Semantics and meaning

http://compcogscisydney.org/psyc3211/

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*mild content notice for sexual/sexist language

Where are we?

- L1: Connectionism
- L2: Statistical learning
- L3: Semantic networks
- L4: Wisdom of crowds
- L5: Cultural transmission
- L6: Summary

Structure of the lecture

- Refresher:
  - Semantic priming
  - Semantic networks
- The small world of words project
- Structure in semantic networks:
  - Local structure
  - Remote associations
  - Large scale structure
- Semantic networks of individuals
- Semantic networks over development

“You shall know a word by the company it keeps”
- John Firth, 1957

“The interest of psychologists in associations has always been misguided because the whole classical analysis of associations centered around the circumscribed and uninteresting problem of stimulus - response, of what follows what.”
- James Deese, 1965

Semantic priming (Meyer 2014)

Semantic priming well established

AMIDST THE RECENT furor over failures to replicate some empirical results on behavior priming by social psychologists ("Fresh misconduct charges hit Dutch social psychology," F. v. Kolfschooten, News & Analysis, 9 May, p. *566*; "Replication effort provokes praise—and 'bullying' charges," J. Bohannon, In Depth, 23 May, p. 788; "Psychologist's defense challenged," F. v. Kolfschooten, In Depth, 30 May, p. 957), it is important to emphasize that some basic behavior-priming effects are real, robust, and easily replicable even if others are much more problematic.

For example, if an English reader is presented with a printed word like "dog," then on average, s/he will be at least 10 to 20% faster at recognizing and responding to a subsequent associated word like "cat" when it is presented within a few seconds after the previous word. This psychological phenomenon, called "semantic priming," has been demonstrated many times during past decades; the mental processes and brain mechanisms that mediate it are at least moderately well understood (*1–3*). Many other highly reliable priming phenomena like this have been found in human perception, memory, and language processing (*4*). Consequently, in his 23 May In Depth story, J. Bohannon's statement that "...for behavior priming...the results [of recent replication attempts] are particularly grim" should have been much more carefully qualified.

To be specific, the recent failed replication attempts concern much more exotic types of putative behavior priming [e.g., the ones reported originally in (*5–8*); see (*9*)]. Viewed from a metaphorical perspective, what some social psychologists have done is essentially like trying to show that presenting the printed word "dog" may incline English-reading adult male humans more toward visiting remote "cathouses" (slang for brothels) even after substantial amounts of time (several minutes or more) have elapsed since the original exposure to "dog." Much further research is needed for assessing to what extent such behavior-priming effects are real. Meanwhile, until the necessary research has been completed, journalists in the public news media [e.g., (*10*)] and scientist authors of popular best-selling books [e.g., (*11*)] that prominently tout these less-substantiated, albeit intriguing, phenomena should treat them with considerable caution, uncertainty, and skepticism.

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9. For example, Bargh *et al.* (*5*) claimed that surreptitiously exposing college students to printed words like "bingo," "gray," and "Florida," which may be related to old age in the United States, primed them to walk more slowly as they later exited the laboratory. However, multiple failures to replicate this specific behavior-priming effect have been subsequently reported (*12*, *13*).
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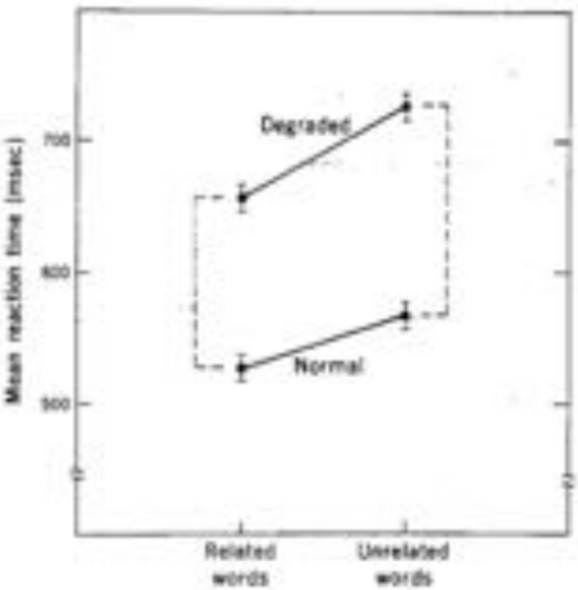
11. D. Kahneman, *Thinking: Fast and Slow* (Farrar, Straus, and Giroux, New York, 2011).
12. S. Doyen *et al.*, *PLOS One* **7**, 1 (2012).
13. H. Pashler, C. Harris, N. Coburn, "Elderly-related words prime slow walking" (2011); http://psychfiledrawer.org/replication.php?attempt=MTU%3D.

Semantic priming

(Meyer and Schvaneveldt 1976)



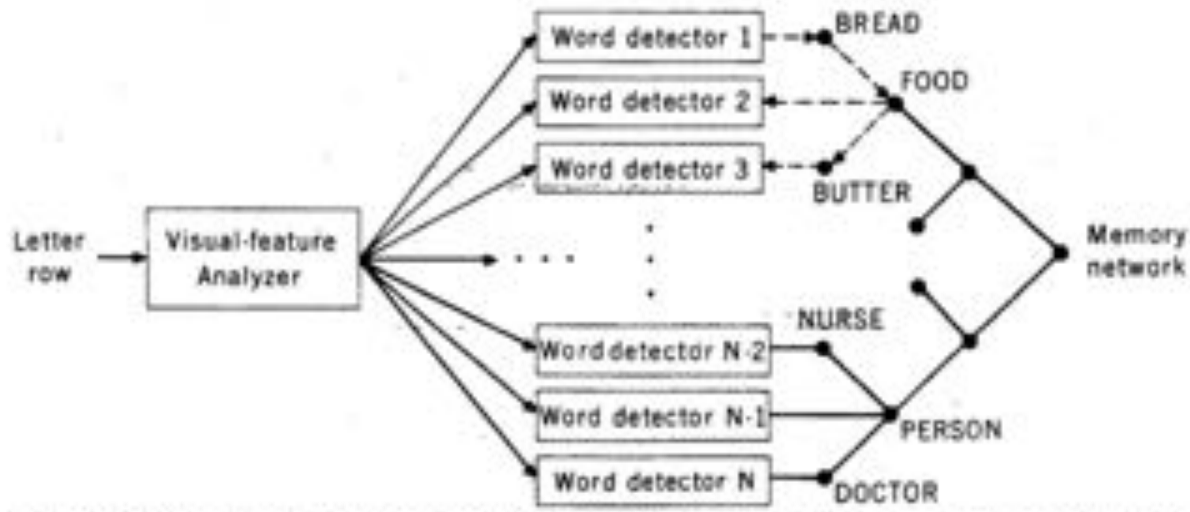


Fig. 5 (left). Mean reaction times (± 1 standard error) to recognize the second words from pairs with related or unrelated meanings and normal or degraded letters. Dashed brackets indicate the different effects of degradation as a function of the words' semantic relations. Fig. 6 (right). Outline of a model for combining sensory and semantic information to recognize printed words. Dashed lines indicate the possible spread of excitation from the detector of one word (for example, BREAD) to the detectors of other related words (for example, FOOD and BUTTER).

Semantic networks

(Collins & Loftus 1975)

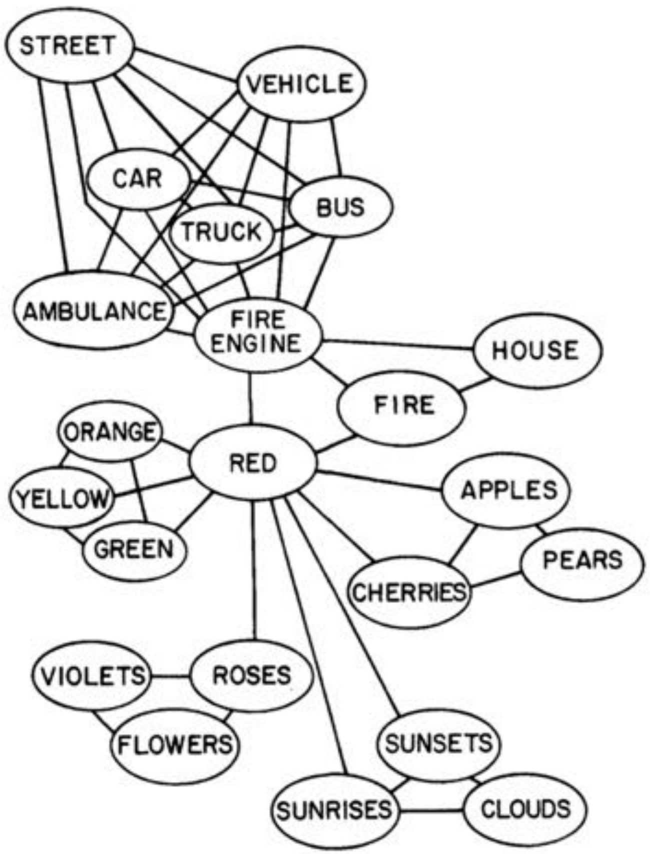


FIGURE 1. A schematic representation of concept relatedness in a stereotypical fragment of human memory (where a shorter line represents greater relatedness).

Semantic memory

- Concepts organized as nodes in a network
- Edges connect related concepts
- Edges can describe different relations
- Edges can be different lengths

Memory retrieval

- Activation spreads along the edges
- Activation decays over time

Spreading over <u>what</u>?

