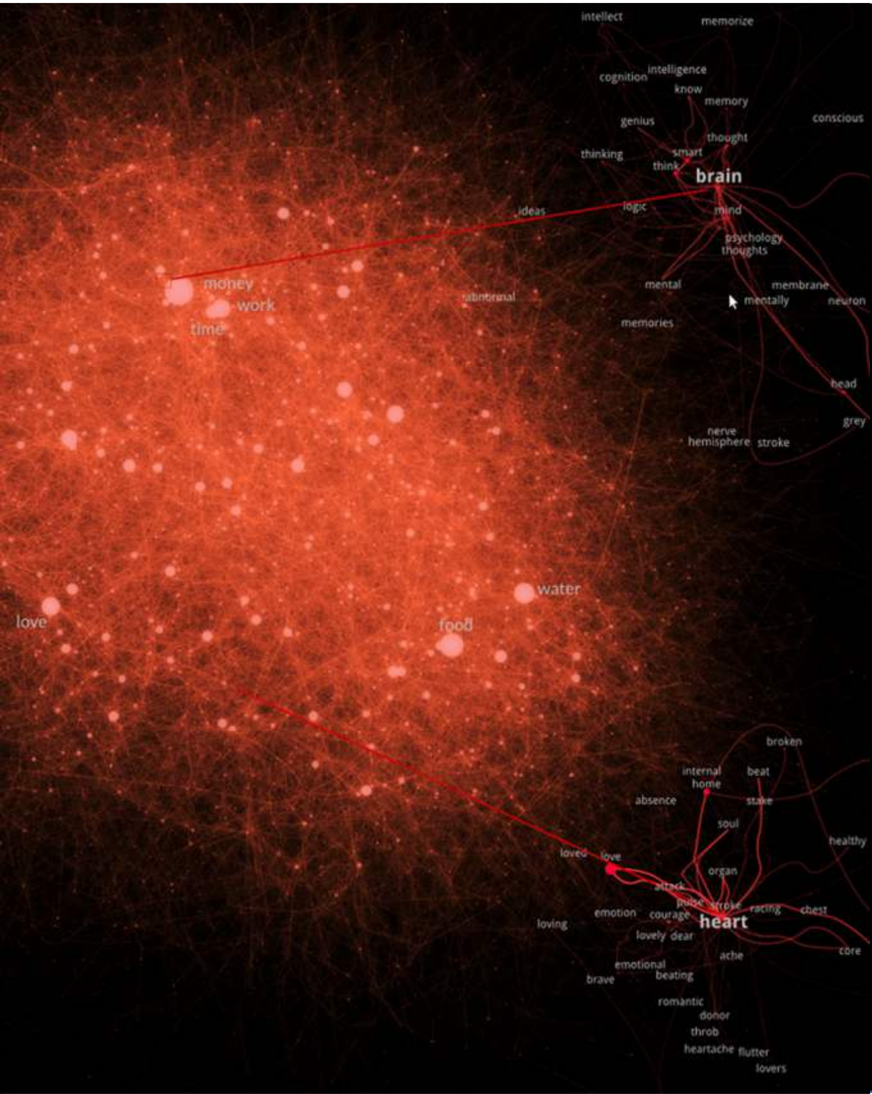


An introduction to multi-scale semantic network analysis

2023 Wellington Vocabulary Research Summer School

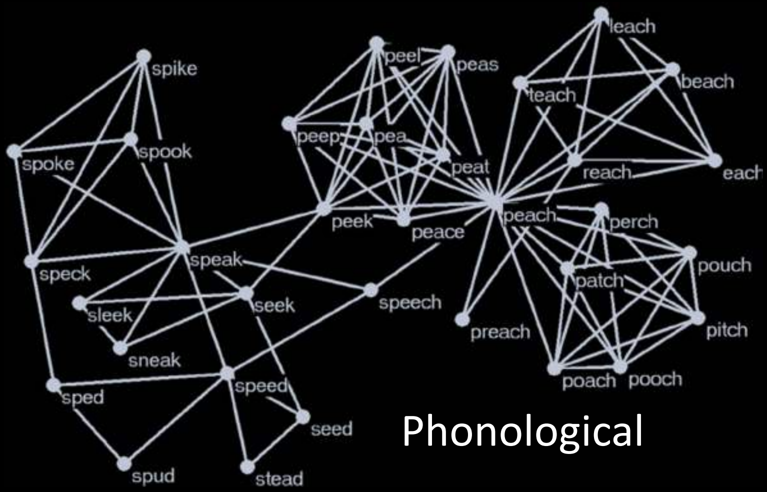
Simon De Deyne

simon.dedeyne@unimelb.edu.au

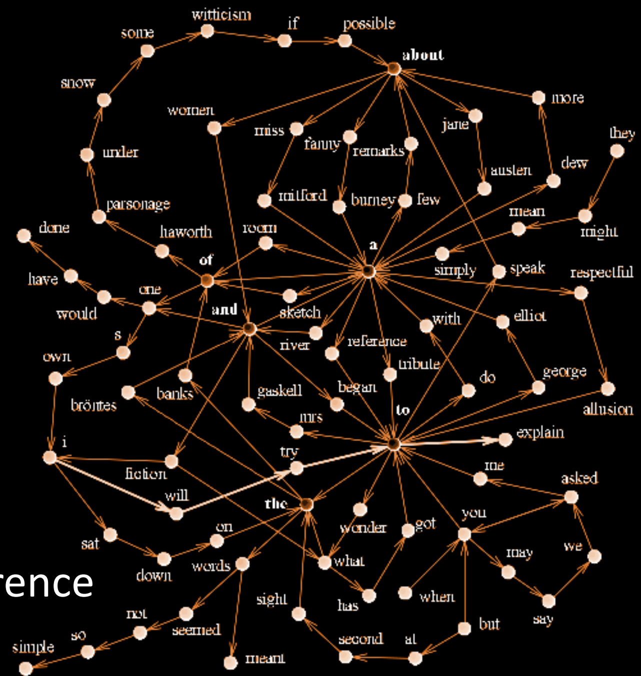
THE UNIVERSITY OF MELBOURNE

Complex Human Data Hub
School of Psychological Sciences

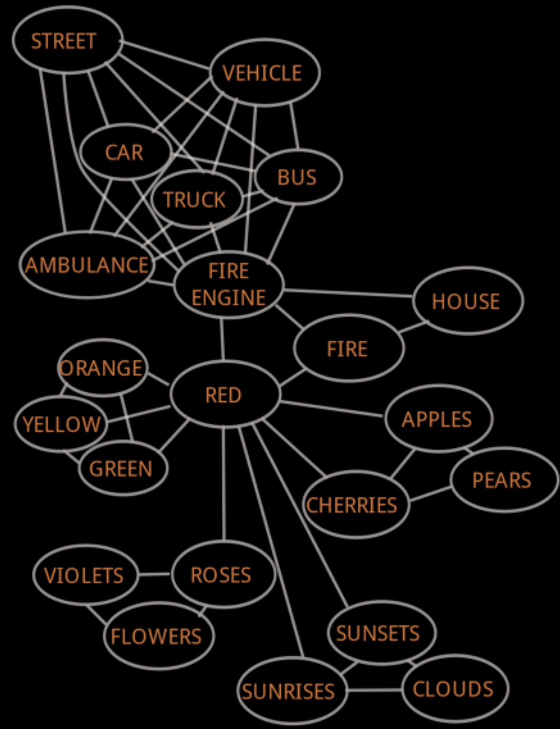
Language Networks



Phonological



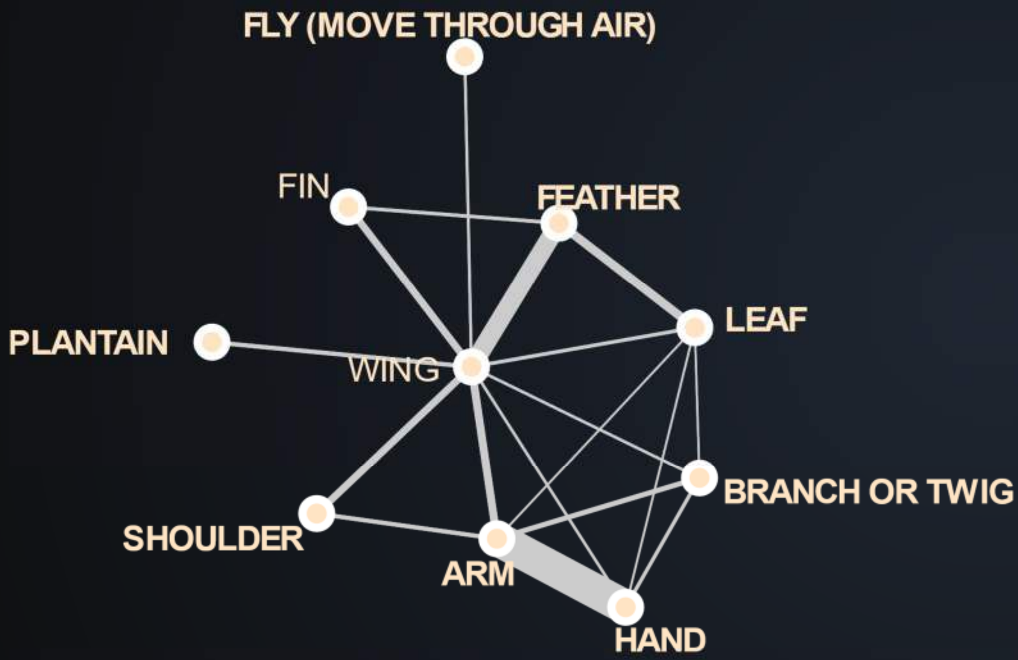
Co-occurrence



