


Deep Learning for NLP

Semantics


- How does a computer understand meaning?

- Dictionary
- Thesuras
- WordNet

Dictionary



murder


/ˈmɜːdər/ 

noun

1. the unlawful premeditated killing of one human being by another.
"the brutal murder of a German holidaymaker"
synonyms: [killing](#), [homicide](#), [assassination](#), [liquidation](#), [extermination](#), [execution](#), [slaughter](#), [butchery](#), [massacre](#); [More](#)
2. *informal*
a very difficult or unpleasant task or experience.
"the 40-mile-per-hour winds at the summit were murder"
synonyms: [hell](#), hell on earth, a nightmare, an ordeal, a trial, a frustrating/unpleasant/difficult experience, [misery](#), [torture](#), [agony](#)
"driving there was murder"

verb

1. kill (someone) unlawfully and with premeditation.
"he was accused of murdering his wife's lover"
synonyms: [kill](#), put/do to death, [assassinate](#), [execute](#), [liquidate](#), [eliminate](#), [neutralize](#), [dispatch](#), [butcher](#), cut to pieces, [slaughter](#), [massacre](#), wipe out, mow down; [More](#)
2. *informal*
punish severely or be very angry with.
"my father will murder me if I'm home late"

 Translations, word origin and more definitions

Semantics

- How does a computer understand meaning?

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

He handed her a glass of **bardiwac**.

Beef dishes are made to complement the **bardiwacs**.

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

Word Sense Disambiguation

- What is the meaning of “Bank”?
 - he sat on the bank of the river and watched the currents --> sloping land
 - a huge bank of earth --> a long ridge or pile
 - The State Bank has allowed me the loan --> Financial Institution

Meaning and Neighbourhood

You shall know a word by the company it keeps!

Meaning of a word can be derived from the meaning of its contexts

Meaning and Neighbourhood

You shall know a word by the company it keeps!

Meaning of a word can be derived from the meaning of its contexts

AKA

The Distributional Hypothesis

Semantics

Meaning of a word can be derived from
the meaning of its *contexts*

Context??

He handed her a glass of **bardiwac**.

Beef dishes are made to complement the **bardiwacs**.

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

Context??

- I love playing **cricket**
- Sachin is a **cricketer**
- **Cricket** is played using a bat and a ball
- Sourav plays **cricket**
- Sachin is the highest test scorer
- Maradona plays football
- ...
- ...

Context

- He handed her a glass of **bardiwac**.
- Beef dishes are made to complement the **bardiwacs**.
- Malbec, one of the lesser-known **bardiwac** grapes, responds well to Australia's sunshine.
- I love playing **cricket**
- Sachin is a **cricketer**
- **Cricket** is played using a bat and a ball
- Sourav plays **cricket**
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Central/
Target Word



The diagram illustrates the concept of context for a target word. It features two columns of sentences. In the left column, the word 'bardiwac' is highlighted in red in three sentences. In the right column, the word 'cricket' is highlighted in orange in five sentences. Arrows from each of these highlighted words point towards a central point at the bottom of the slide, which is labeled 'Central/Target Word' in blue text.