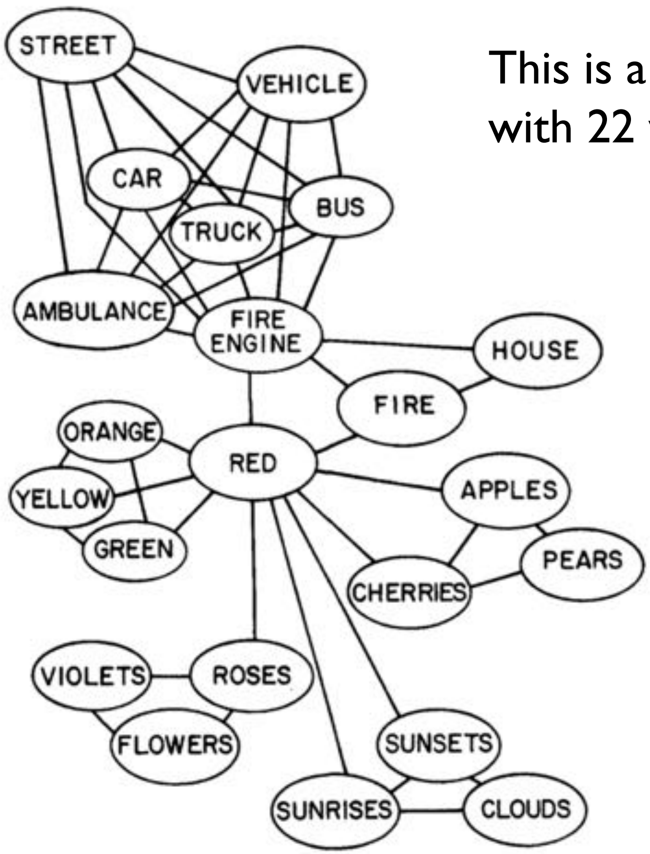
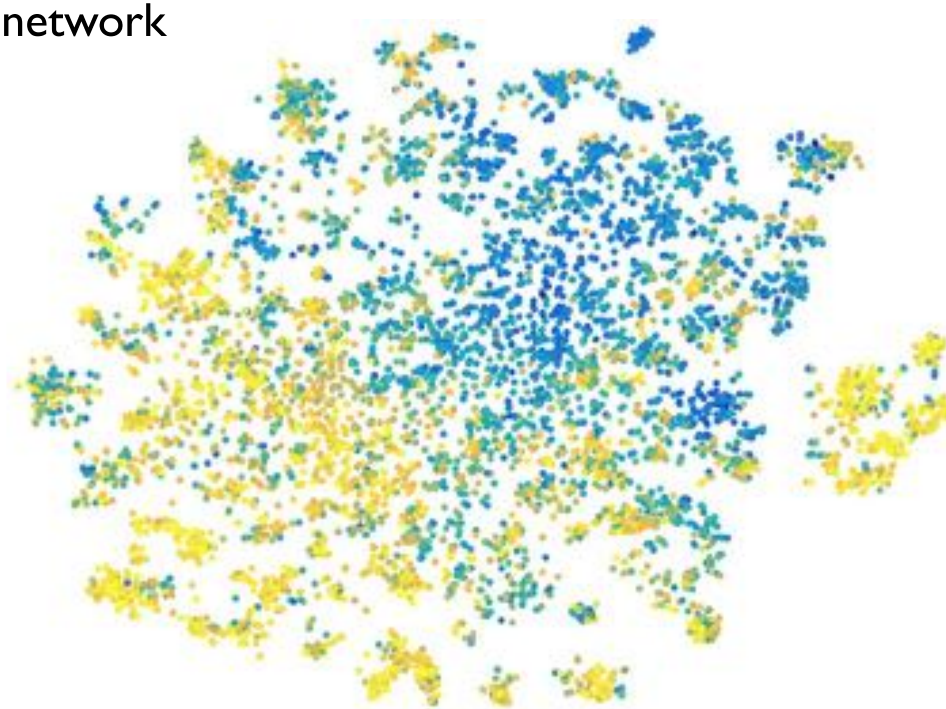


FIGURE 1. A schematic representation of concept relatedness in a stereotypical fragment of human memory (where a shorter line represents greater relatedness).

This is a simple network with 22 words



This is approximately 12,000 words

The "Small World of Words" English word association norms for over 12,000 cue words.

Simon De Deyne[1], Danielle J. Navarro[2], Amy Perfors[1], Marc Brysbaert[3], and Gert Storms[4]

[1]University of Melbourne, School of Psychological Sciences, 3010 VIC, Australia
[2]University of New South Wales, School of Psychology, 2052 NSW, Australia
[3]Ghent University, Department of Psychology, 9000 Ghent, Belgium
[4]KU Leuven, Department of Psychology, 3000 Leuven, Belgium

Abstract

Word associations have been used widely in psychology, but the validity of their application strongly depends on the number of cues included in the study and the extent to which they probe all associations known by an individual. In this work, we address both issues by introducing a new English word association dataset. We describe the collection of word associations for over 12,000 cue words, currently the largest such English-language resource in the world. Our procedure allowed subjects to provide multiple responses for each cue, which permits us to measure weak associations. We evaluate the utility of the dataset in several different contexts, including lexical decision and semantic categorization. We also show that measures based on a mechanism of spreading activation derived from this new resource are highly predictive of direct judgments of similarity. Finally, a comparison with existing English word association sets further highlights systematic improvements provided through these new norms.

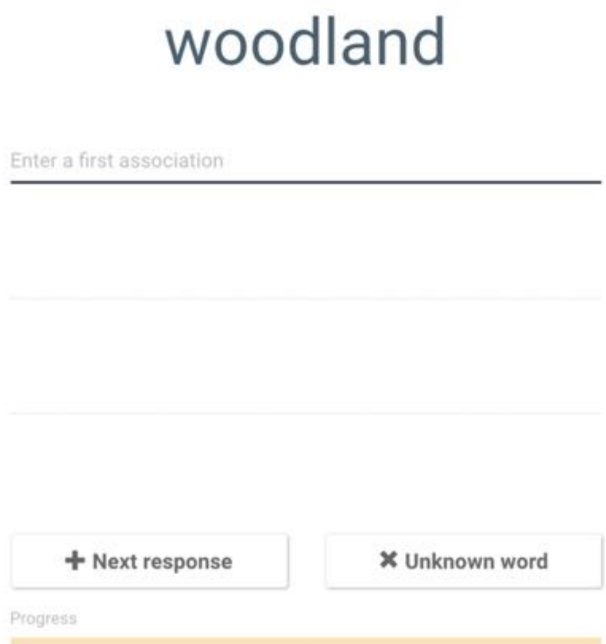
Keywords: Word associations, mental lexicon, networks, similarity, spreading activation

(De Deyne et al, in press)

https://smallworldofwords.org/en/project/home

The "small world of words" norms

(De Deyne et al, in press)



- Large scale online study
- 90,701 native English speakers
- 81% American English speakers
- 62% identified as female
- Average age 36
- Educated: 43% with college degree

- Participants shown a *cue* word
- Asked to type the first three *response* words that come to mind

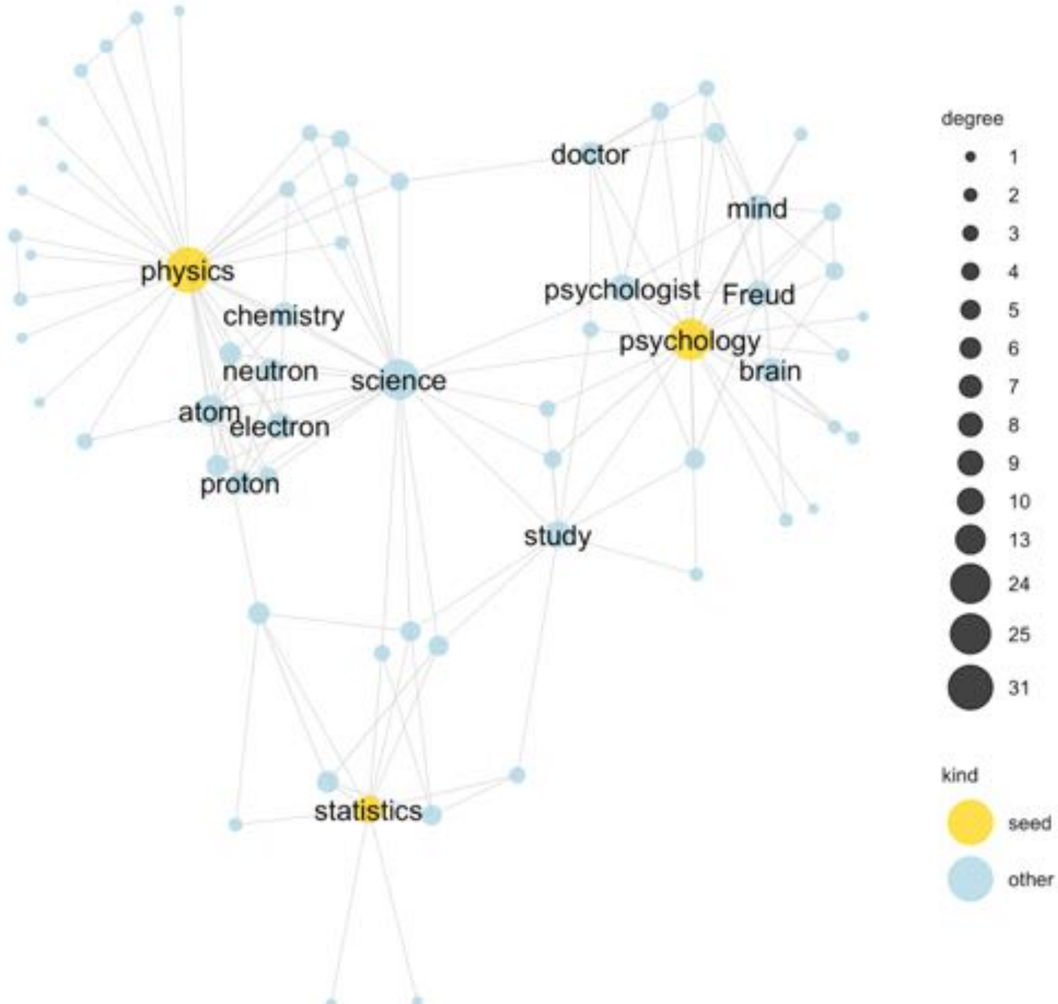
- Data for 12,292 cue words
- 100 participants per cue
- About 3.6 million responses

