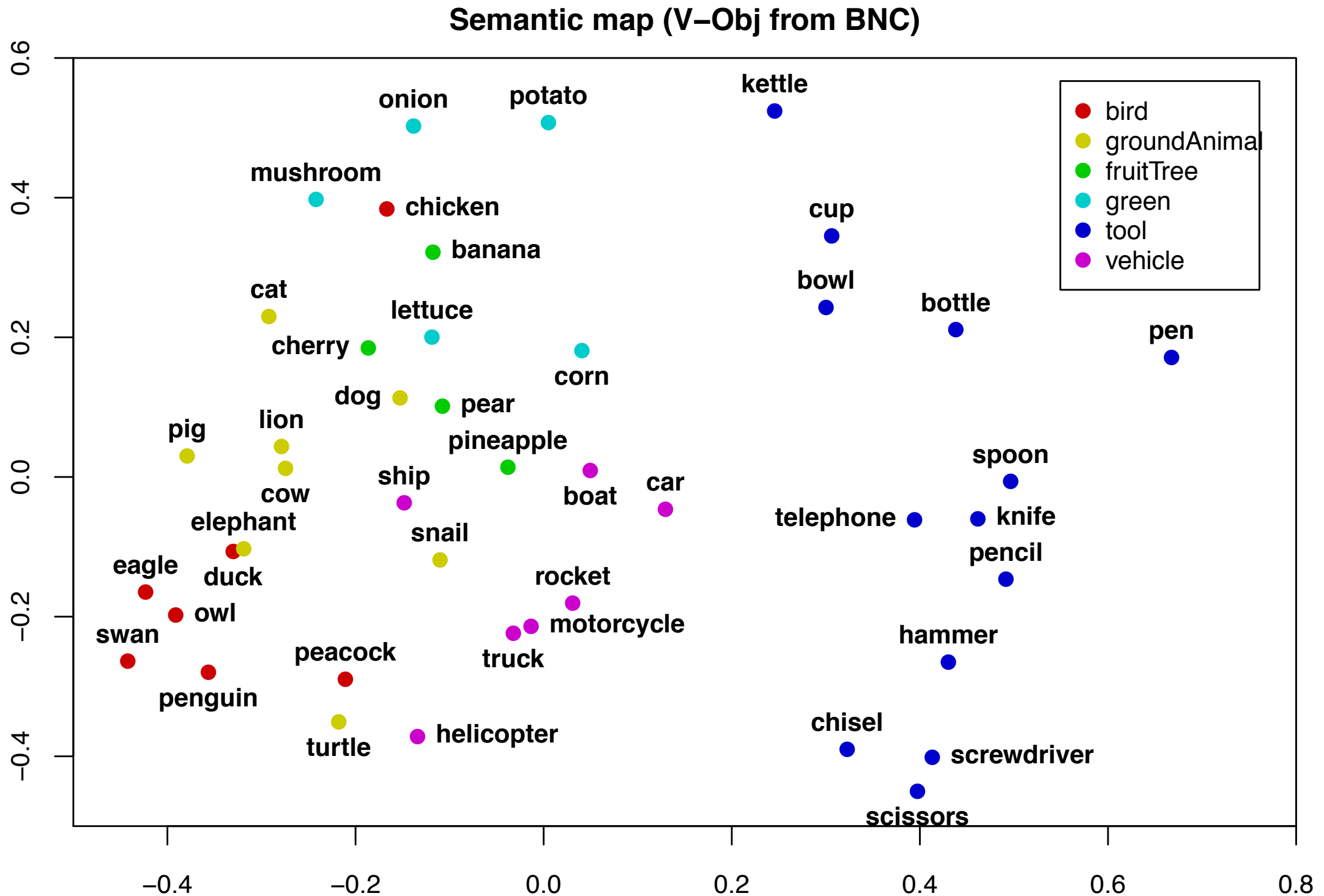
- Co-occurrence in string can over-estimate whether the two words really belong together.

the Qataris had watched **Abu Dhabi** grow like a hot-house **flower**, but decided