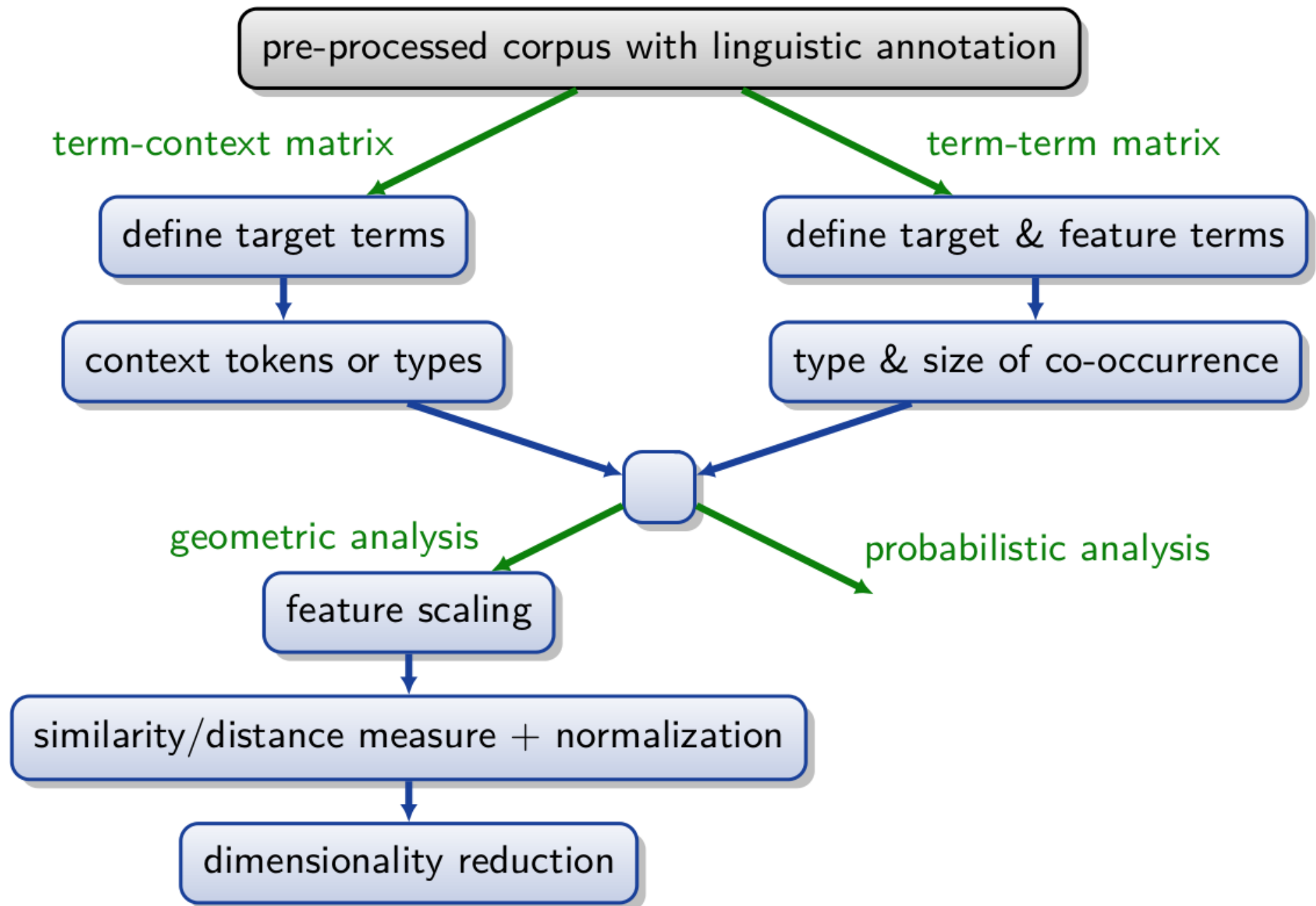
Context

- He handed her a glass of **bardiwac**.
- Beef dishes are made to complement the **bardiwacs**.
- Malbec, one of the lesser-known **bardiwac** grapes, responds well to Australia's sunshine.
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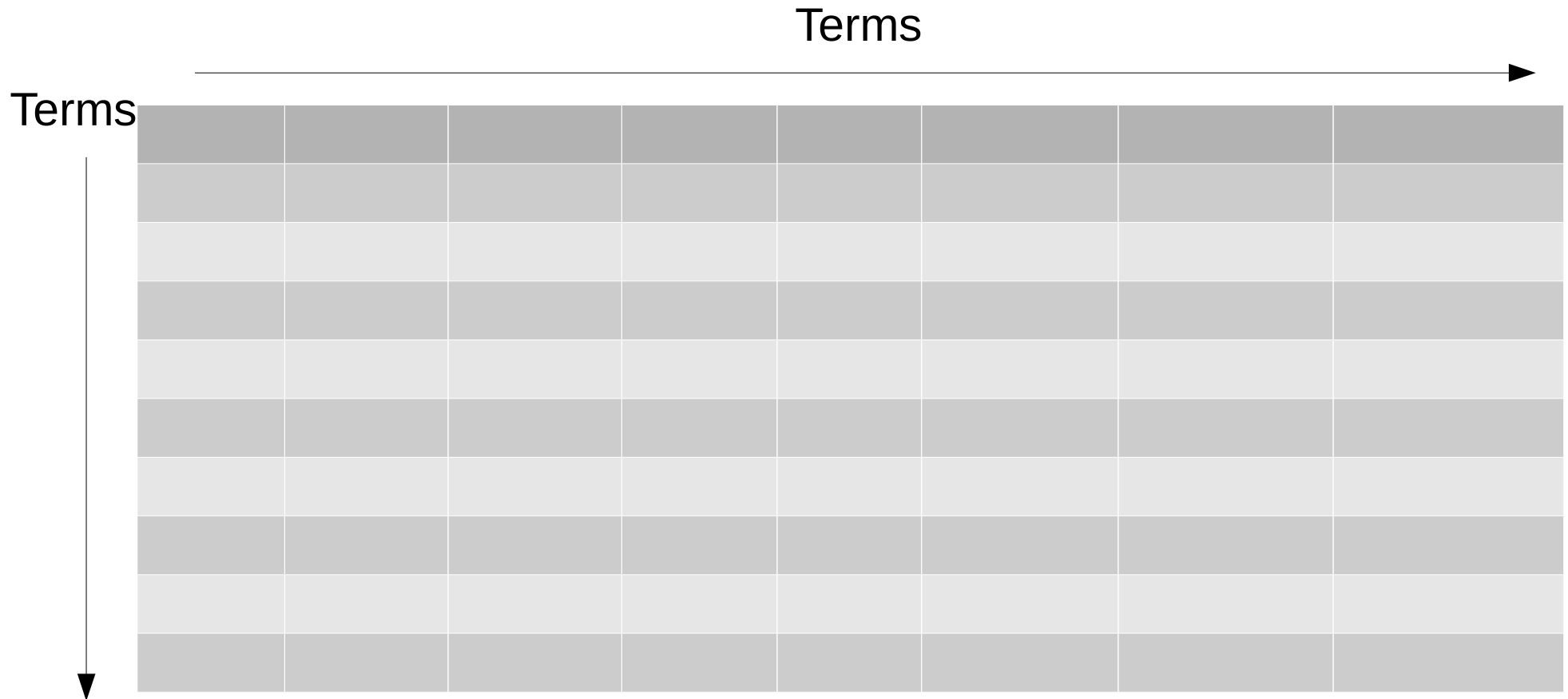


Context Word

Building a distributional model



Construction of co-occurrence matrix



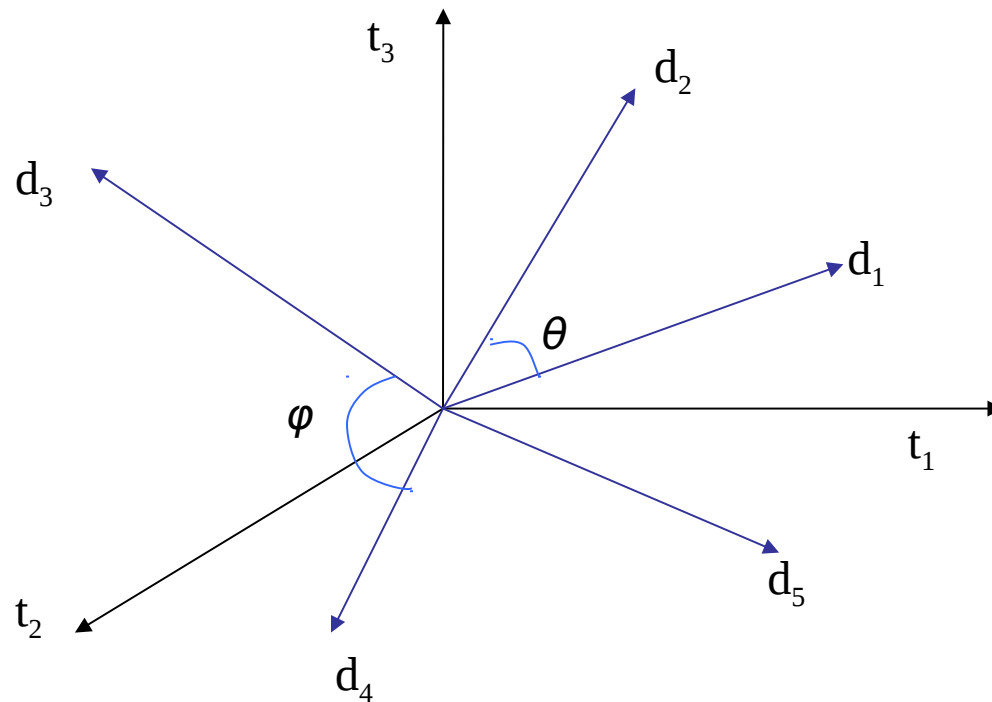
Geometric interpretation

- ▶ 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

| | 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

Intuition



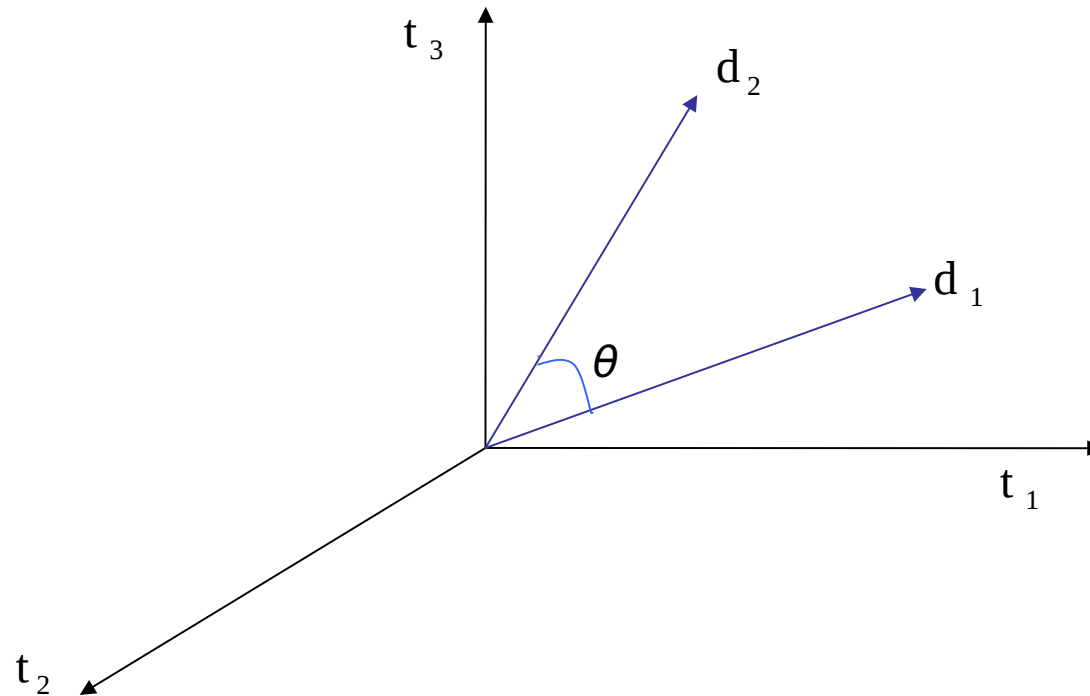
Postulate: Words that are “close together” in the vector space talk about the same things.

Desiderata for proximity

- If d_1 is near d_2 , then d_2 is near d_1 .
- If d_1 near d_2 , and d_2 near d_3 , then d_1 is not far from d_3 .
- No word is closer to d than d itself.

Cosine similarity

- Distance between vectors d_1 and d_2 captured by the cosine of the angle θ between them.



Similarity measures

- There are many different ways to measure how similar two documents are, or how similar a document is to a query
- The **cosine measure** is a very common similarity measure
- Using a similarity measure, a set of documents can be compared to a query and the most similar document returned

The cosine measure

- For two vectors d and d' the cosine similarity between d and d' is given by:

$$\frac{d \times d'}{|d||d'|}$$

- Here $d \times d'$ is the vector product of d and d' , calculated by multiplying corresponding frequencies together
- The cosine measure calculates the angle between the vectors in a high-dimensional virtual space

Example

- Let $d = (2, 1, 1, 1, 0)$ and $d' = (0, 0, 0, 1, 0)$
 - $d \times d' = 2 \times 0 + 1 \times 0 + 1 \times 0 + 1 \times 1 + 0 \times 0 = 1$
 - $|d| = \sqrt{(2^2 + 1^2 + 1^2 + 1^2 + 0^2)} = \sqrt{7} = 2.646$
 - $|d'| = \sqrt{(0^2 + 0^2 + 0^2 + 1^2 + 0^2)} = \sqrt{1} = 1$
 - $\text{Similarity} = 1 / (1 \times 2.646) = 0.378$
- Let $d = (1, 0, 0, 0, 1)$ and $d' = (0, 0, 0, 1, 0)$
 - $\text{Similarity} =$

Class Assignments

- Let $d = (1,0,0,0,1)$ and $d' = (0,0,0,1,0)$
 - Similarity =
- Let $d = (21,10,25,30,1)$ and $d' = (10,20,50,11,54)$
 - Similarity =
- Let $d1 = (21,10,25,30,1)$, $d2 = (10,20,50,11,54)$ and $d3 = (13, 16,1,10,5)$
 - Similarity $(d1,d2) =$
 - Similarity $(d2,d3) =$
 - Similarity $(d3,d1) =$

Which pair is most similar??