Local structure

- Construct a "neighbourhood" network by spreading from cue words

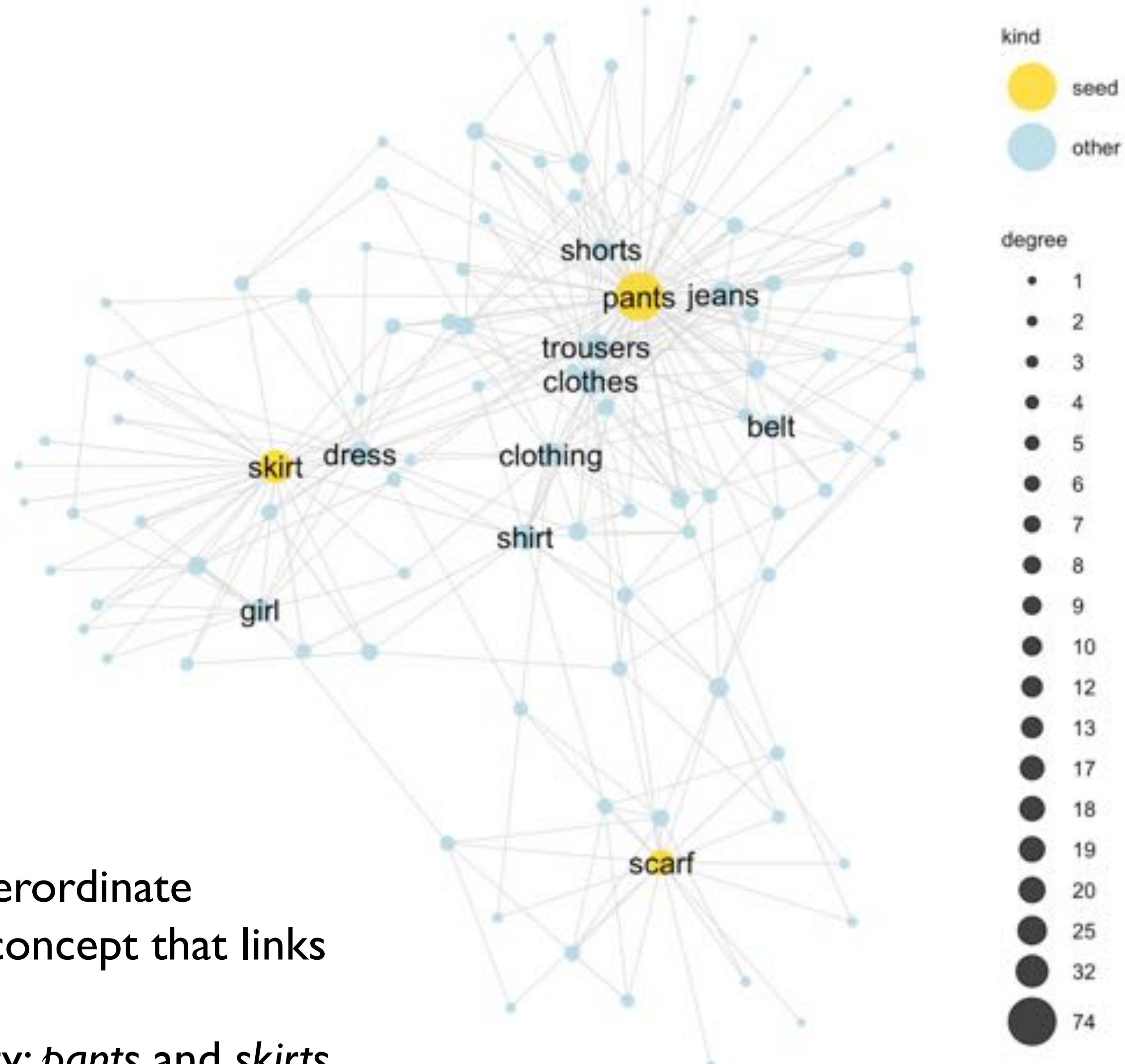
Example 1

- Cue: (*physics*, *psychology*, *statistics*)
- *Science* is the concept that links them together



(The layout is a data visualisation that tries to ensure that distances on the screen are similar to the distances in the network)

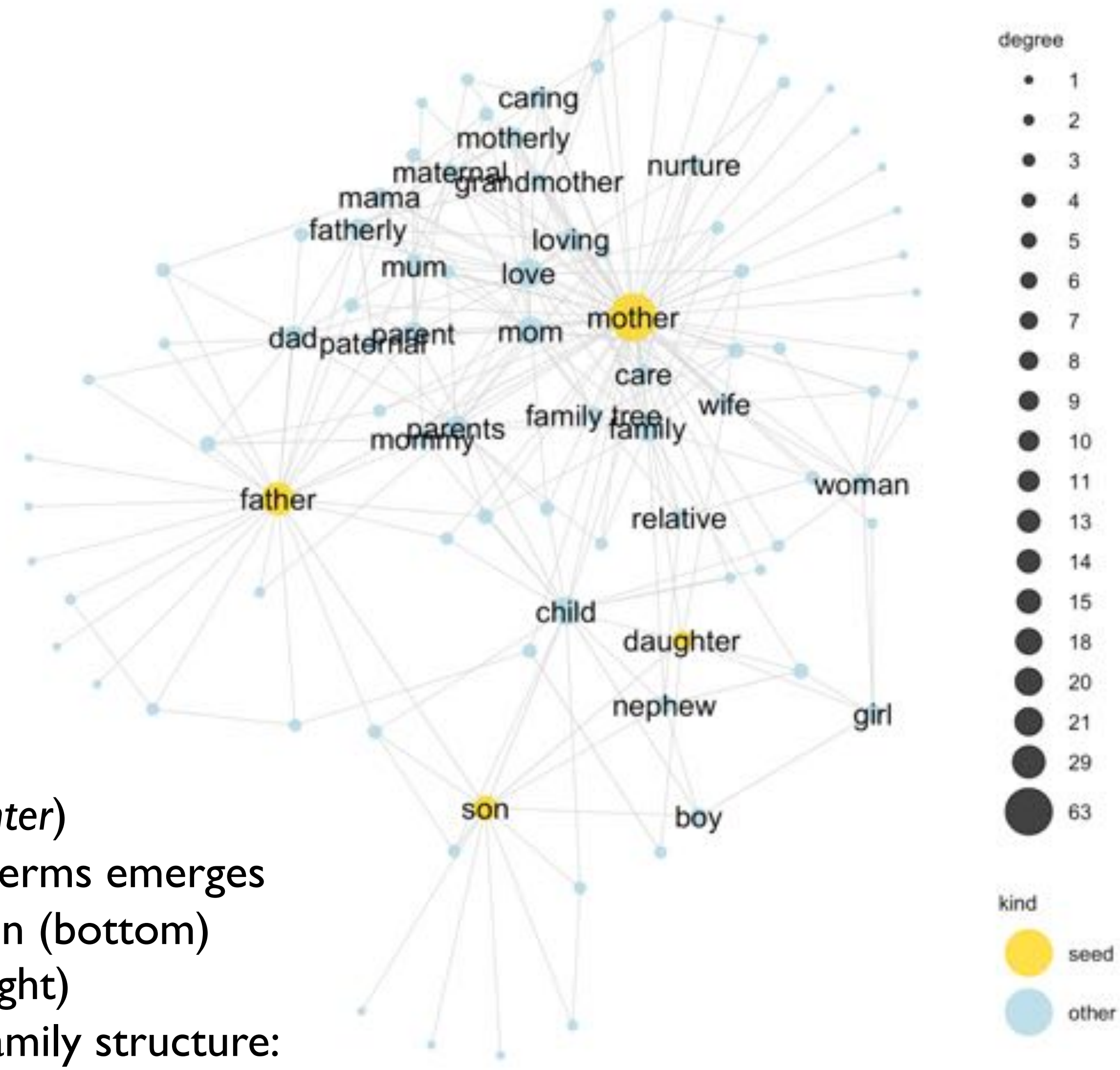
Local structure



Example 2

- Cue: (*pants*, *skirt*, *scarf*)
- Again we see the relevant superordinate category, *clothing*, arise as the concept that links them together
- The network encodes typicality: *pants* and *skirts* are “better” examples of *clothing* than *scarves*
- The network picks out other clothes

Local structure



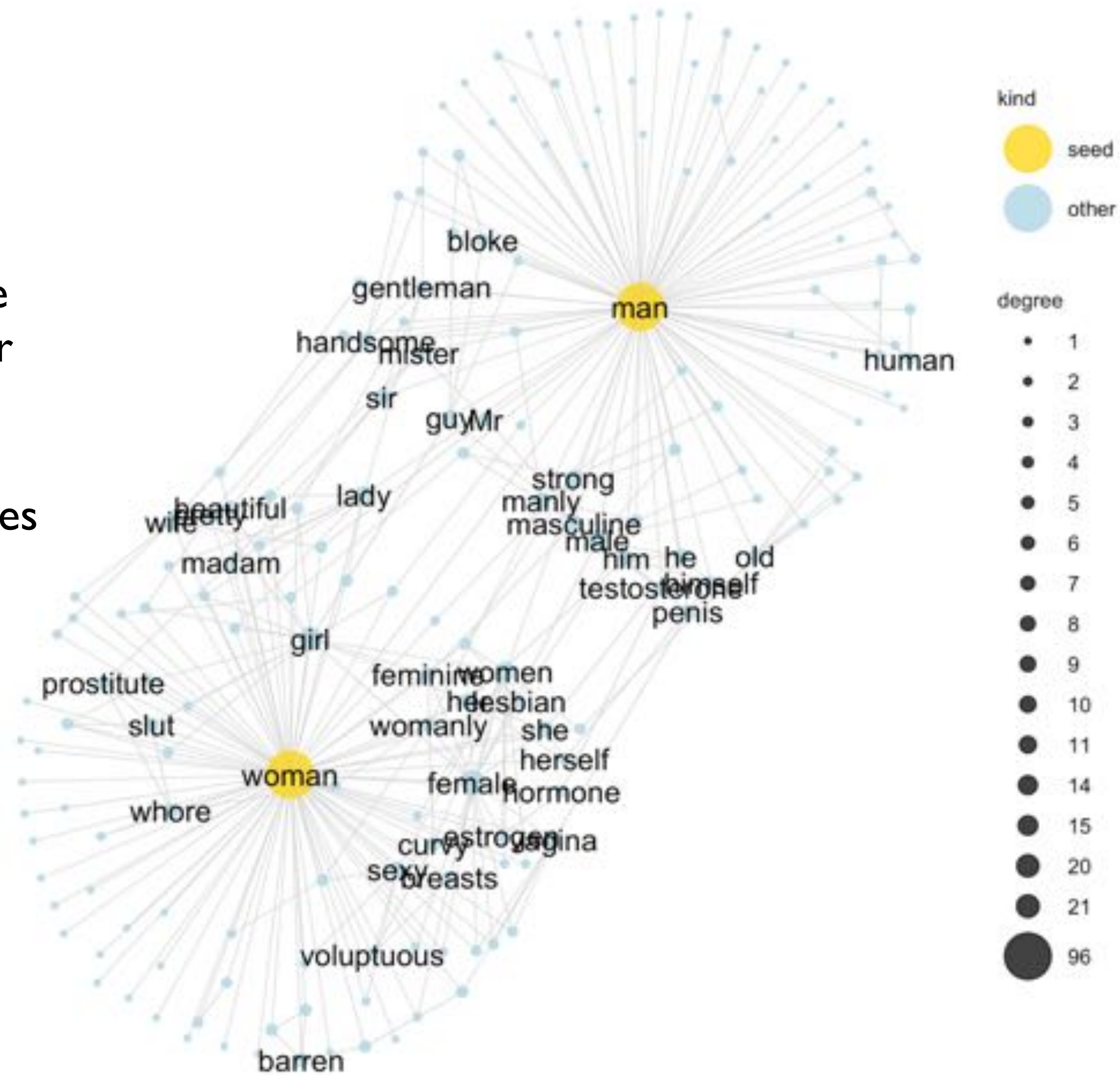
Example 3

- Cue: (*mother*, *father*, *son*, *daughter*)
- The <u>structure</u> of the kinship terms emerges
  - Parents (top) and children (bottom)
  - Male (left) and female (right)
- Encodes <u>assumptions</u> about family structure:
  - Mother is more central
  - Mother is more loving
  - Etc.