- Fix this with more complex features which e.g. capture grammatical relations between words (Lin 98).
 - ▶ instead of counting “*flower* appears in window of length 7 around *Abu Dhabi*”,
 - ▶ count “*flower* occurs as subject of *grow*”



Results



(Evert, NAACL tutorial 2010)

Results

hope (N):

optimism 0.141, chance 0.137, expectation 0.136, prospect 0.126,
dream 0.119, desire 0.118, fear 0.116, effort 0.111, confidence 0.109, promise 0.108

hope(V):

would like 0.158, wish 0.140, plan 0.139, say 0.137, believe 0.135, think 0.133,
agree 0.130, wonder 0.130, try 0.127, decide 0.125

brief (N):

legal brief 0.139, affidavit 0.103, filing 0.098, petition 0.086,
document 0.083, argument 0.083, letter 0.079, rebuttal 0.078, memo 0.077, article 0.076

brief (A):

lengthy 0.256, hour-long 0.191, short 0.173, extended 0.163, frequent 0.162,
recent 0.158, short-lived 0.155, prolonged 0.149, week-long 0.149, occasional 0.146

Problems

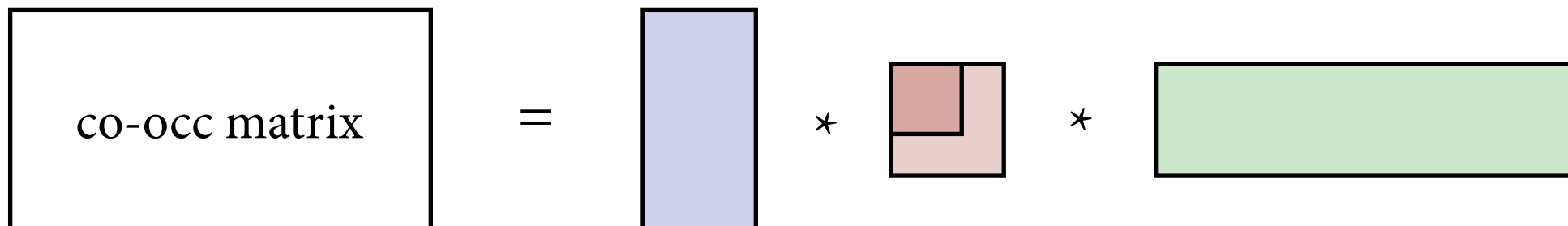
- Similarity = synonymy?
 - ▶ Antonyms are basically as distributionally similar as synonyms:

brief (A): lengthy 0.256, hour-long 0.191, short 0.173, extended 0.163, frequent 0.162, recent 0.158, short-lived 0.155, prolonged 0.149, week-long 0.149, occasional 0.146

- Distributional similarity is not referential similarity. Distinguishing synonyms from antonyms is notoriously hard problem.

Dimensionality reduction

- Raw co-occurrence vectors have very high dimension (one for each context word).
- Typical approach: dimensionality reduction.
 - ▶ improves efficiency; can filter out random noise
- For instance, *Latent Semantic Analysis* reduces dimensionality via singular value decomposition.



Compositional distrib semantics

- Can we compute distributional representations for larger phrases compositionally?
- E.g. Mitchell & Lapata 08: obtain co-occ vector for larger phrase by adding vectors for its parts.
- Seems linguistically meaningless, but correlates with human judgments about similarity.