Cosine similarity

$$\text{sim}(d_j, d_k) = \frac{\vec{d}_j \cdot \vec{d}_k}{\|\vec{d}_j\| \|\vec{d}_k\|} = \frac{\sum_{i=1}^n w_{i,j} w_{i,k}}{\sqrt{\sum_{i=1}^n w_{i,j}^2} \sqrt{\sum_{i=1}^n w_{i,k}^2}}$$

- Cosine of angle between two vectors
- The denominator involves the lengths of the vectors.



Normalization

Geometric interpretation

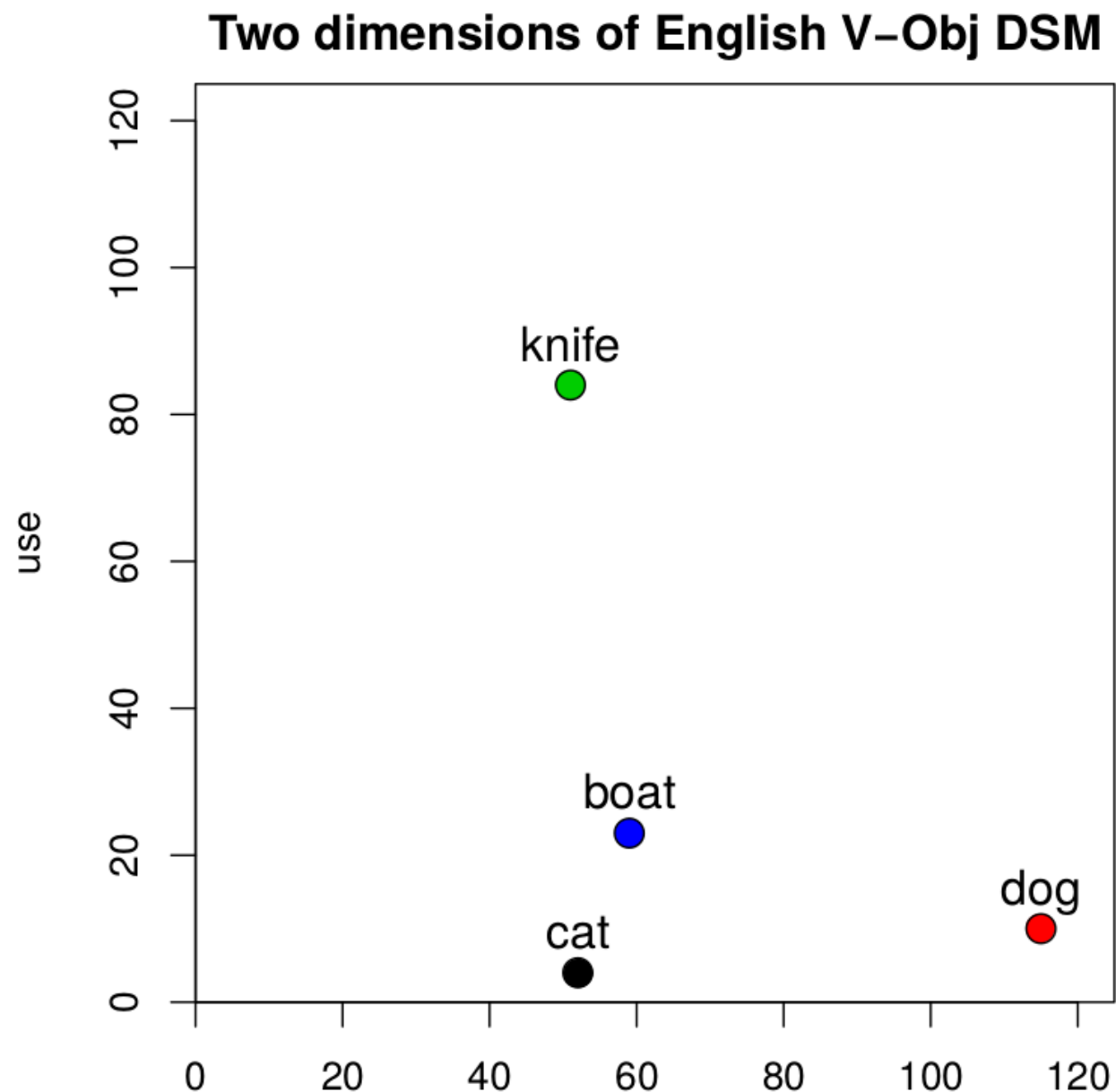
- ▶ row vector \mathbf{x}_{dog} describes usage of word *dog* in the corpus
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co-occurrence matrix \mathbf{M}