Local structure

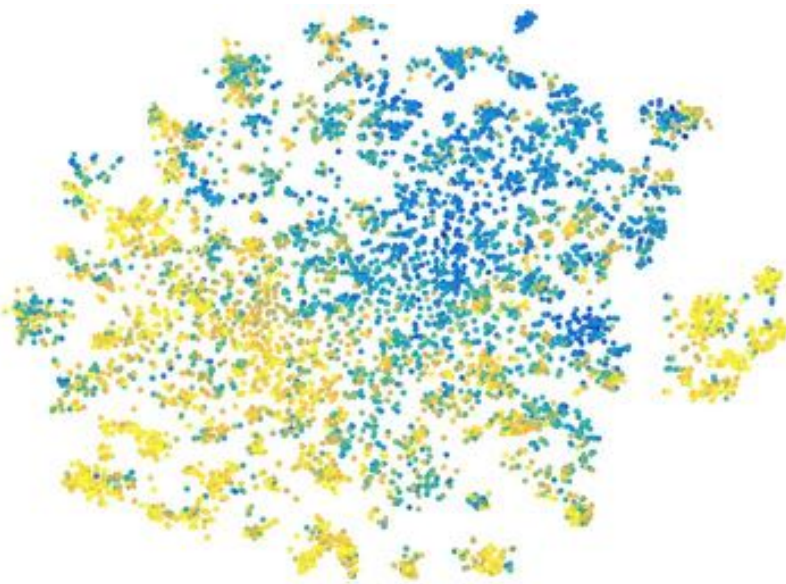
Example 4

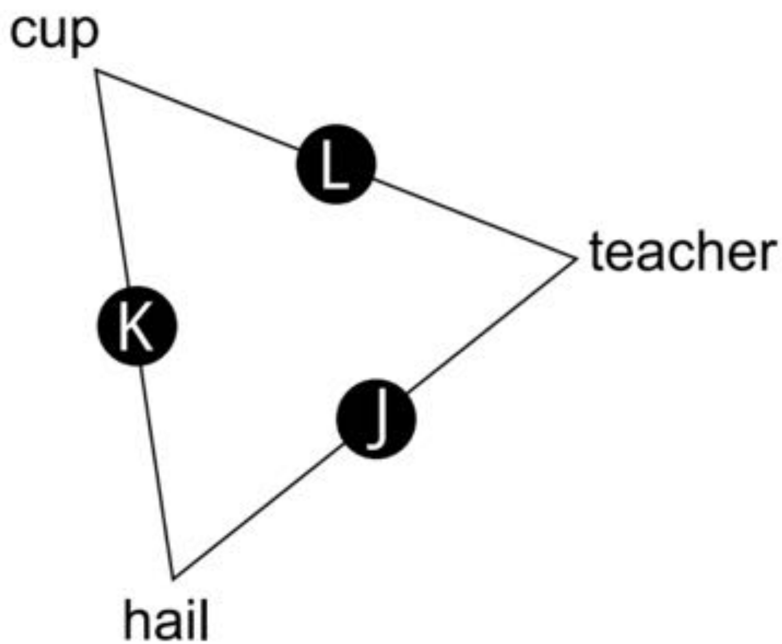
- Cue: (*man*, *woman*)
- The network encodes a lot of implicit knowledge and prejudices about our categories
- The semantic network encodes the gender biases in the language ☹



Non-obvious structure?

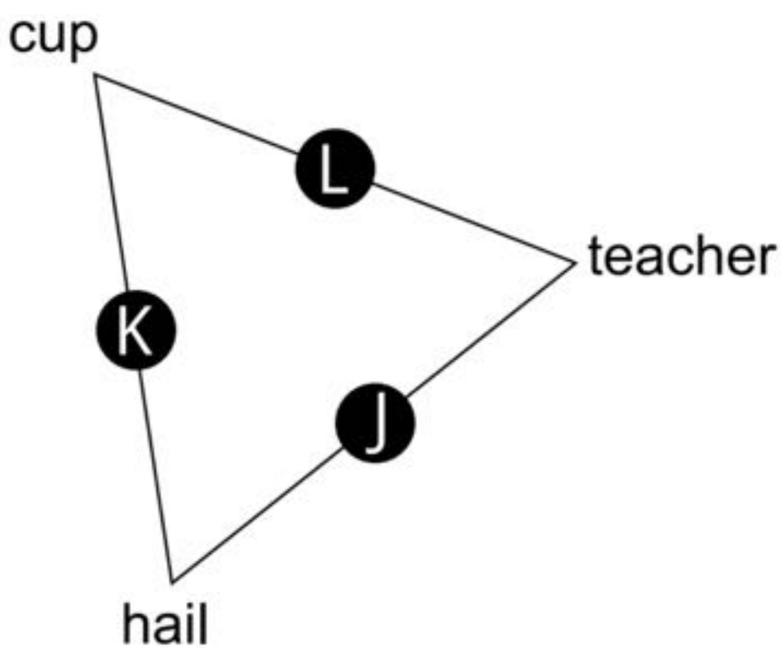
(Measuring remote associations)




cup
L
teacher
K
J
hail

Remote associations

(De Deyne et al 2016)

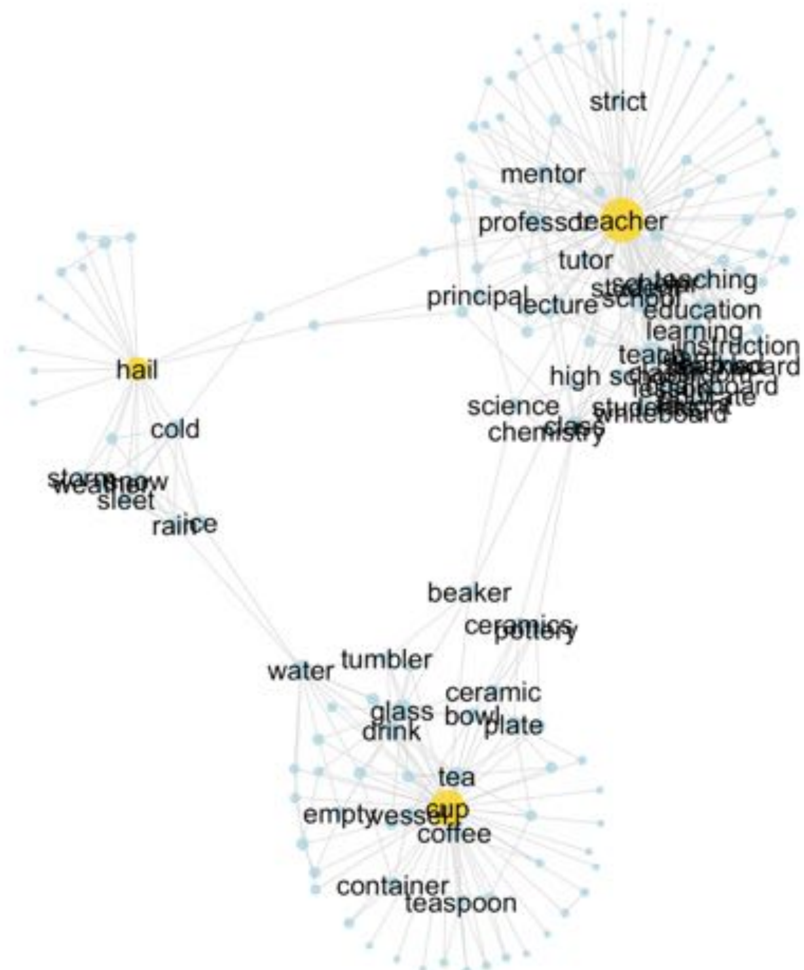


- Triad task: present people with three very dissimilar words, select the pair that is most similar
- e.g., click "L" for cup and teacher
- Task designed to match stimuli on various other measures (e.g., word frequency, abstractness)
- If semantic networks are genuinely capturing something other than just "strong relationships", we should be able to predict people's choices

Remote associations

(De Deyne et al 2016)

- There are no direct connections here
- There are more "short paths" connecting *cup* and *teacher* than either of the other two possibilities
- The network predicts that there should be a modest bias to prefer cup-teacher as the most similar pair



Remote associations

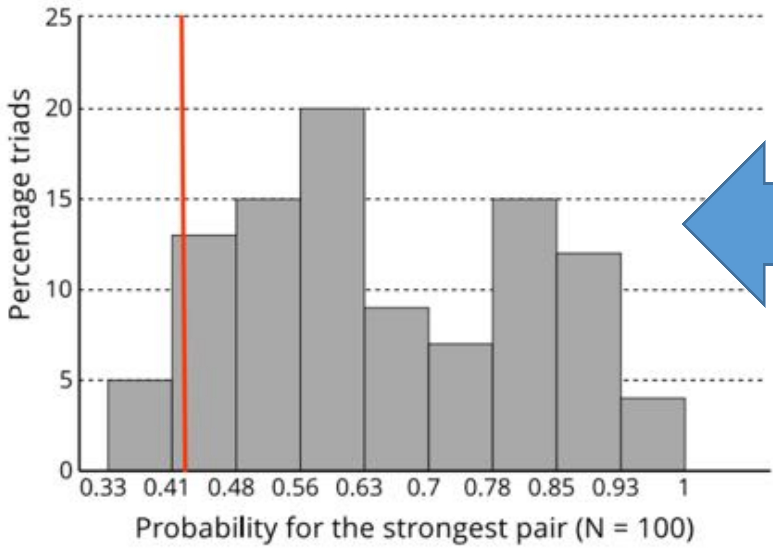
(De Deyne et al 2016)

Stimulus	English Translation
haan – rok – **sneeuw**	rooster – skirt – snow
kroon – **reus** – toeter	crown – giant – horn
kabel – **kruid** – **prop**	cable – weed – gag
idioot – **vitamine** – **zondag**	idiot – vitamin – Sunday
pastoor – **vleugel** – voetbal	pastor – wing – soccer ball
actie – klant – **slag**	action – customer – stroke
beroep – **gevaar** – rust	profession – danger – half time
afdak – beschuit – **elastiek**	overhang – rusk – elastic
paling – **stengel** – tunnel	eel – stem – tunnel
bom – gips – **haard**	bomb – plaster cast – fireplace
beker – hagel – **juf**	cup – hail – teacher
korst – **schrift** – **vlinder**	crust – writing – butterfly
akker – **deeg** – knuffel	field – dough – stuffed animal
horloge – koningin – **vierkant**	watch – queen – square
gewicht – lawaai – **oefening**	weight – noise – exercise
koffer – **mes** – plein	suitcase – knife – square
kwartier – **proef** – voertuig	quarter – test – vehicle