Semantic

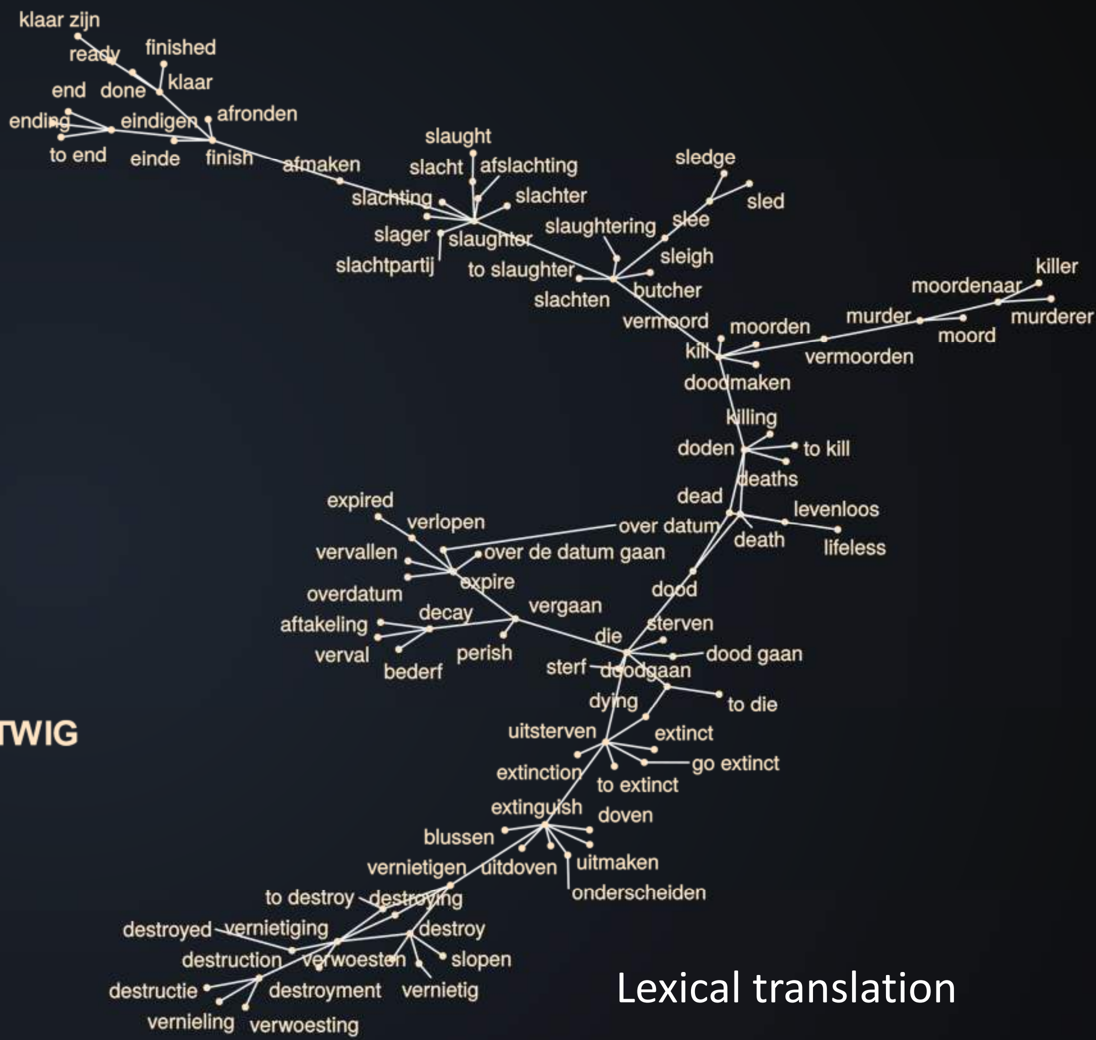
Structure can be studied
simultaneously at different levels

Multiple languages



Colexification

https://clics.clld.org/

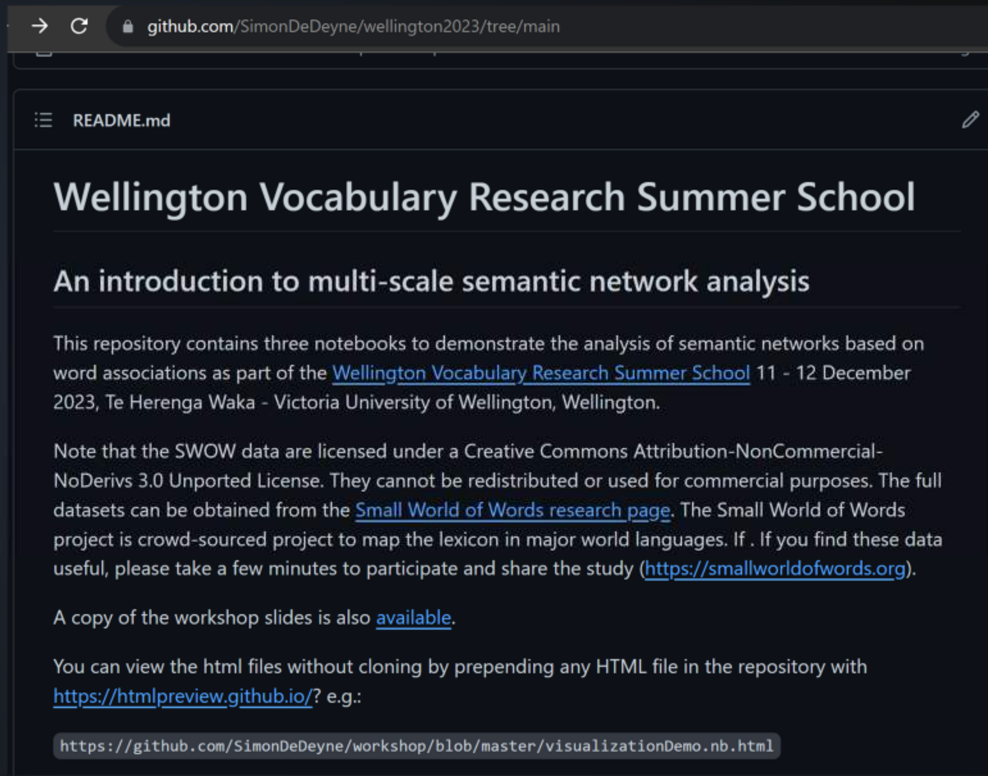


Lexical translation

Today's goals

- Gentle introduction to semantic network analysis
    - Centrality
    - Similarity and relatedness
    - Assortativity and Clustering
- Applied to Word Association Networks and psycholinguistic datasets

Not covered: Statistical network models, EGA, Multiplex networks, Graph embeddings, Missing Link Prediction


github.com/SimonDeDeyne/wellington2023/tree/main

README.md

Wellington Vocabulary Research Summer School

An introduction to multi-scale semantic network analysis

This repository contains three notebooks to demonstrate the analysis of semantic networks based on word associations as part of the Wellington Vocabulary Research Summer School 11 - 12 December 2023, Te Herenga Waka - Victoria University of Wellington, Wellington.