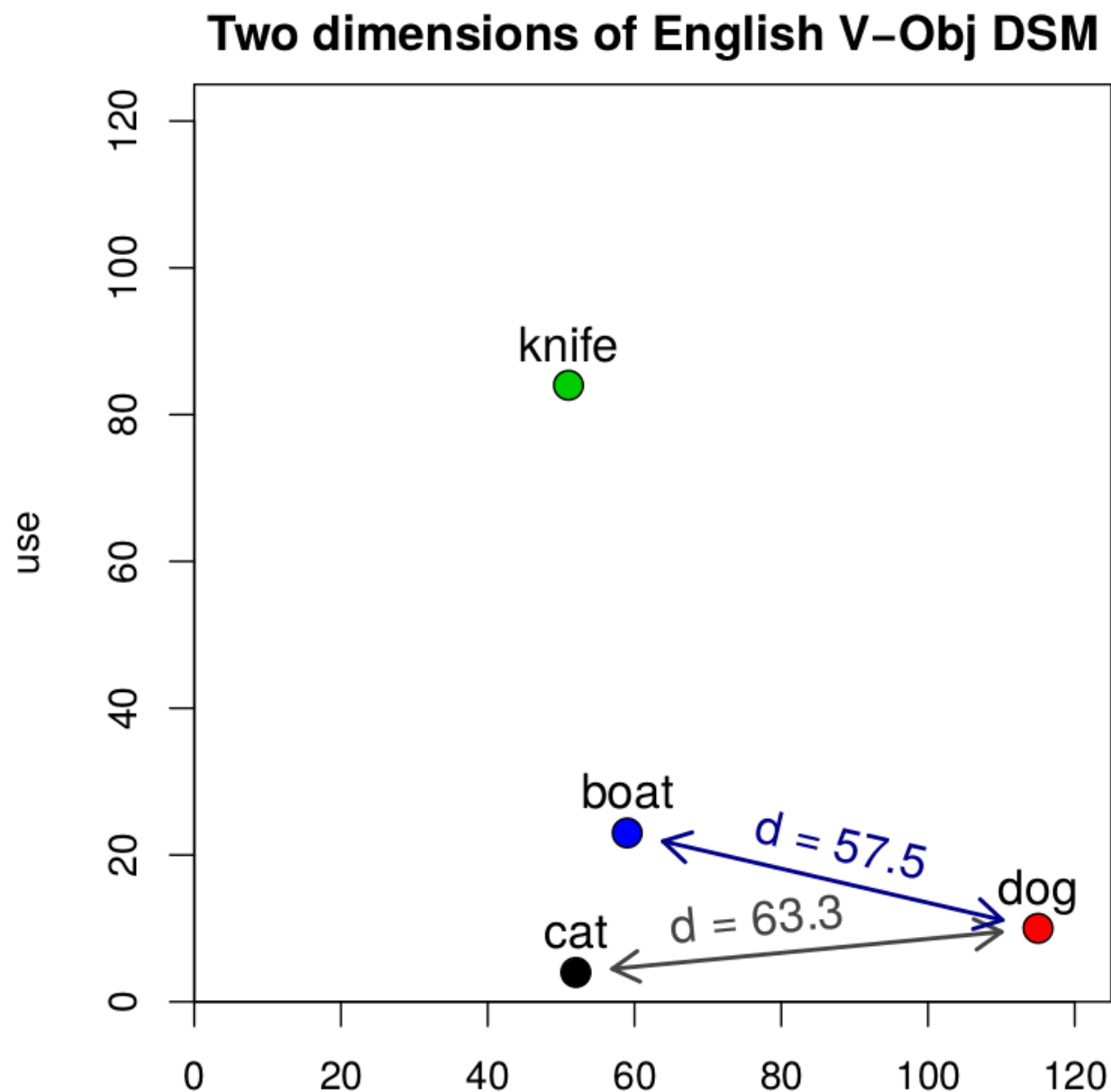
Geometric interpretation

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



Geometric interpretation

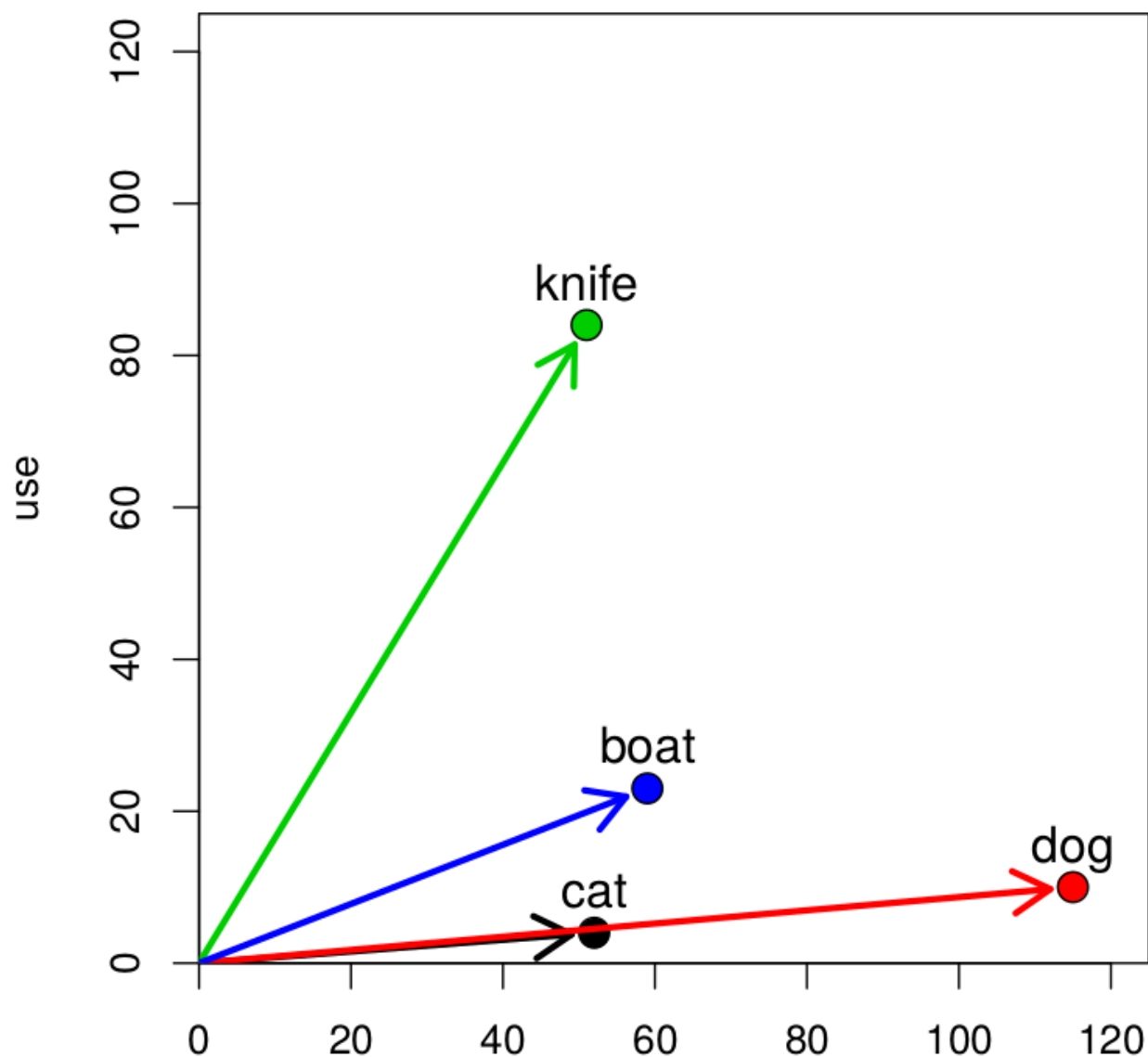
- ▶ similarity = spatial proximity
(Euclidean dist.)
- ▶ location depends on frequency of noun
($f_{\text{dog}} \approx 2.7 \cdot f_{\text{cat}}$)