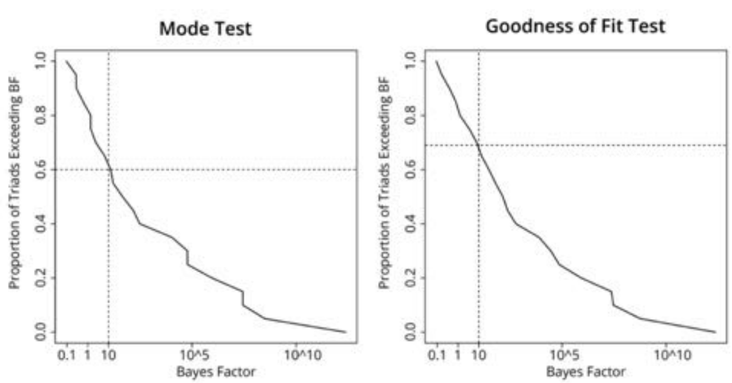
The predicted pair is the more commonly chosen

Remote associations

(De Deyne et al 2016)



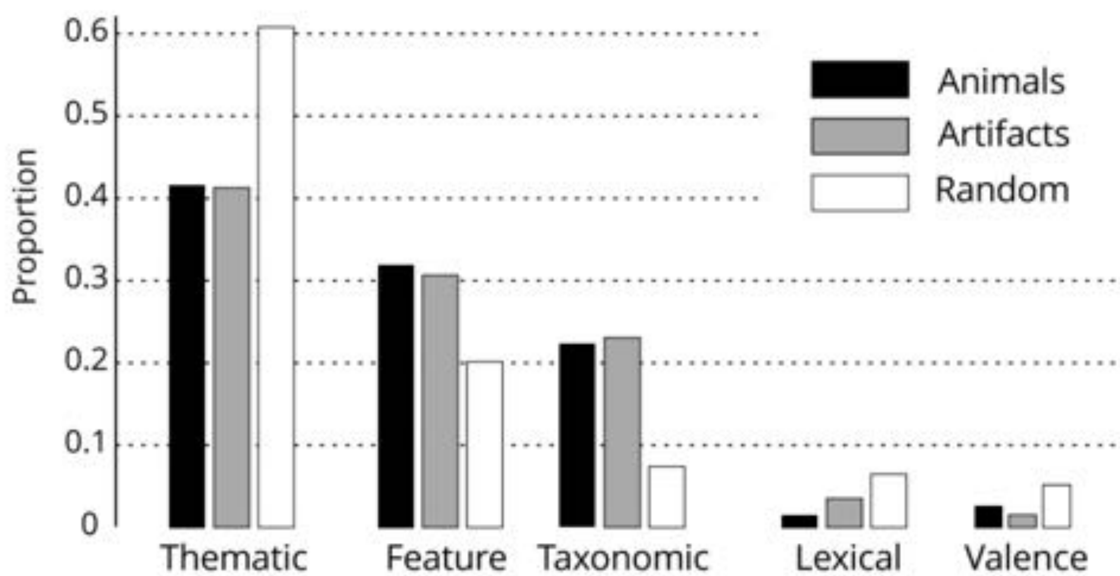
- Histogram of the proportion of people making the most-common choice, across triads
- There is a (surprising?) amount of agreement across people



(Hypothesis testing for this isn't trivial… details of the analysis not important for this class)

Remote associations

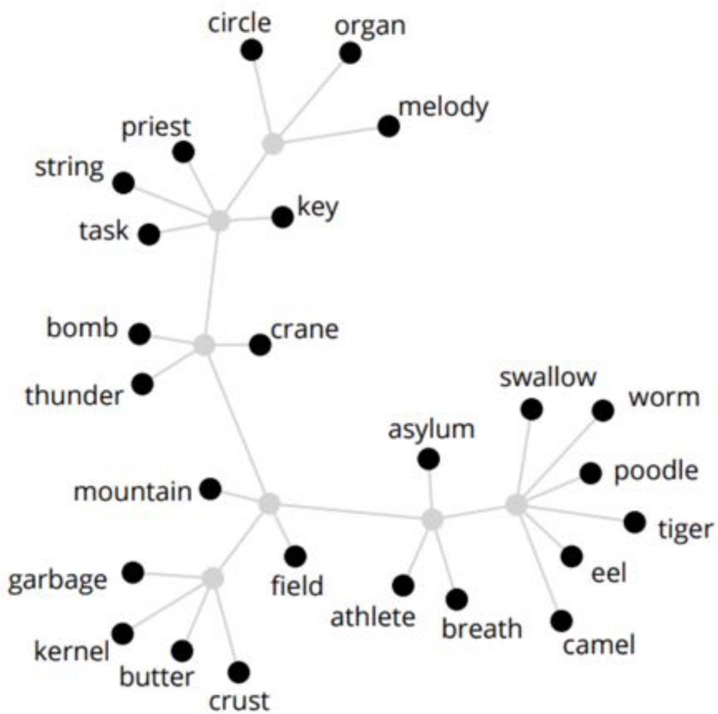
(De Deyne et al 2016)



- Maybe there's an unmeasured confound?
- Just *ask* people why they made their choices and see
- Doesn't *seem* to be anything systematic
- People give *lots* of different explanations/rationalisations for their choices!

Remote associations

(De Deyne et al 2016)



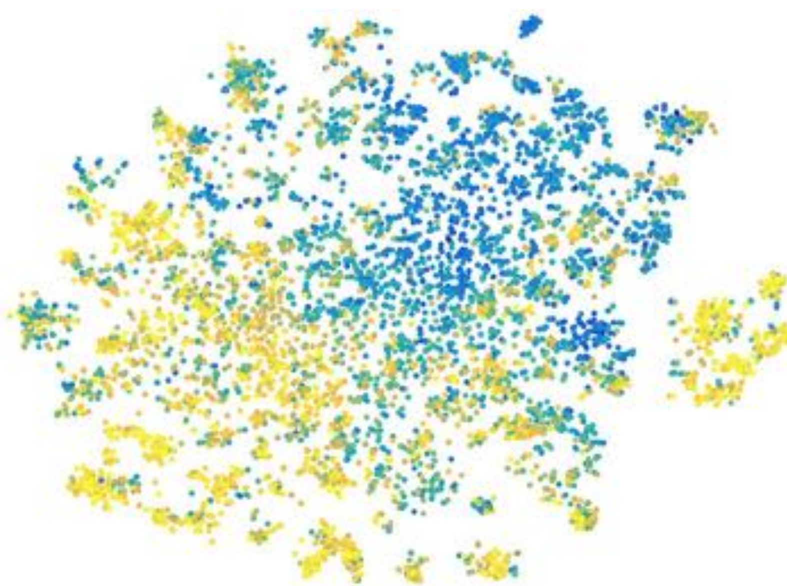
This "taxonomic" structure is pretty meaningless and misses lots of important details!

Why does a semantic network account work so well? I don't know

A suspicion:

- Networks can represent arbitrary structure easily
- Other methods we tried using (e.g., hierarchical, taxonomic structures) weren't very flexible and gave nonsense answers
- Might be as simple as… we have lots of data and a flexible tool for summarising it ☺

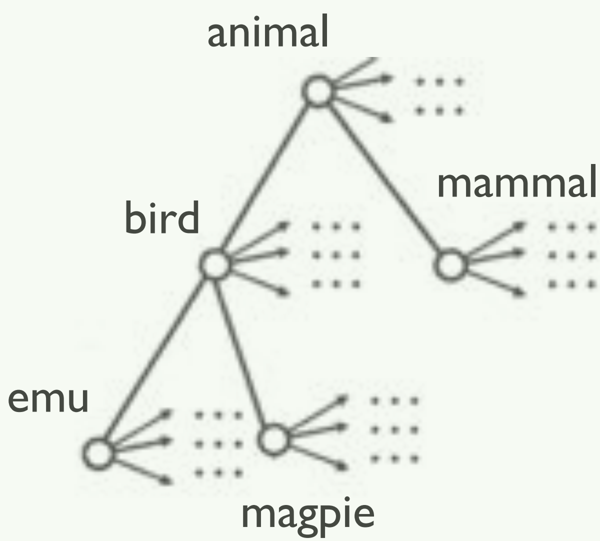
Large scale structure



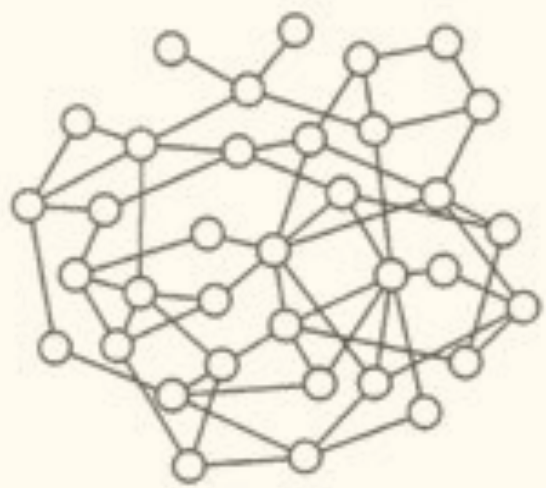
How are semantic networks organized?

(Steyvers & Tenenbaum 2005)

Hierarchical network?

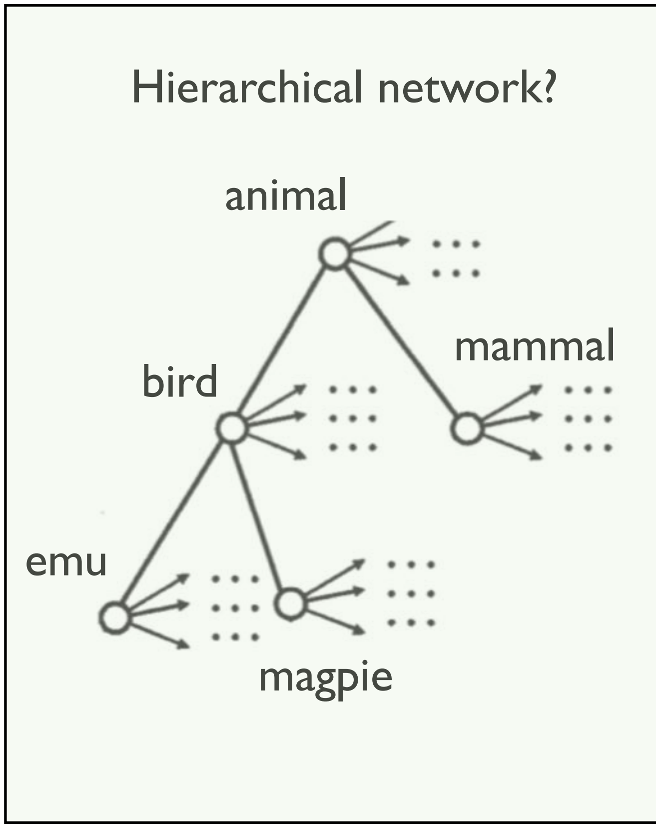


Unstructured network?