Note that the SWOW data are licensed under a Creative Commons Attribution-NonCommercial-NoDerivs 3.0 Unported License. They cannot be redistributed or used for commercial purposes. The full datasets can be obtained from the Small World of Words research page. The Small World of Words project is crowd-sourced project to map the lexicon in major world languages. If . If you find these data useful, please take a few minutes to participate and share the study (https://smallworldofwords.org).

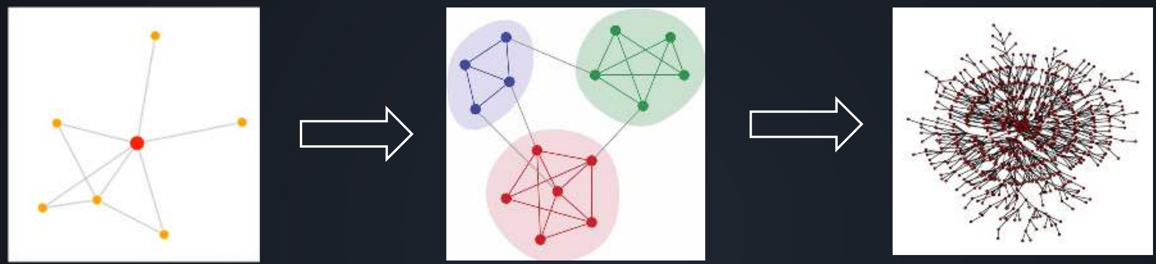
A copy of the workshop slides is also available.

You can view the html files without cloning by prepending any HTML file in the repository with https://htmlpreview.github.io/? e.g.:

```
https://github.com/SimonDeDeyne/workshop/blob/master/visualizationDemo.nb.html
```

Why language networks…

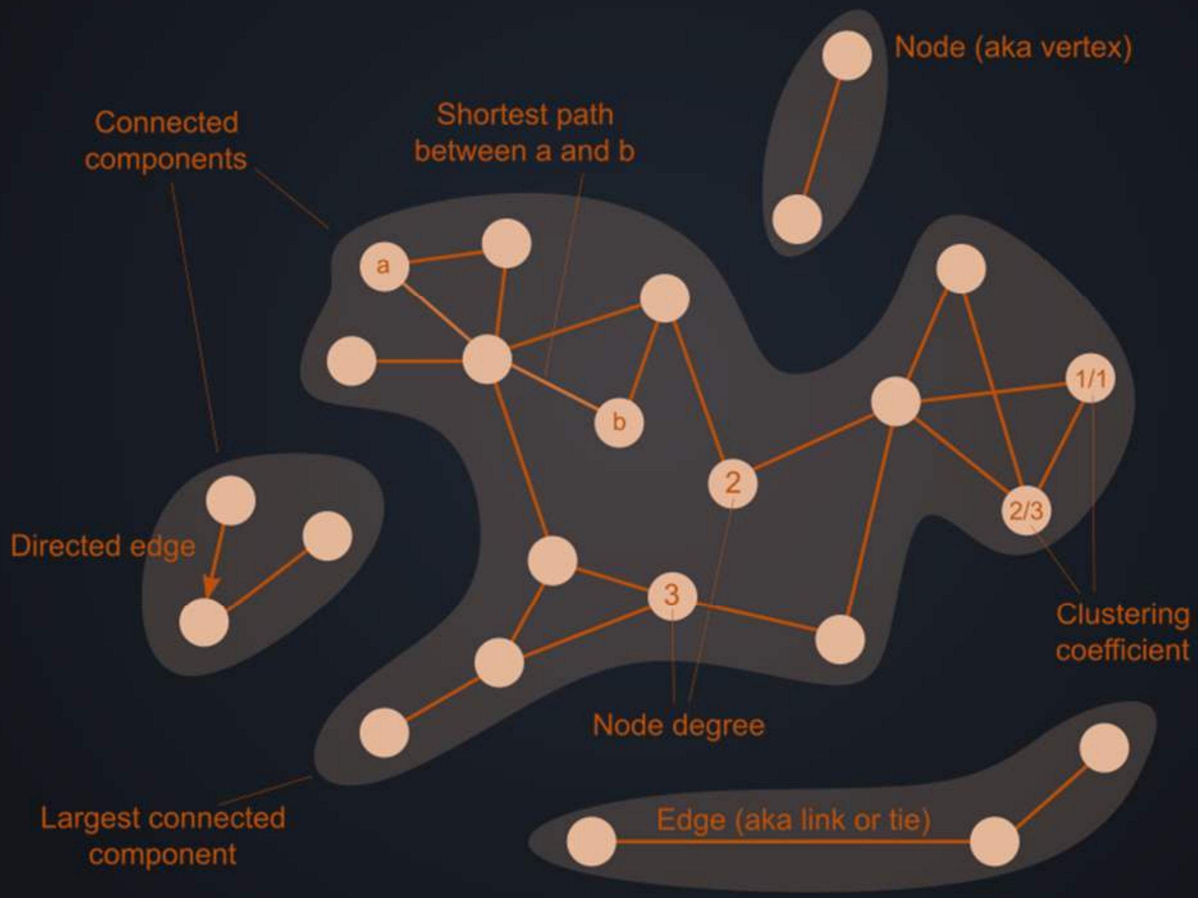
1. Multiple levels of analysis: structure at every scale (local – global)



Local structure of individual nodes | Structure at the intermediate level | Structure of the entire network

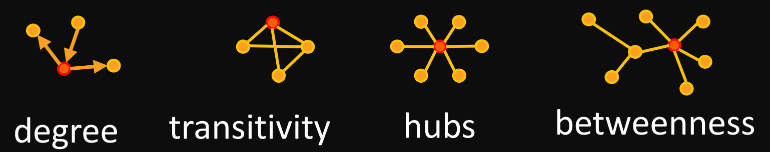
1. Complex networks: more is different: levels tell a distinct story
2. Multiple relations: interactions between syntax, morphology, phonology and semantics
3. Networks as a tool to describe language: often simplification, but scale + transparency