Geometric interpretation

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

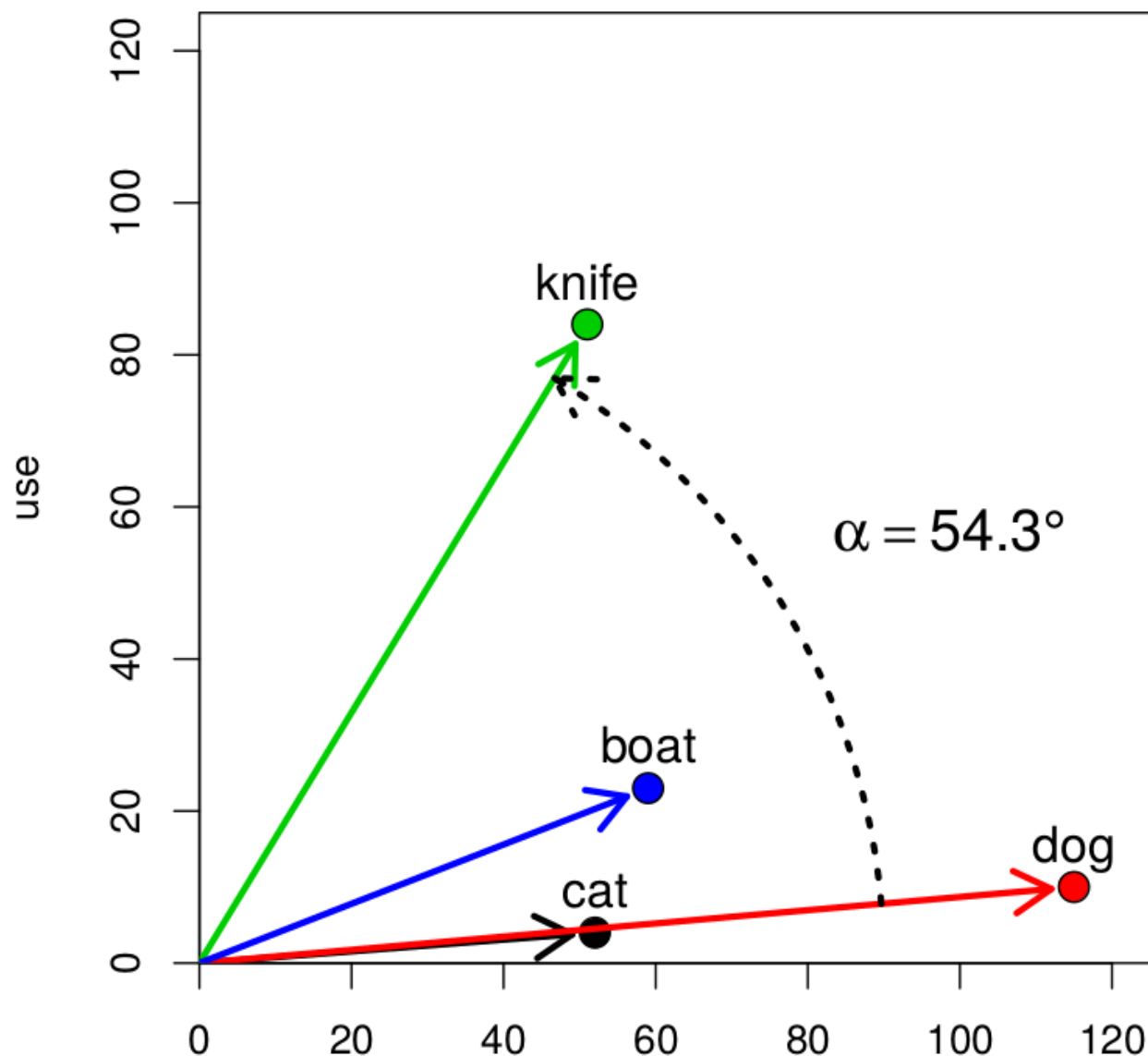
Two dimensions of English V-Obj DSM



Geometric interpretation

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

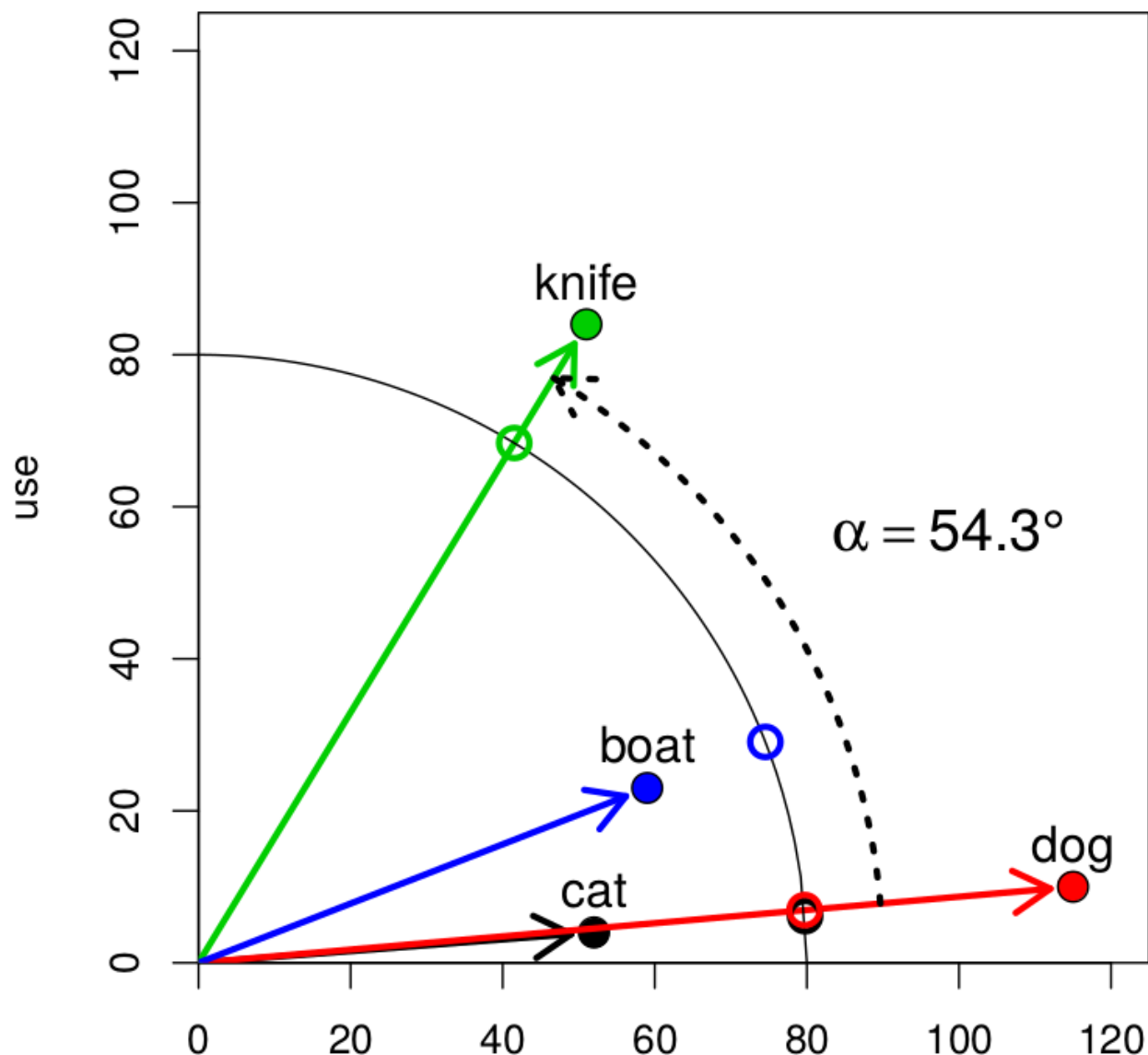
Two dimensions of English V-Obj DSM



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

Two dimensions of English V-Obj DSM




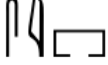


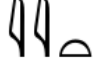
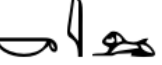







General definition of DSMs

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.


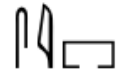

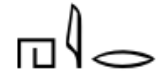
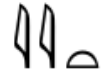
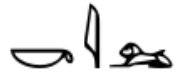

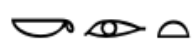





| | get | see | use | hear | eat | kill |
|--------|--------|--------|--------|--------|--------|--------|
| knife | 0.027 | -0.024 | 0.206 | -0.022 | -0.044 | -0.042 |
| cat | 0.031 | 0.143 | -0.243 | -0.015 | -0.009 | 0.131 |
| dog | -0.026 | 0.021 | -0.212 | 0.064 | 0.013 | 0.014 |
| boat | -0.022 | 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, ...

A thought experiment: deciphering hieroglyphs


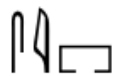











| | |  |  |  |  |  |  |
|----------|---|--|---|---|---|---|---|
| (knife) |  | 51 | 20 | 84 | 0 | 3 | 0 |
| (cat) |  | 52 | 58 | 4 | 4 | 6 | 26 |
| ??? |  | 115 | 83 | 10 | 42 | 33 | 17 |
| (boat) |  | 59 | 39 | 23 | 4 | 0 | 0 |
| (cup) |  | 98 | 14 | 6 | 2 | 1 | 0 |
| (pig) |  | 12 | 17 | 3 | 2 | 9 | 27 |
| (banana) |  | 11 | 2 | 2 | 0 | 18 | 0 |

A thought experiment: deciphering hieroglyphs

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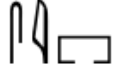



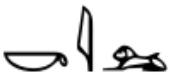







$$\text{sim}(\text{triangle, vertical stroke, house}, \text{wavy line, lotus flower, vertical stroke}) = 0.770$$

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 |
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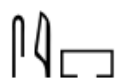

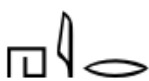
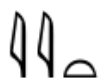
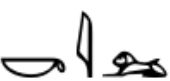







$$\text{sim}(\text{hand, vertical stroke, bowl}, \text{square, vertical stroke, bowl, vertical stroke, triangle}) = 0.939$$

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 |

$$\text{sim}(\text{hand, vertical line, triangle}, \text{oval, eye, semi-circle}) = 0.961$$

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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| pig |  | 12 | 17 | 3 | 2 | 9 | 27 |
| banana |  | 11 | 2 | 2 | 0 | 18 | 0 |