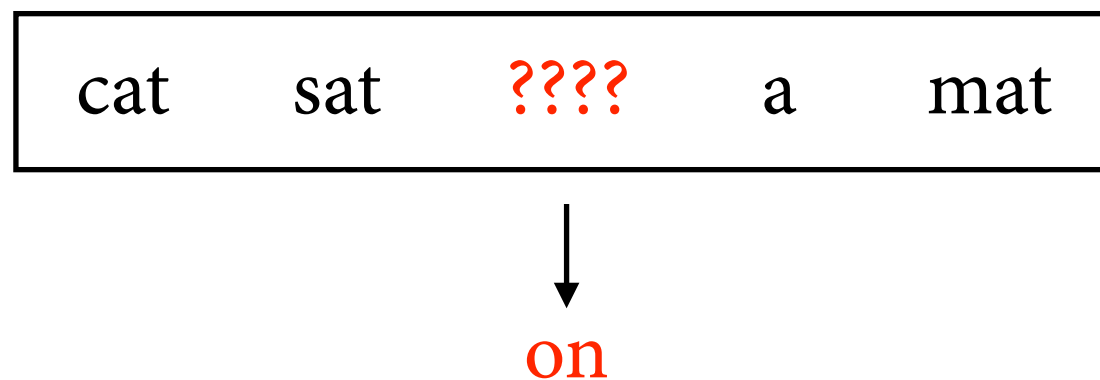
Compositional distrib semantics

- Baroni & Zamparelli 10: “Nouns are vectors, adjectives are matrices” (= functions).
 - ▶ learn matrices for adjectives such that $A * N$ approximates co-occ vector for “A N” (for all N)
- This mirrors functional relations in classical semantics construction.

<i>bad</i> <i>luck</i>	<i>electronic</i> <i>communication</i>	<i>historical</i> <i>map</i>
bad bad weekend good spirit	elec. storage elec. transmission purpose	topographical atlas hist. material
<i>important route</i>	<i>nice girl</i>	<i>little war</i>
important transport important road major road	good girl big girl guy	great war major war small war
<i>red cover</i>	<i>special collection</i>	<i>young husband</i>
black cover hardback red label	general collection small collection archives	small son small daughter mistress

Word embeddings

- Goal: language modeling. Let's try to predict the missing word in a given context.



- Key question: How do we represent words?
→ word embeddings

Word embeddings

- One-hot encoding: Every word a 0-1 vector.

$$\begin{array}{cccc}
 \text{cat} & \text{sat} & \text{a} & \text{mat} \\
 \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} & \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} & \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}
 \end{array}
 \begin{array}{c}
 \uparrow \\
 |V| \\
 \downarrow
 \end{array}$$

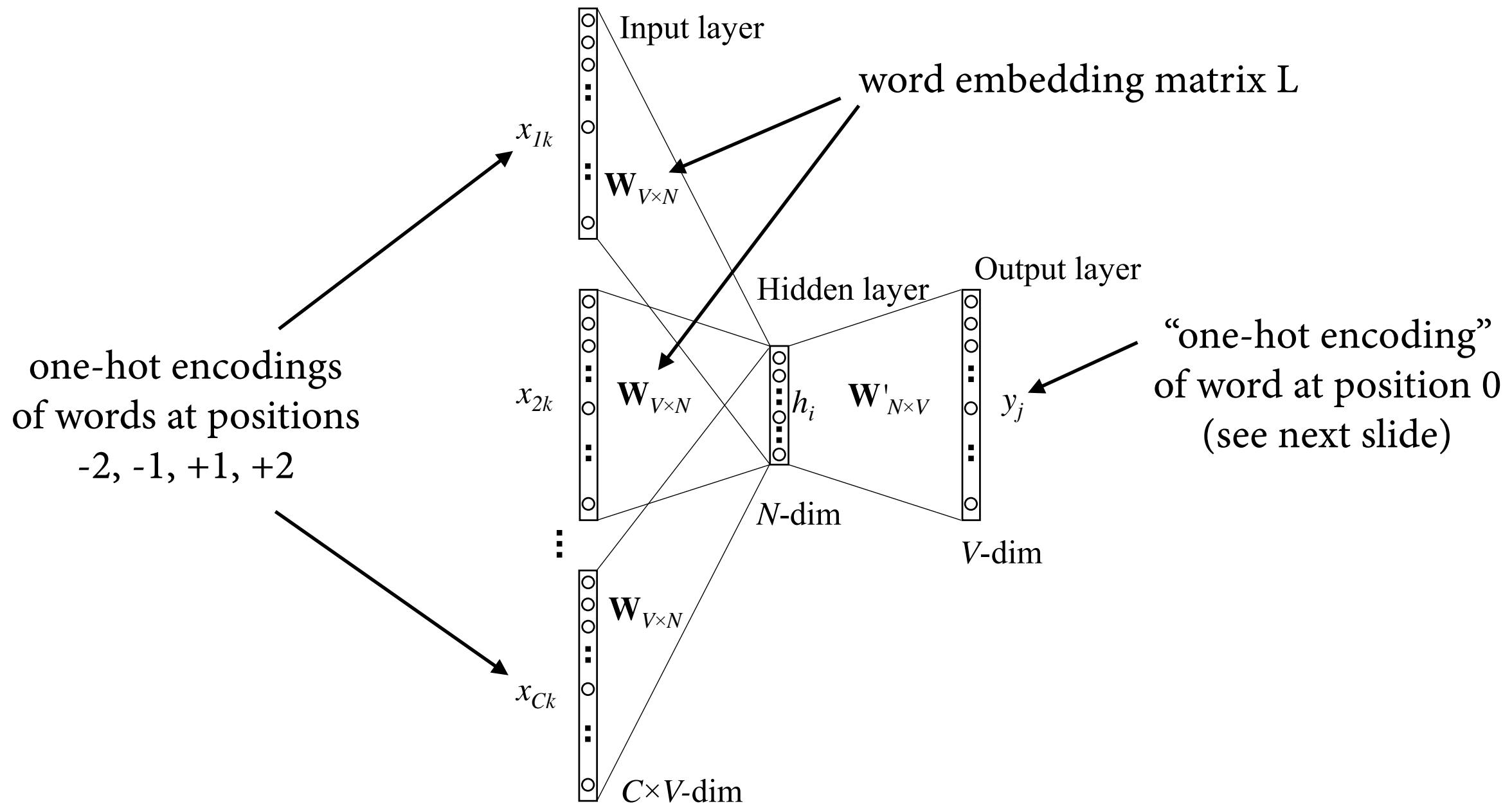
- Word embeddings: $n \times |V|$ matrix L which maps each one-hot encoding into n -dimensional vector.