Network Measures



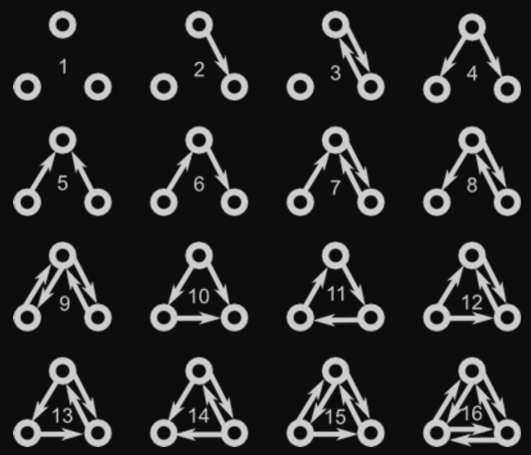
Microscopic structure

Centrality



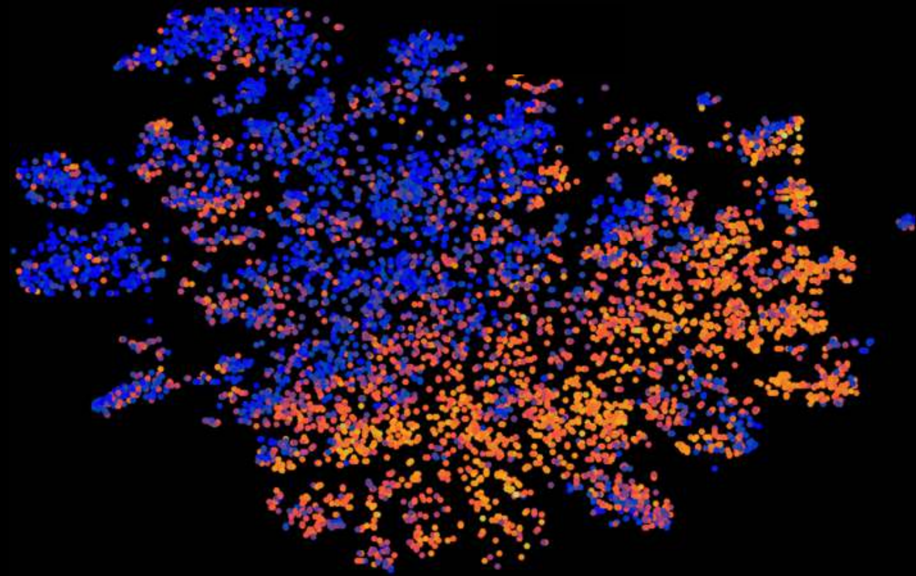
Concrete words have "lower degree" than abstract words
Dense phonological neighbourhoods, affect lexical retrieval times. Semantic rich neighbourhoods have processing advantages

Motives



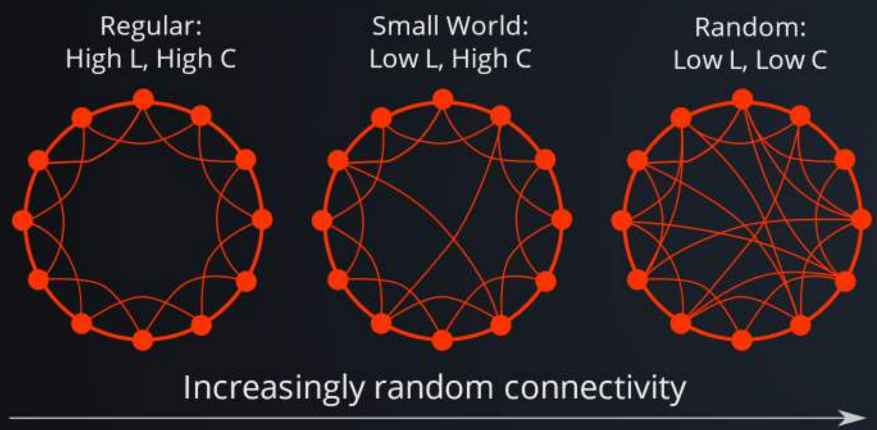
Classify different language networks based on their *motive signatures* (Biemann, et al. 2016)

Mesoscopic structure



Macroscopic structure

Small World Scale-Free Networks



- Short Average Path length (L)
- High Clustering (C)
- Hubs: (good, bad, woman, old)
- Scale-free: degree distribution = power law