Nearest neighbours

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

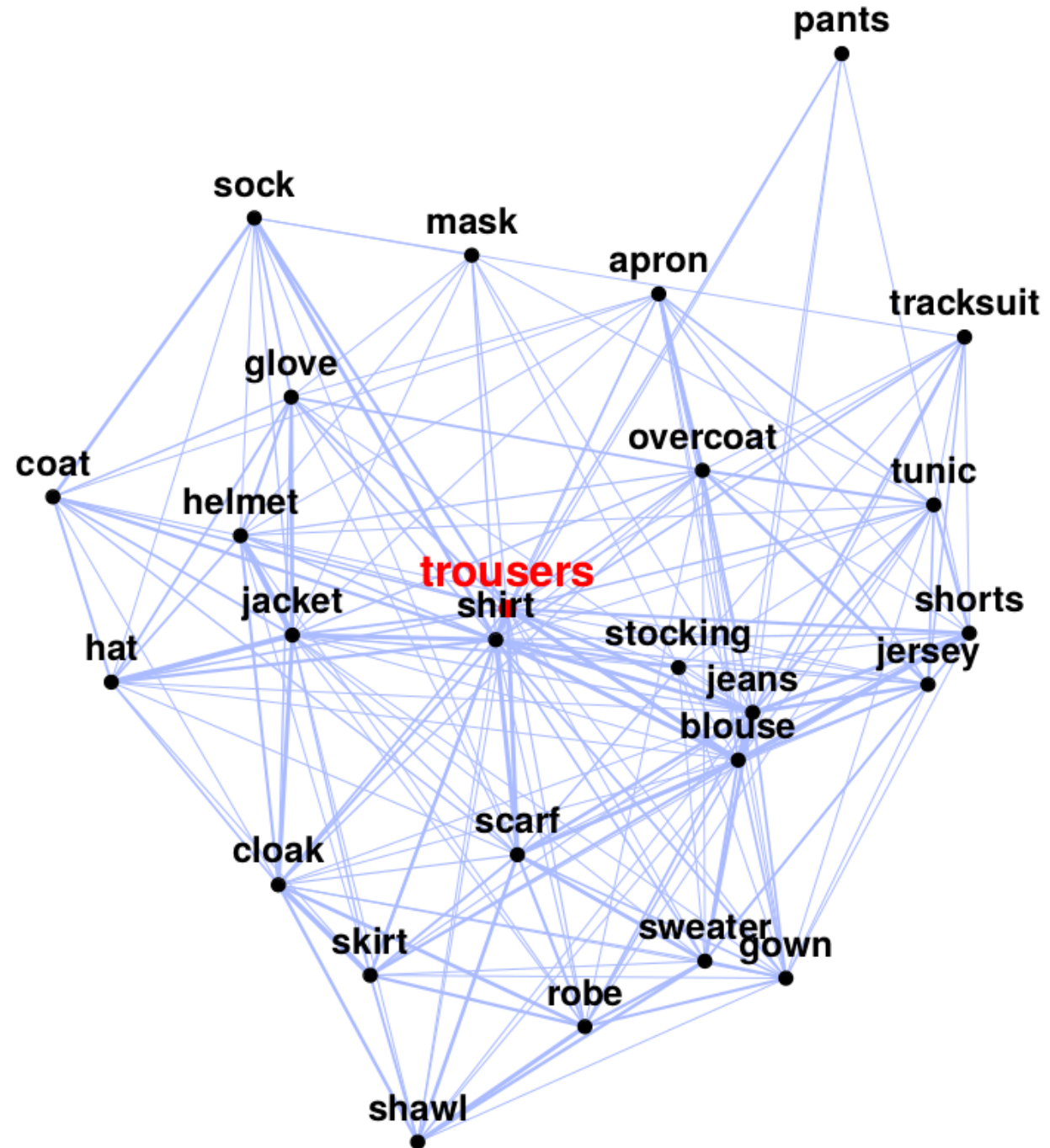
Neighbours of **trousers** (cosine angle):

👉 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), ...

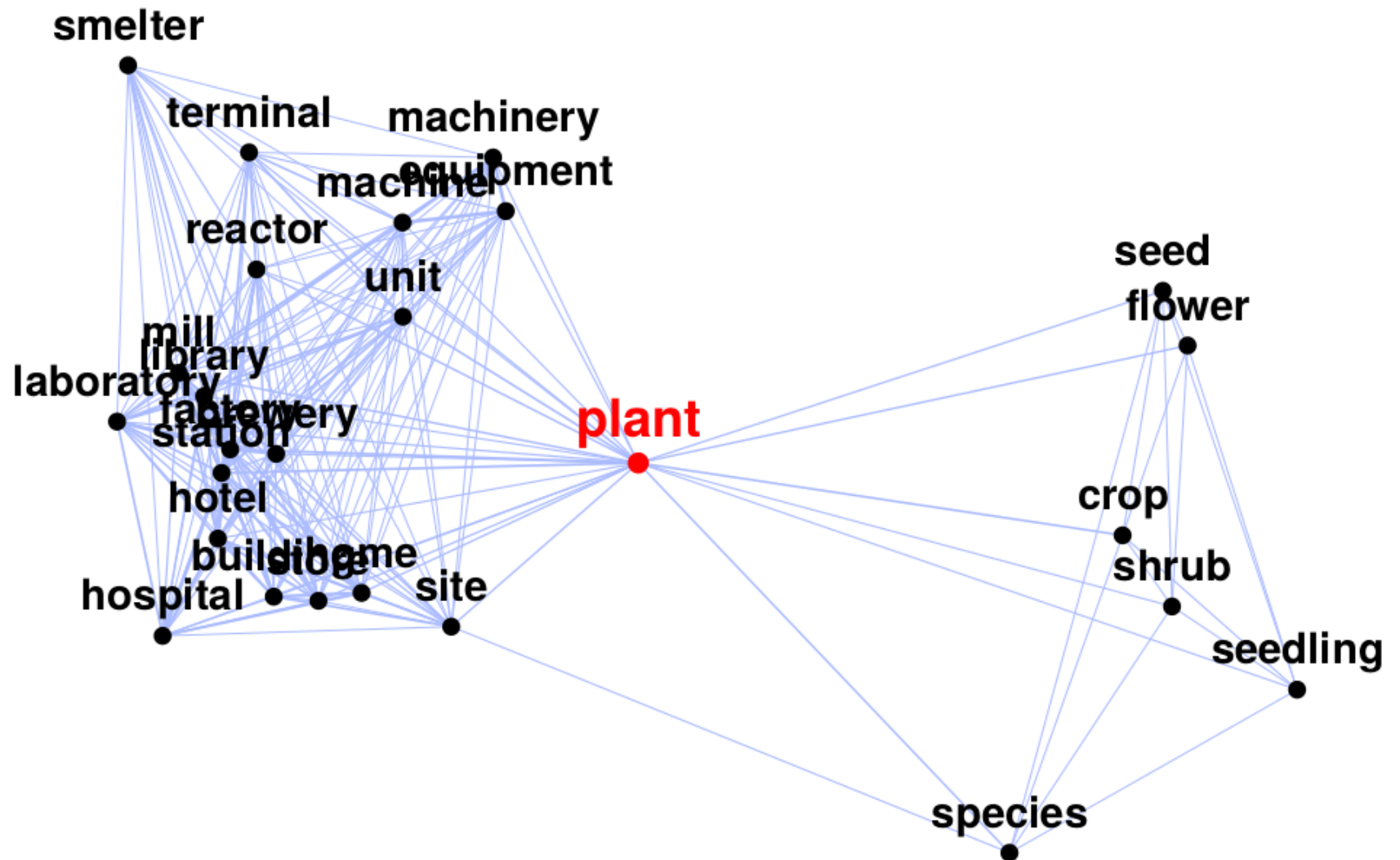
Neighbours of **rage** (cosine angle):

👉 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), ...