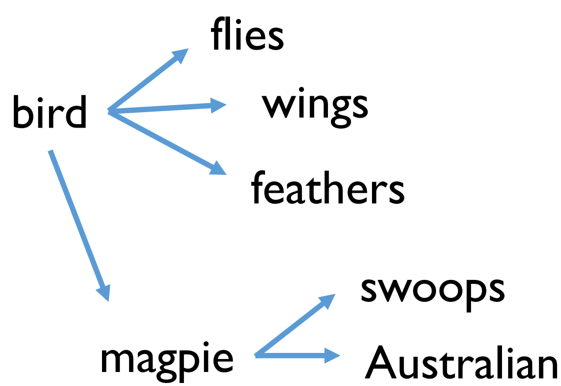
“Small world” graph

How are semantic networks organized?



This is unlikely

- There's no evidence for it in word association networks
- If networks are hierarchical we should be slower to verify "high level" features…



- "Magpie" is closer to "swoops" than "wings"
- We should be faster to verify "magpies swoop" than "magpies have wings"
- Not generally true

How are semantic networks organized?

(Steyvers & Tenenbaum 2005)

What's the difference?

- Small world graphs have "surprisingly" short paths between nodes
- Small world graphs have a lot of "clustering"

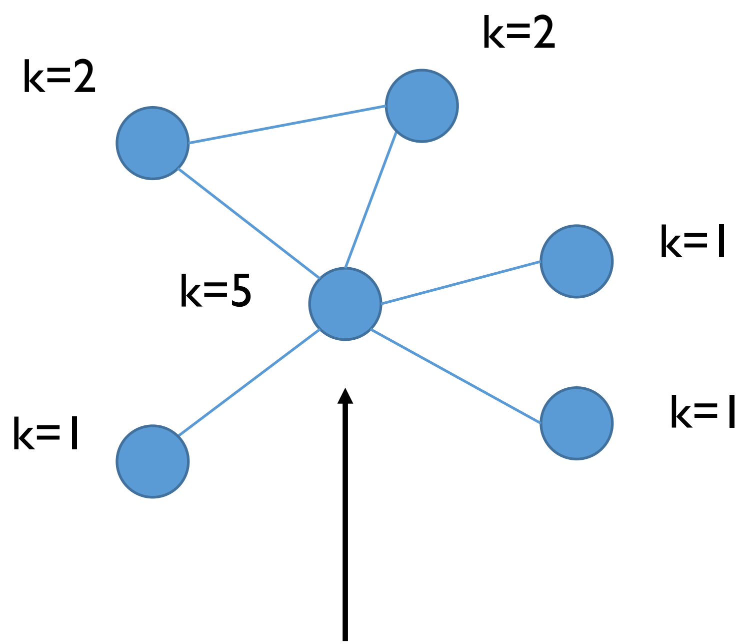
Unstructured network?

"Small world" graph

How are semantic networks organized?

(Steyvers & Tenenbaum 2005)

The degree of a node k is the number of connections it has

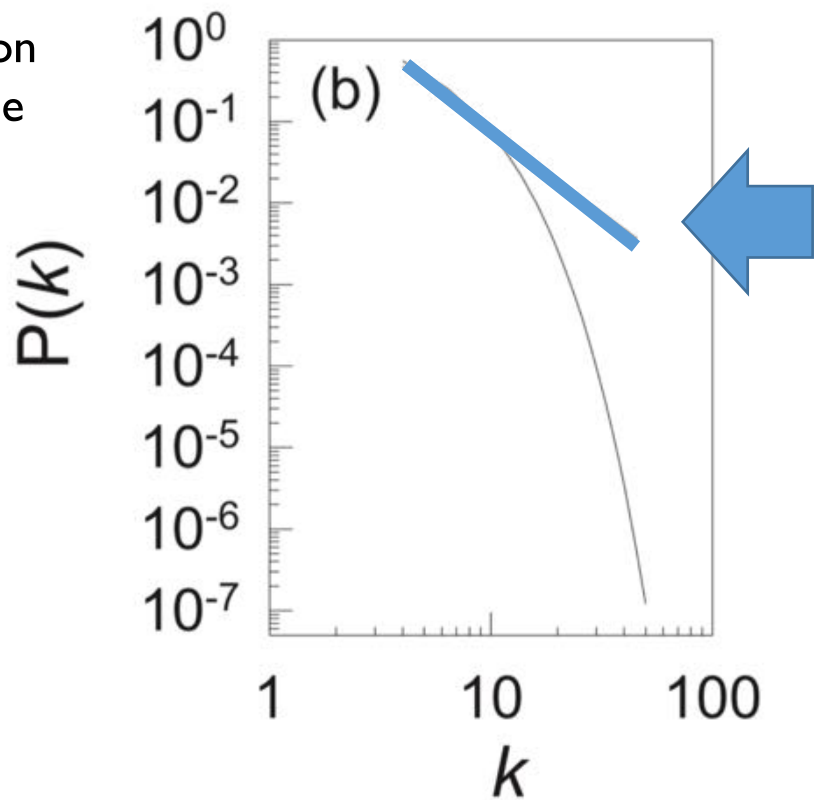


Key property of small-world graphs: a small number of "hub" nodes with very high connectivity

How are semantic networks organized?

(Steyvers & Tenenbaum 2005)

The proportion of nodes in the network with degree = k



The degree, k

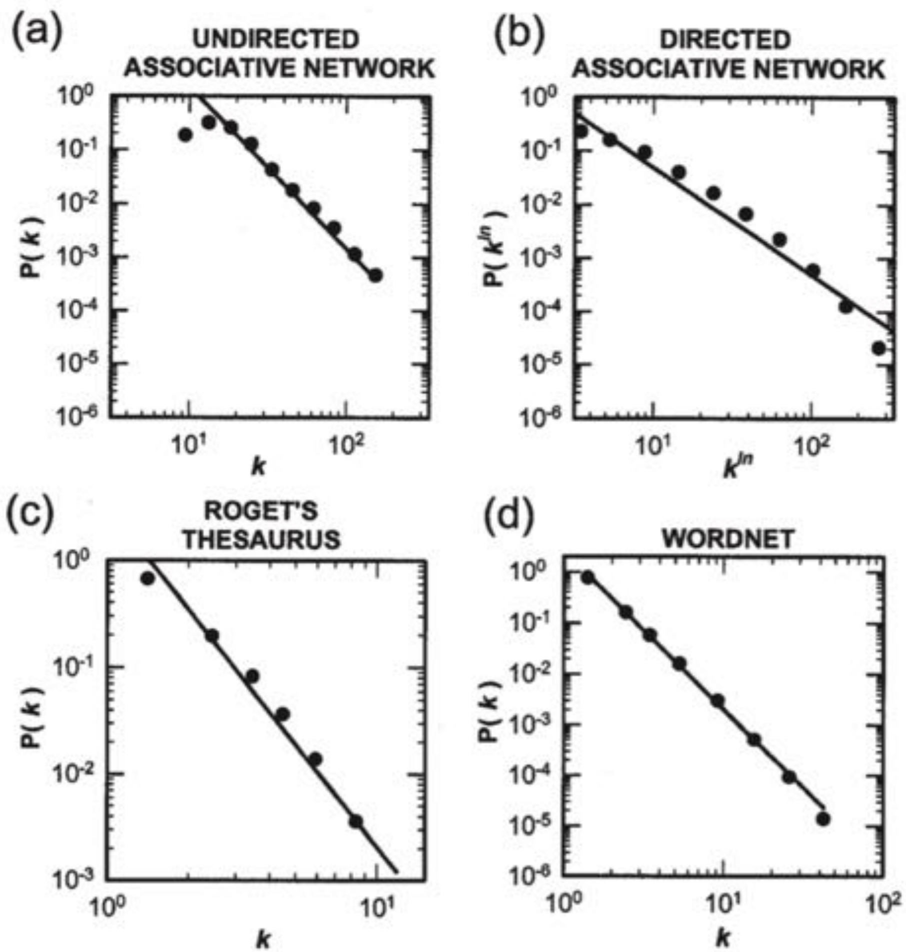
The diagnostic signature we're looking for is a power law for the degree distribution

A "power law" is linear when plotted on a log-log scale

(* technical details hidden here)

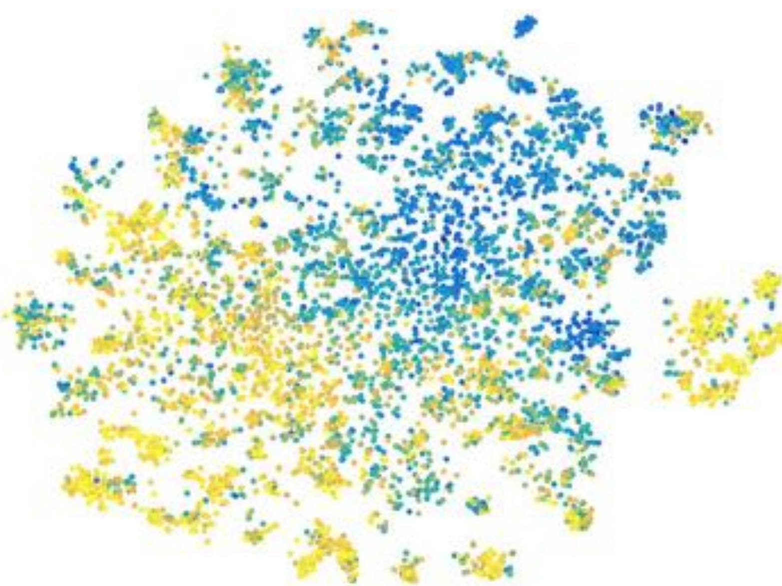
How are semantic networks organized?