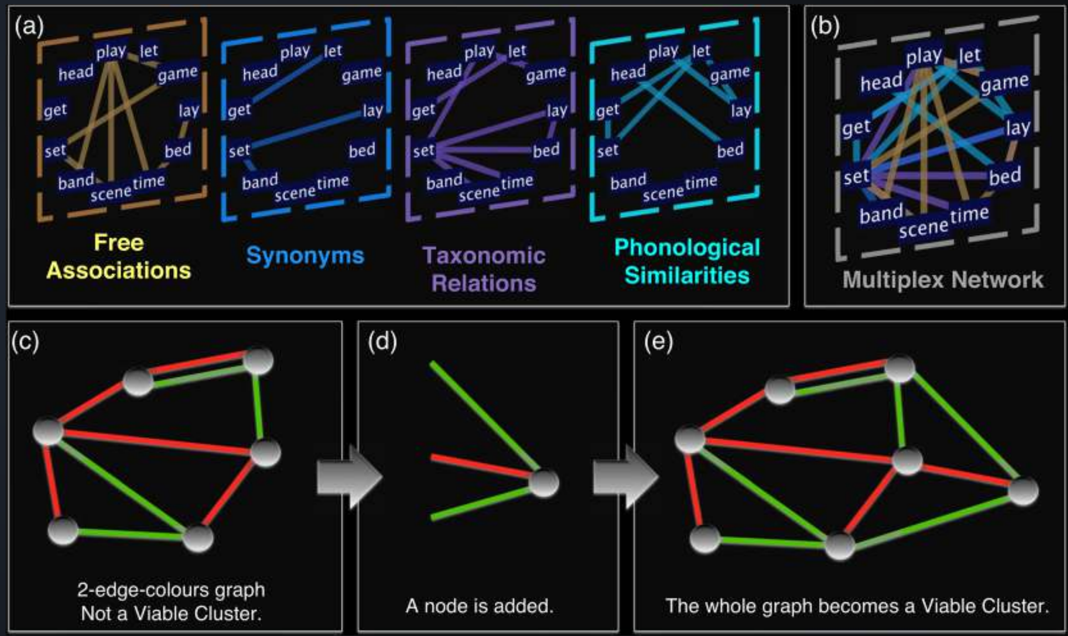
- Highly navigable structure, robustness to random failure
- Common in many naturally evolving systems
- Possible mechanism: Preferential Attachment (Steyvers & Tenenbaum , 2014)

Multilevel analysis – Multiplex graphs

Explosive language learning in humans (Stella et al., Scientific Reports, 2018).

Idea:

- Manipulate presence of links according to age-of-acquisition
- What determines tipping points in connectivity ?



Small World of Words project

Build a realistic approximation of the mental lexicon
in major world languages

De Deyne & Storms, 2008, De Deyne et al., 2013;
De Deyne et al. (2019), Cabana et al., 2023

SMALL WORLD OF WORDS

Discover what **words** mean
for **people** worldwide

Small World of Words project

+ 550,000 participants

https://smallworldofwords.org/project

Empirical lexico-semantic network

MAIN CHARACTERISTICS

- <u>Free</u> association
- Edges, nodes and weights observed
- Meaning = spreading activation over weighted edges
- Sizeable implementation covering most words

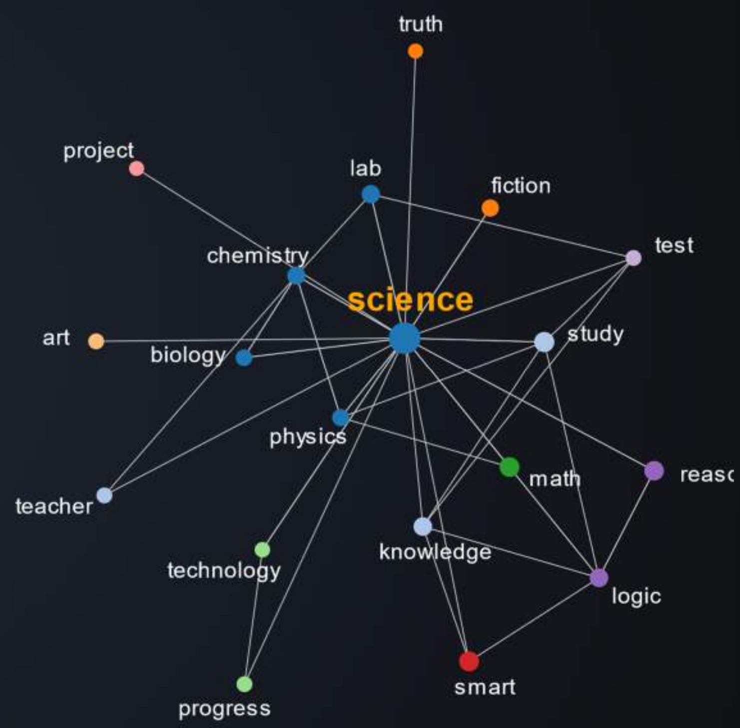
WORD ASSOCIATION TASK

- 12,000 English cue words, +80,000 pps
- <u>Continued Responses</u>: R1, R2, R3
- 3M association responses

Why continued associations?

Single Responses

- General drawback of word associations (Aitchison, 2003)
- Lack of weak responses problematic for various tasks including mediated priming (Chwilla et al., 2000)



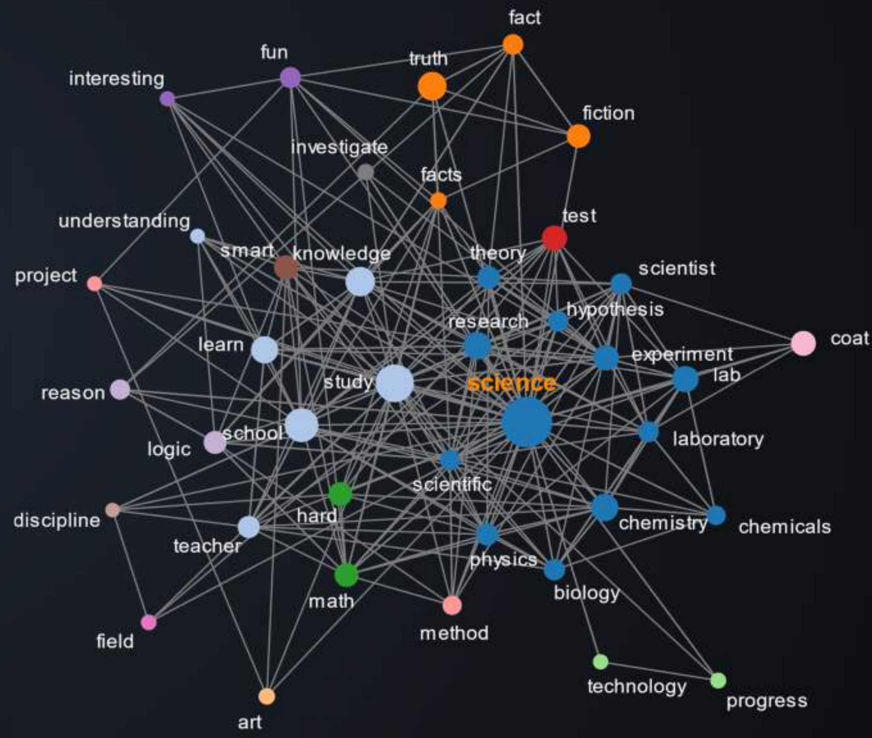
Why continued associations?