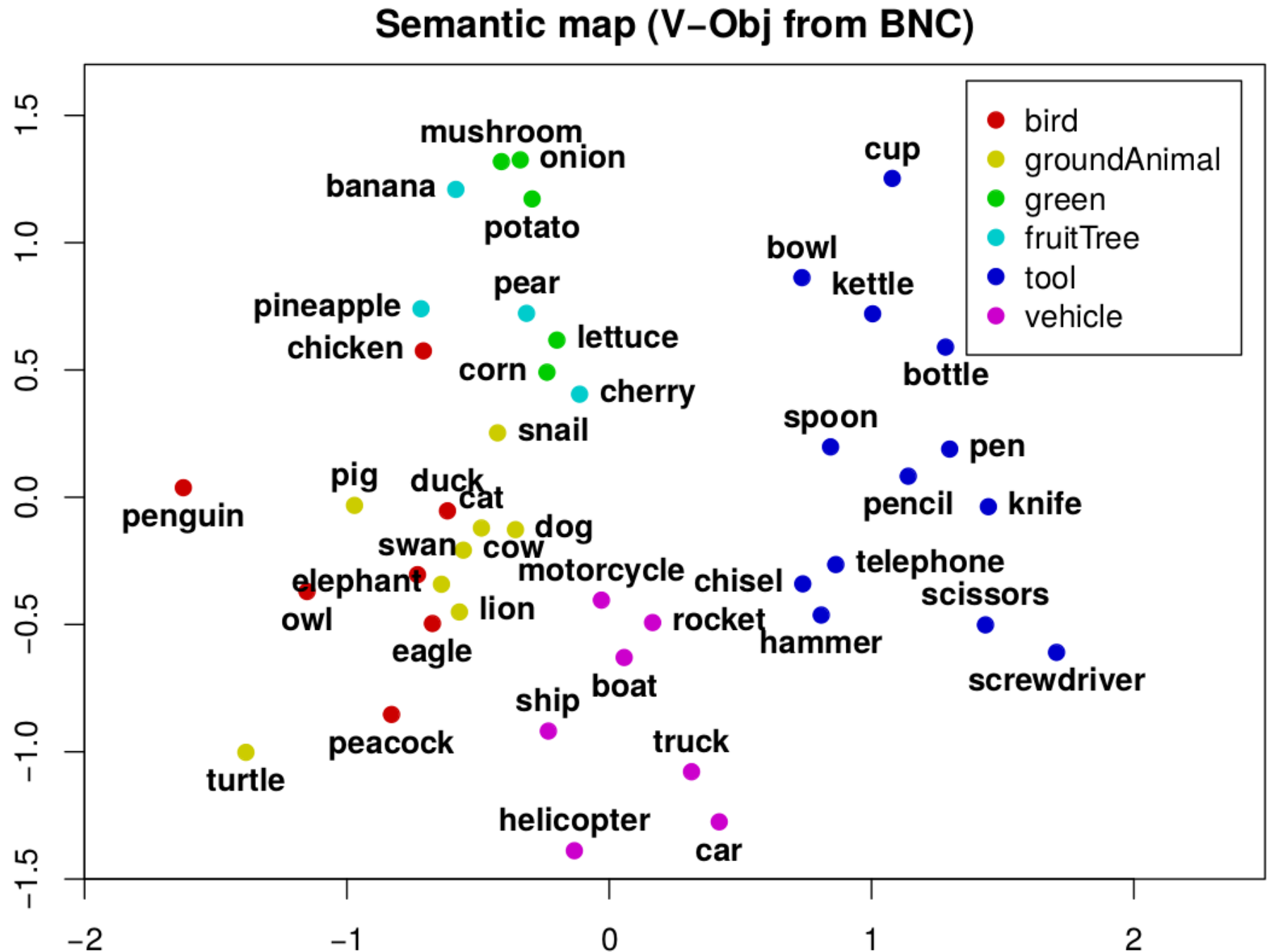
Nearest neighbours with similarity graph