$$L = \begin{bmatrix} \text{the} & \text{cat} & \text{mat} & \dots & \dots & \dots \end{bmatrix}_n$$

$|V|$
 $\begin{bmatrix} \bullet & \bullet & \bullet & \dots & \bullet & \bullet \end{bmatrix}$
 $\begin{bmatrix} \bullet & \bullet & \bullet & \dots & \bullet & \bullet \end{bmatrix}$
 $\begin{bmatrix} \bullet & \bullet & \bullet & \dots & \bullet & \bullet \end{bmatrix}$
 $\begin{bmatrix} \bullet & \bullet & \bullet & \dots & \bullet & \bullet \end{bmatrix}$

CBOW

= continuous bag of words



similarly, skip-gram model predicts context from word

Softmax

- Can't force NN to assign exactly one neuron the value 1 in the output layer.
- Instead, convert output layer into a PD over possible words using the *softmax* function:

$$P(y_j \mid x_1, \dots, x_C) = \frac{e^{y_j}}{\sum_i e^{y_i}}$$

- Objective function in training: $\log P(y_j \mid x_1, \dots, x_C)$.

Results

Accuracy on MS Sentence Completion Task

Architecture	Accuracy [%]
4-gram [32]	39
Average LSA similarity [32]	49
Log-bilinear model [24]	54.8
RNNLMs [19]	55.4
Skip-gram	48.0
Skip-gram + RNNLMs	58.9

Was she his [client | musings | discomfigure | choice | opportunity],
his friend, or his mistress?

All red-headed men who are above the age of [800 | seven | twenty-one |
1,200 | 60,000] years are eligible.

That is his [generous | mother's | successful | favorite | main] fault,
but on the whole he's a good worker.

(Mikolov et al. 2013)

Results

(on analogy task)

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

(vector with highest cosine similarity to $L(\text{Paris}) - L(\text{France}) + L(\text{Italy})$ etc.)

Conclusion

- “Knowledge bottleneck” is a serious problem in computational semantics.
- Important topic in current research: *distributional* methods for semantic similarity of words.
- Current trends:
 - ▶ combine with compositional semantics
 - ▶ neural methods