Single Responses

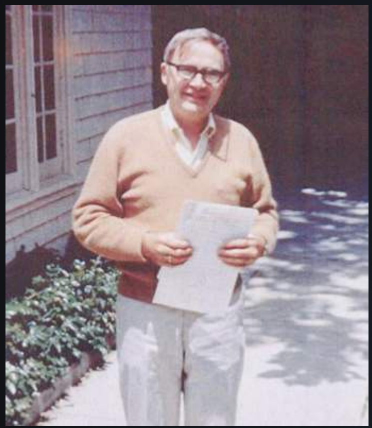
- General drawback of word associations (Aitchison, 2003)
- Lack of weak responses problematic for various tasks including mediated priming (Chwilla et al., 2000)

Dominance Effects

- umbrella: 90% of people provide rain
- Possible other associates?

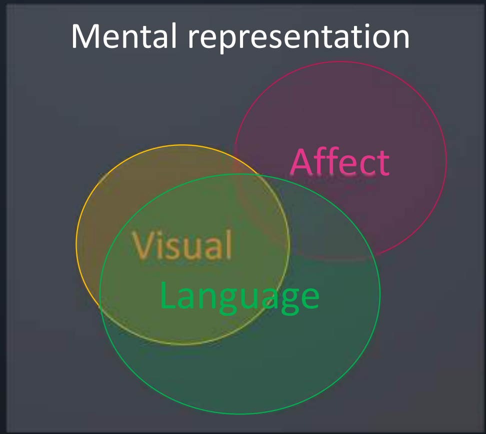


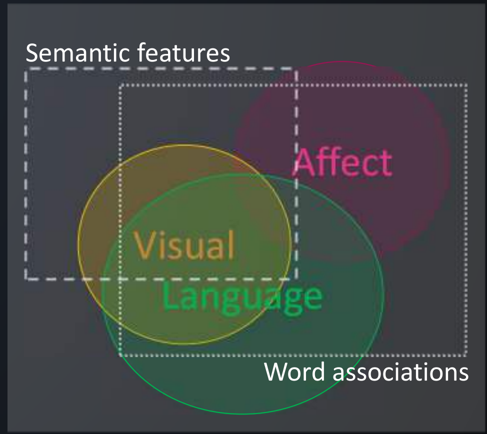
The structure of associations in language and thought



James Deese (1965):
"The interest of psychologists in associations has always been misguided… the whole classical analysis of associations centered around the circumscribed and uninteresting problem of stimulus – response, of what follows what."

Ufimtseza (2014)
"Associative verbal networks reflects the entire previous verbal and nonverbal experience of native speakers."