Nearest neighbours with similarity graph

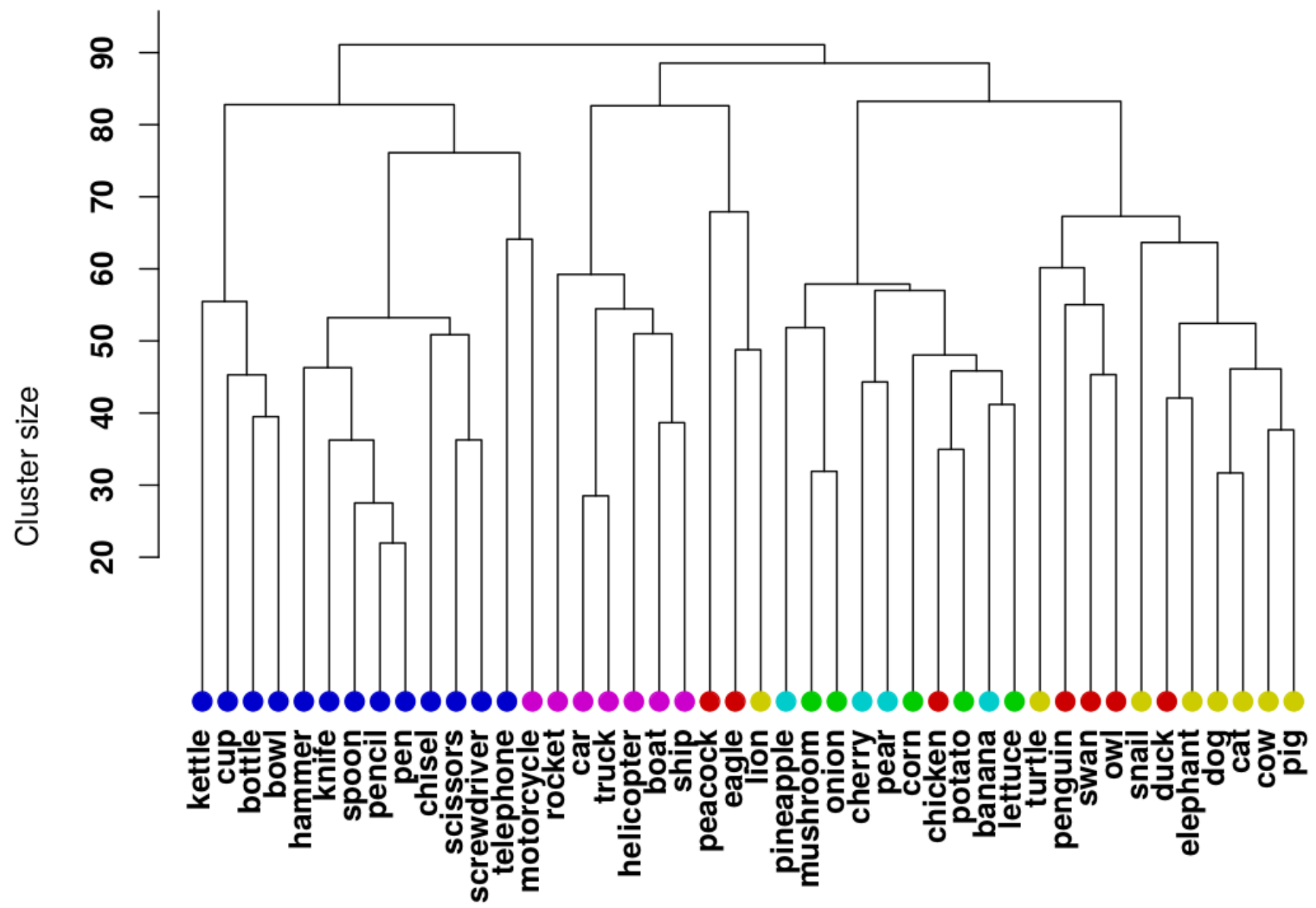


Semantic maps



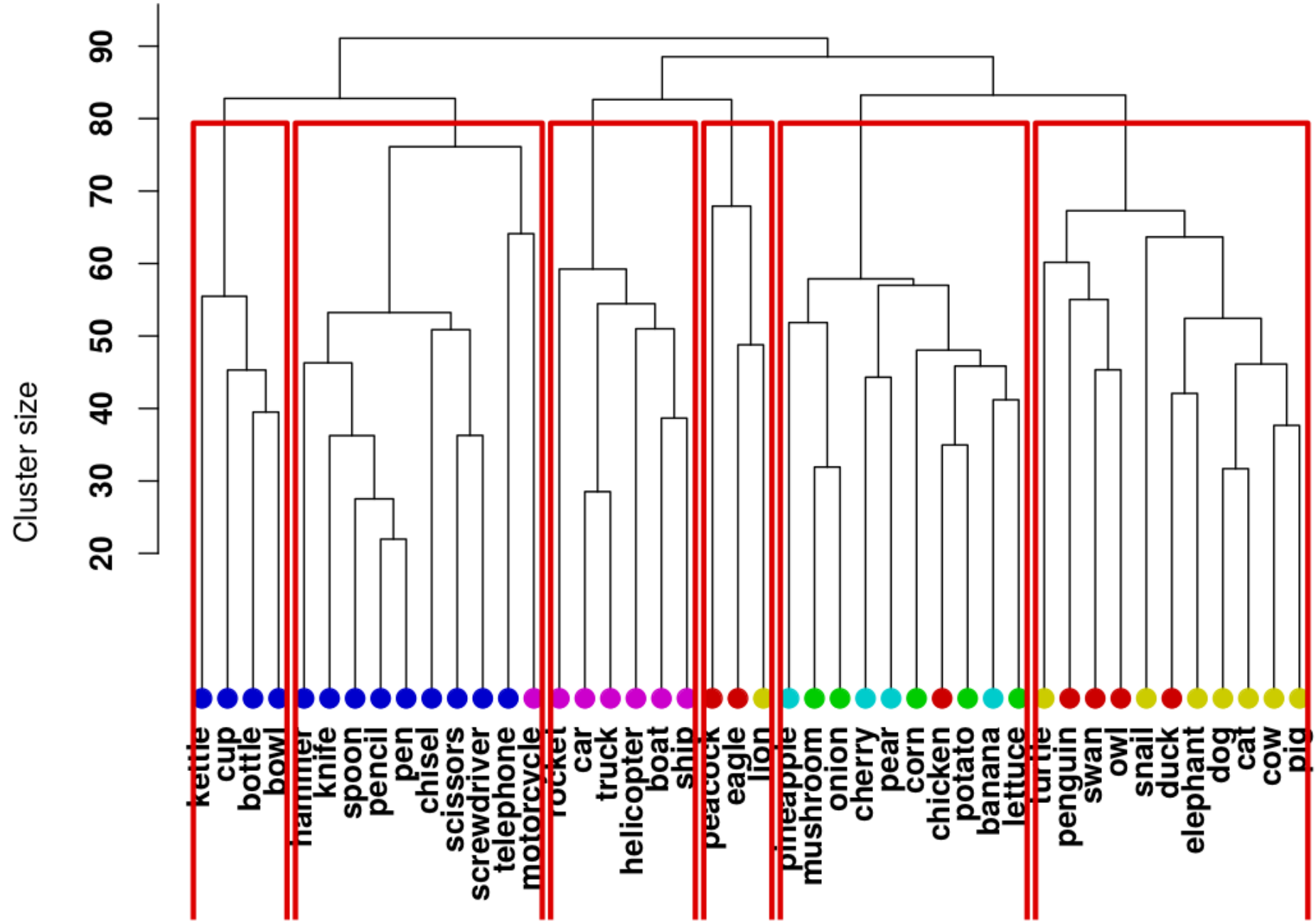
Clustering

Clustering of concrete nouns (V-Obj from BNC)



Clustering

Clustering of concrete nouns (V-Obj from BNC)



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.

Assignment 1.1

- a) Given an English corpus construct a term-term co-occurrence matrix
- b) Compute and display top 10 similar words in the corpus

(The corpus will be provided to you. You only need to construct the cooccurrence matrix)

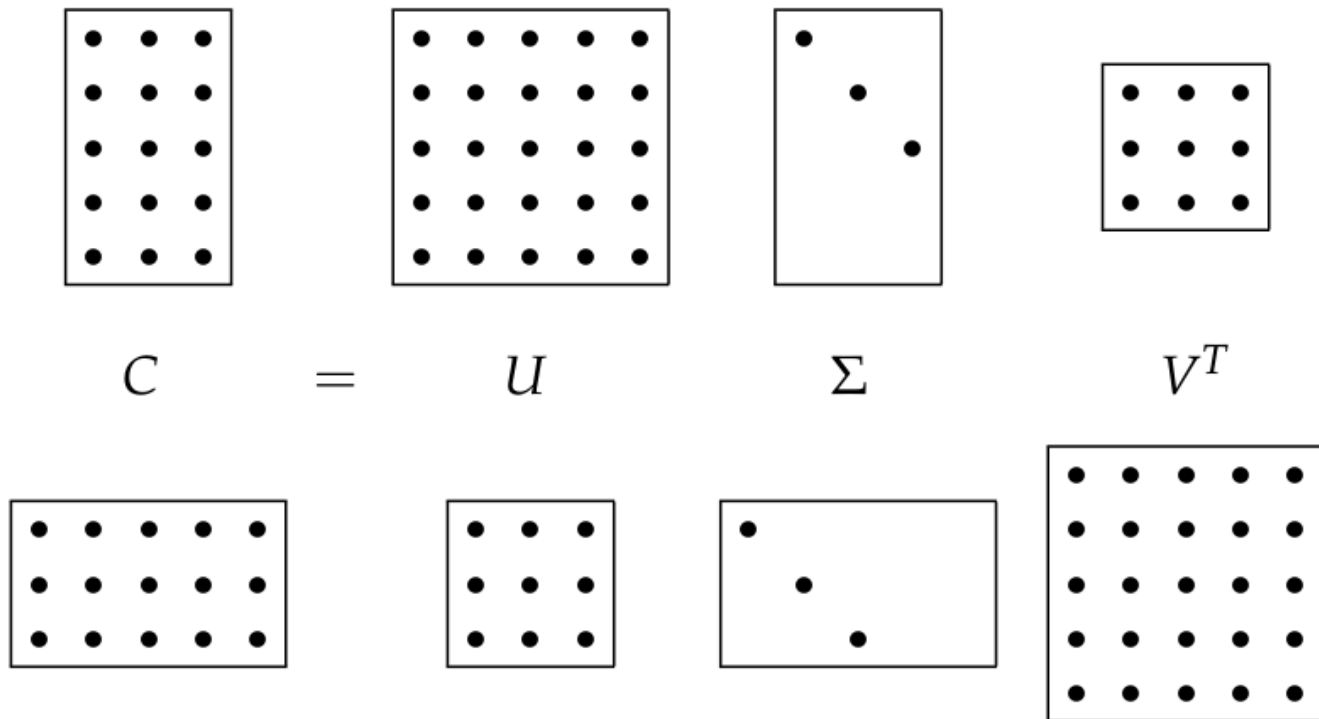
Real world scenerio: Sparce matrix

| | i | love | playing | cricket | sachin | is | a | cricketer | played | using | bat | and | ball | sourav | plays | sachine | the | highest | test | scorer | maradona |
|-----------|---|------|---------|---------|--------|----|---|-----------|--------|-------|-----|-----|------|--------|-------|---------|-----|---------|------|--------|----------|
| football | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| i | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| love | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| playing | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| cricket | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| sachin | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| is | 0 | 0 | 0 | 1 | 1 | 0 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| a | 0 | 0 | 0 | 0 | 1 | 2 | 2 | 1 | 1 | 1 | 2 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| cricketer | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| played | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| using | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| bat | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| and | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| ball | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| sourav | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| plays | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 |
| sachine | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| the | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| highest | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 |
| test | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 0 |
| scorer | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| maradona | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| football | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |

SVD: Intuition

- Singular Value Decomposition

$$C = U\Sigma V^T$$



Semantics

Wordnet

Wordnet

- **A lexical knowledgebase based on conceptual lookup**

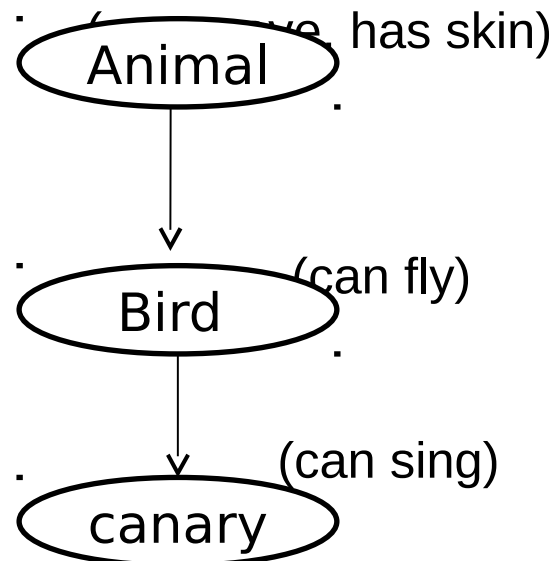
Organizing concepts in a semantic network.

- **Organize lexical information in terms of word meaning, rather than word form**

Wordnet can also be used as a thesaurus.

Psycholinguistic Theory

- Human lexical memory for nouns as a hierarchy.
- *Can canary sing?* - *Pretty fast response.*
- *Can canary fly?* - *Slower response.*
- *Does canary have skin?* – *Slowest response.*



Wordnet - a lexical reference system based on psycholinguistic theories of human lexical memory.

Relational and Componential Semantics

Relational Semantics (Words can disambiguate each other) **vs.** Componential Semantics (Words need features for disambiguation)

Example



animal

An

expert

Possible Features: Animate, Human, Carnivorous, Small, Moving

Componential Semantics

Semantic Feature Vector for

cat (animal): $\langle 1, 0, 1, 1, 1 \rangle$

cat (expert): $\langle 1, 1, U, U, 1 \rangle$

Relational Semantics

cat (animal): {cat, feline}

cat (expert): {cat, expert}

Componential Semantics

- Consider *cat* and *tiger*.
Decide on *componential attributes*.

| | | | |
|-------|-------------|-------|--------------|
| Furry | Carnivorous | Heavy | Domesticable |
|-------|-------------|-------|--------------|

- For *cat* (Y, Y, N, Y)
- For *tiger* (Y,Y,Y,N)

**Complete and correct
Attributes are difficult
to design.**

Semantic relations in wordnet

1. Synonymy
2. Hypernymy / Hyponymy
3. Antonymy
4. Meronymy / Holonymy.