(Steyvers & Tenenbaum 2005)



Four different ways of measuring the structure of semantic networks, all of which show the same pattern

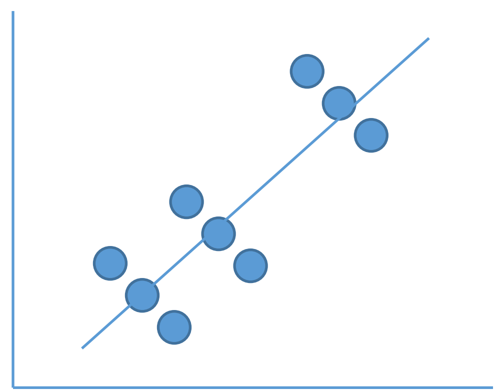
Semantic networks for individuals



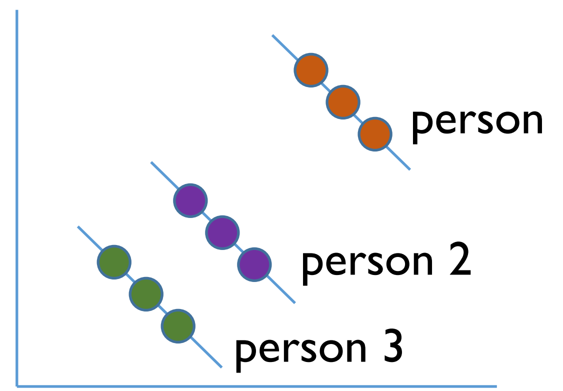
A source of concern

- Most sources of semantic network data aggregate responses from many people
- There are many situations where the data from aggregate systematically misrepresent the data from individuals

Aggregated



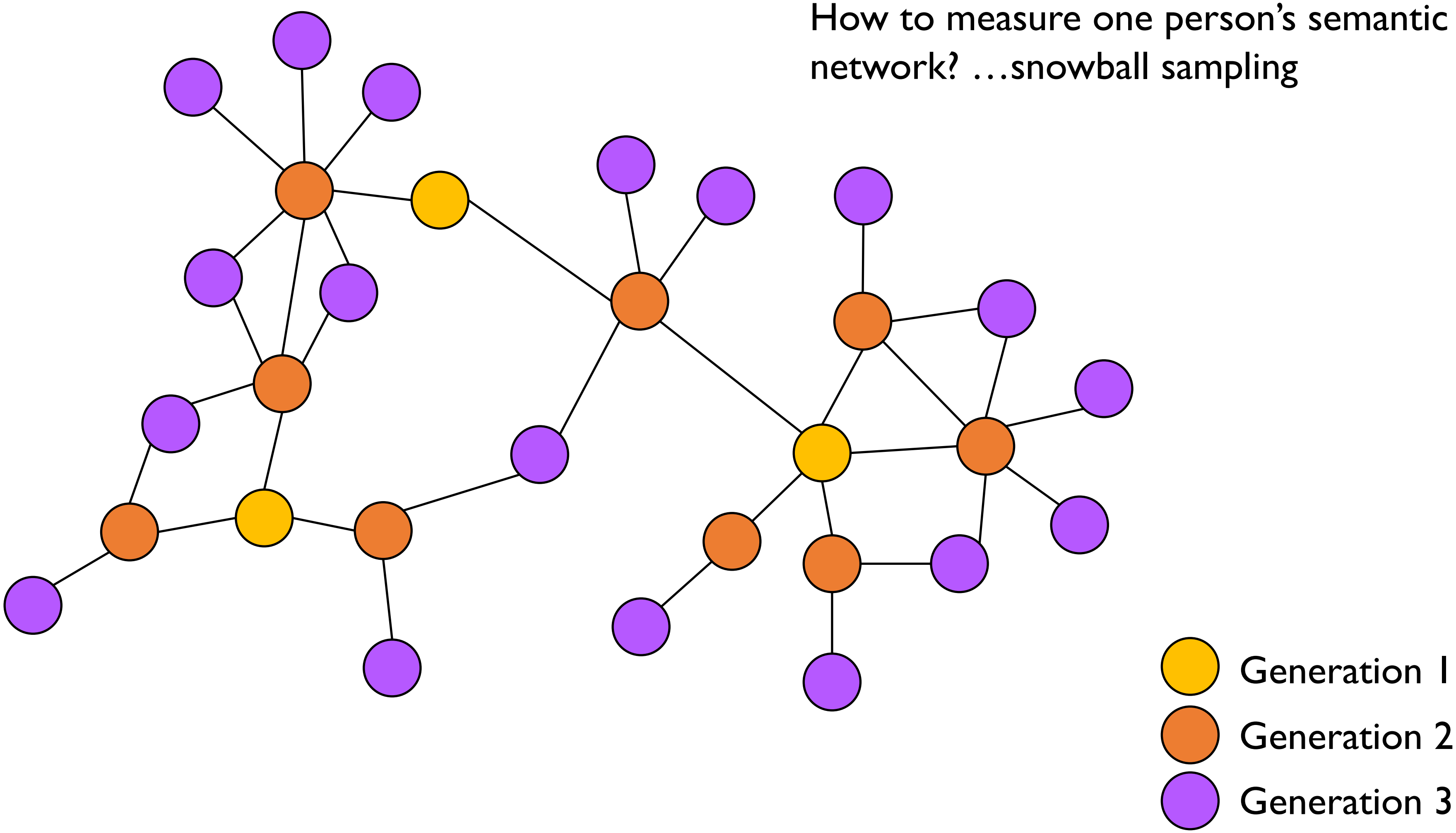
Individual



Semantic networks of individuals

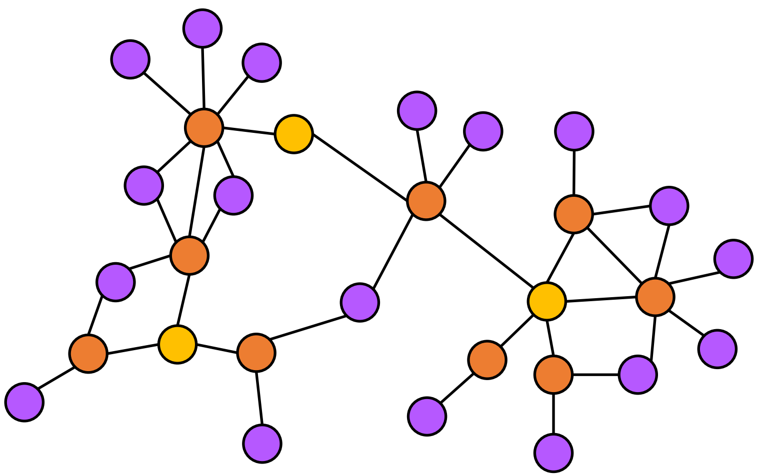
(Morais et al 2013)

How to measure one person's semantic network? …snowball sampling



Semantic networks of individuals

(Morais et al 2013)



- Start with seed words (yellow)
- Get all associations to those words (orange)

- Start with the 2nd generation words (orange)
- Get all associations to those words (purple)

- Etc.

- Complete as many iterations as possible within a 7 week testing period
- Done with 6 individuals
- Total time 30-60 hours per person!

Semantic networks of individuals

(Morais et al 2013)

P 1 (n = 9,429)
Undirected
Directed
P 2 (n = 2,303)
Undirected
Directed
P 3 (n = 5,100)
Undirected
Directed
P 4 (n = 1,358)
Undirected
Directed
P 5 (n = 9,129)
Undirected
Directed
P 6 (n = 3,239)
Undirected
Directed

A lot of variability in the number of words generated: ranges from 1358 to 9429

Semantic networks of individuals

(Morais et al 2013)

	Number of Links
P 1 (n = 9,429)	
Undirected	20,224
Directed	21,631
P 2 (n = 2,303)	
Undirected	4,805
Directed	5,308
P 3 (n = 5,100)	
Undirected	8,904
Directed	10,847
P 4 (n = 1,358)	
Undirected	3,271
Directed	3,729
P 5 (n = 9,129)	
Undirected	22,800
Directed	27,124
P 6 (n = 3,239)	
Undirected	5,738
Directed	7,828

This is reflected in a similar level of variability in the number of links

Semantic networks of individuals

(Morais et al 2013)

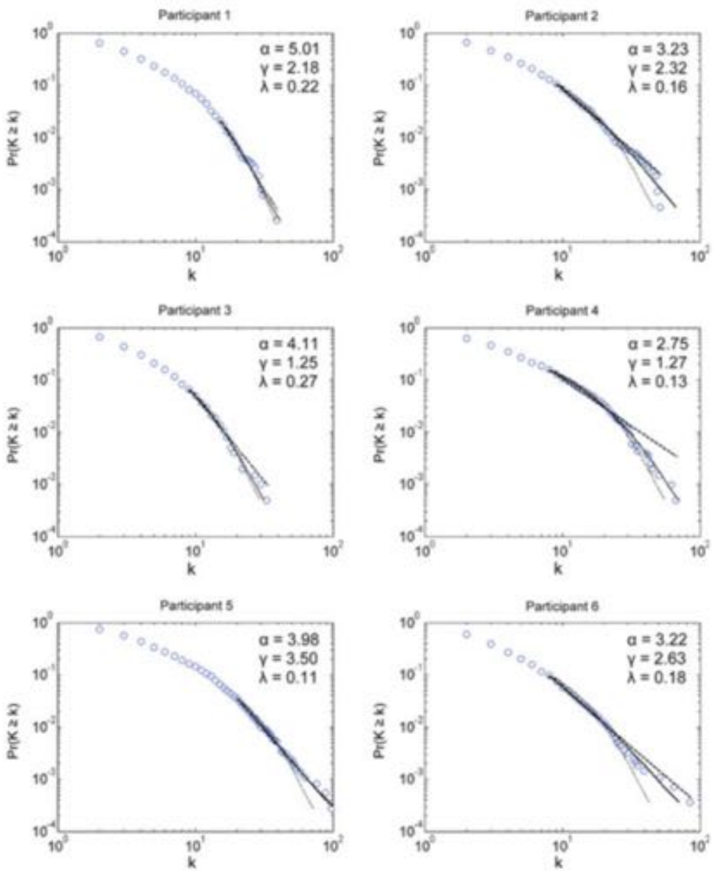
	Number of Links	k
P 1 (n = 9,429)		
Undirected	20,224	4.29
Directed	21,631	2.28
P 2 (n = 2,303)		
Undirected	4,805	4.17
Directed	5,308	2.30
P 3 (n = 5,100)		
Undirected	8,904	3.87
Directed	10,847	2.12
P 4 (n = 1,358)		
Undirected	3,271	4.88
Directed	3,729	2.73
P 5 (n = 9,129)		
Undirected	22,800	5.47
Directed	27,124	2.96
P 6 (n = 3,239)		
Undirected	5,738	4.18
Directed	7,828	2.40

The average connectivity (degree, k) of nodes is more stable across individuals

Overall, individual networks appear to be sparser (lower connectivity, fewer links) than the aggregate ones

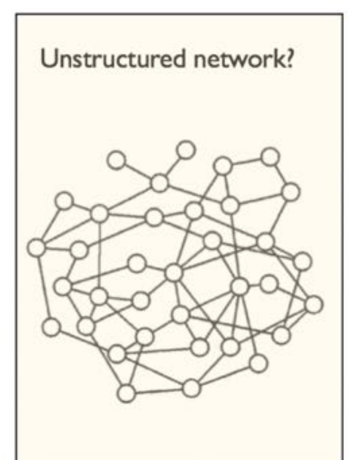
Semantic networks of individuals

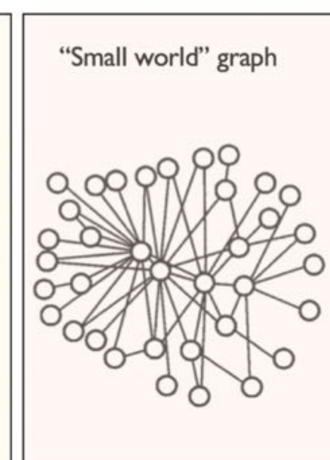
(Morais et al 2013)



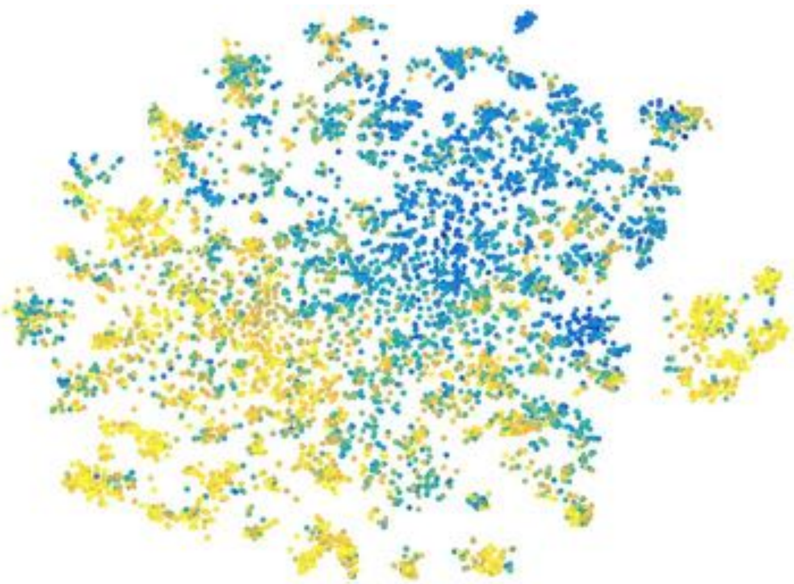
The individual subject networks do show small world structure, but it's not quite as clear cut as for the aggregate networks

(details of this graph not important for this class)





Developmental trajectory



Developmental changes

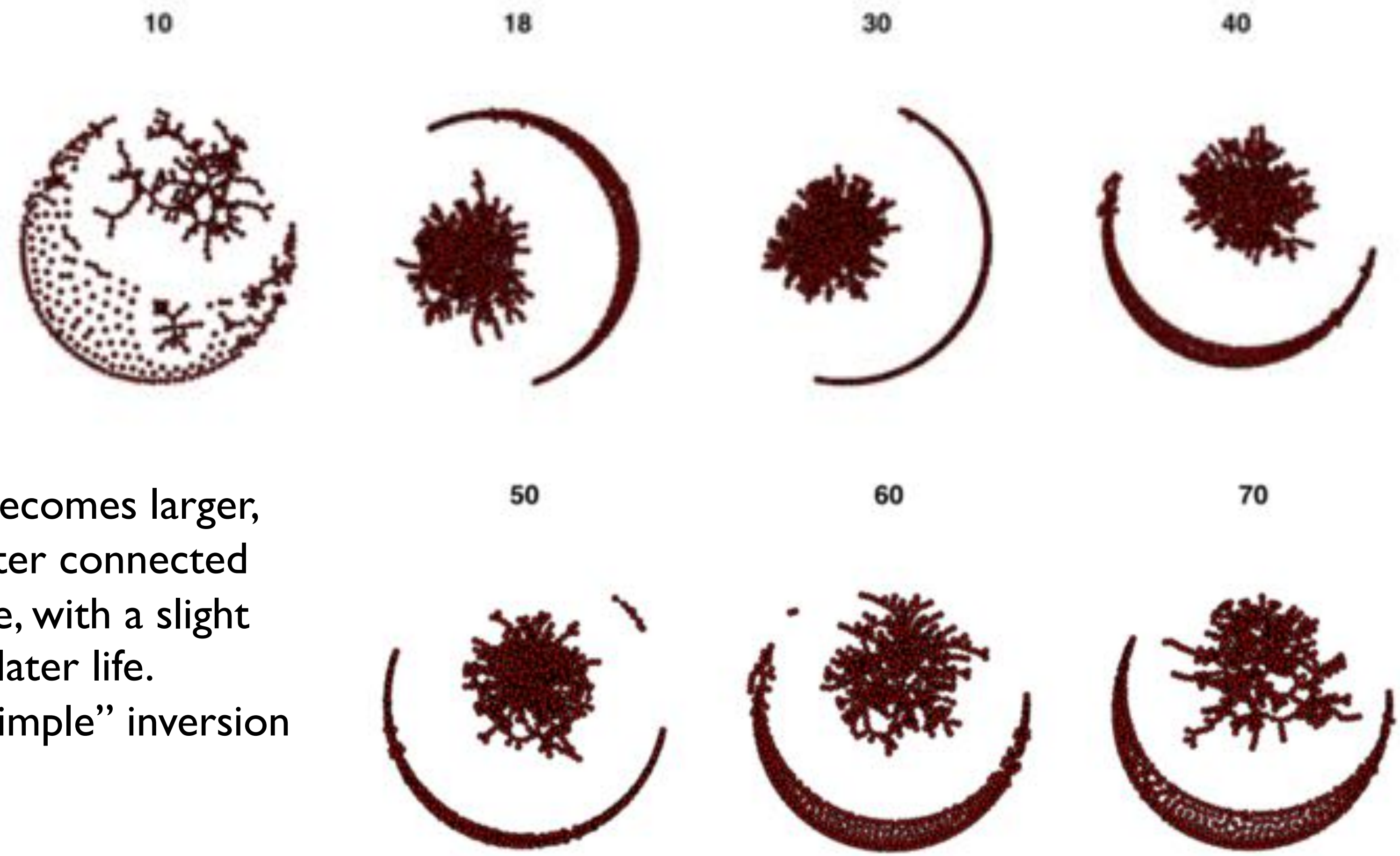
(Dubossarsky et al 2017)

- Large-scale cross sectional study: 8000 people, aged 10-84
- Subset of the Dutch language version of the small world of words study
- The younger age groups supplemented by recruiting from schools in Flanders

Age Group	Average Age	#Participants	Total responses	Unique responses
9-10	9.2	490	36444	6441
11-12	10.5	466	40319	6904
13-14	13.5	502	42625	7970
17-19	18.3	1081	48630	8663
28-32	31.0	1136	49613	8947
38-42	41.0	1152	49626	9501
48-52	51.0	1223	49688	10280
58-62	61.0	1279	49806	11144
+68	71.9	1222	49508	12538

Developmental changes

(Dubossarsky et al 2017)

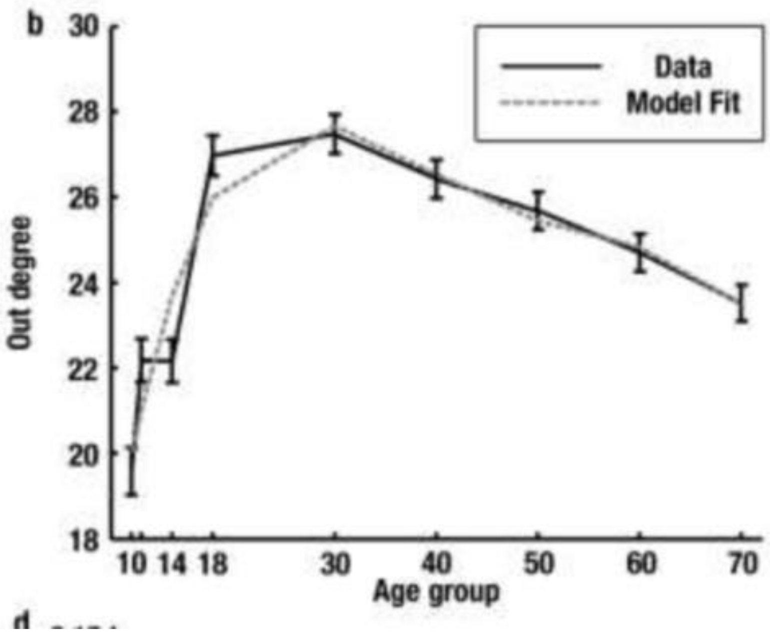


- Network becomes larger, denser, better connected into mid life, with a slight reversal in later life.
- It's not a "simple" inversion though

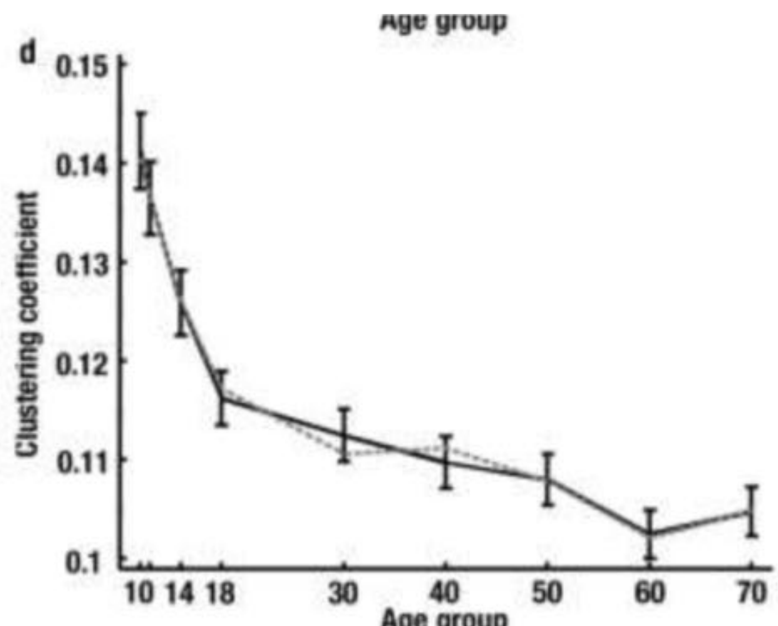
Developmental changes

(Dubossarsky et al 2017)

The average degree (number of connections) of individual node shows the inverted U shape…



But the overall "clustering" in the graph shows a monotonic trend across the lifespan…



Thanks!