Microscopic Level

Identify central or bridging words

Clustering as Semantic richness

Motives as language signatures

Microscopic Structure

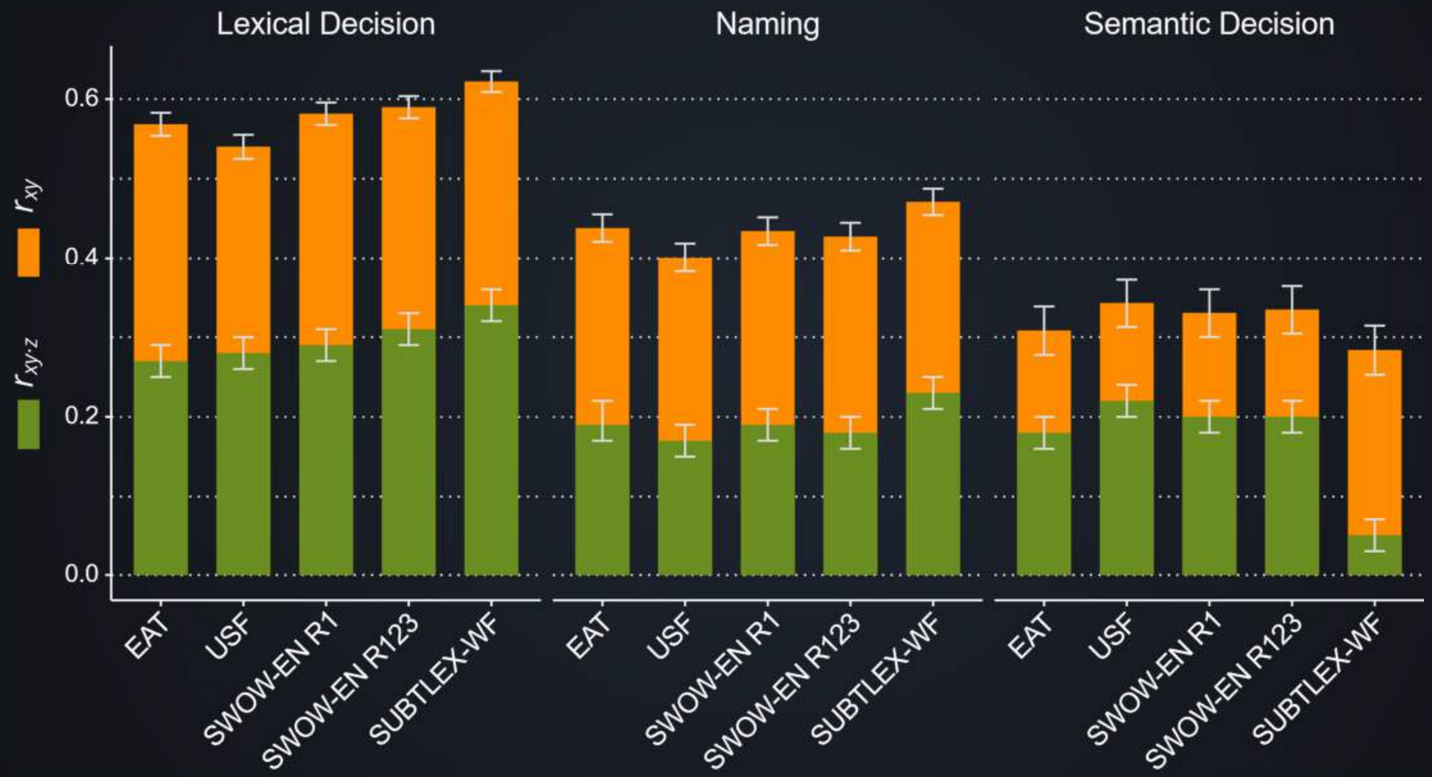
Word association hubs

Dataset	1	2	3	4	5	6	7	8	9	10
SWOW-NL	money	water	food	car	music	pain	tasty	school	child	pretty
SWOW-EN	money	food	water	car	love	music	work	happy	old	bird
EAT	money	water	food	man	car	me	sex	sea	good	home
USF	money	car	water	food	bird	dog	tree	child	good	book

Natural language hubs

Dataset	1	2	3	4	5	6	7	8	9	10
SUBTLEX-NL	go	do	know	come	good	say	see	think	love	sit
SUBTLEX-US	make	do	time	little	people	know	think	way	see	new
BNC	say	see	know	time	year	think	come	last	give	people
KF	say	can	time	new	do	man	make	year	people	little
CELEX-NL	say	see	stand	know	find	time	sit	take	two	woman
CELEX-EN	go	come	say	see	make	stand	good	do	think	big

Centrality in psycholinguistic tasks



Correlation between node in-strength and RT

De Deyne et al. (2019)

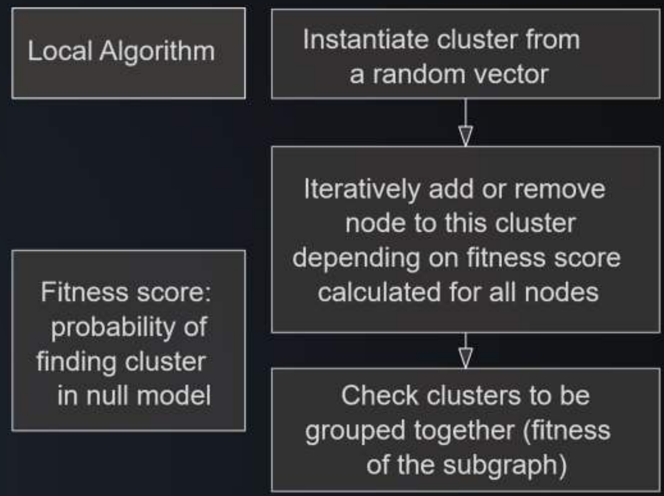
Mesoscopic Level

Identifying (overlapping) clusters and categories at different depths

Explore semantic structure

Method

- Network Community Detection
- Modularity optimisation
- Huge directed weighted graphs
- Statistical approach:
  significance of hierarchical overlapping communities



Results

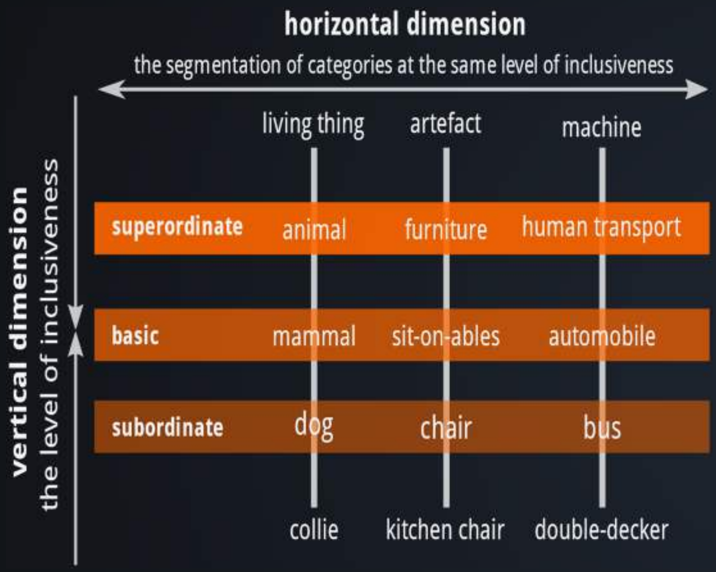
Measure	**1**	**2**	**3**	**4**	**5**
# Communities	2	7	37	161	506
Average size	8588	3049	515	112	25
# Homeless nodes	18	18	39	86	380
# Overlapping nodes	5943	6956	5263	4717	1676
Max(overlapping nodes)	2	7	8	10	6
Mean(p)	0	0.062	0.04	0.035	.051

infreq. words: *codex, agalev,…*

homonyms: *bank*
polysemes: *language*
(nationality, speech, education, communication)

De Deyne, Verheyen, Perfors & Navarro (2015)

Mesoscopic Structure



- Evidence for hierarchical thematic structure across different POS
- Clusters: partly overlapping with central category labels
- Taxonomic structure present when category exemplars (concrete nouns) are isolated

Widespread Thematic structure

***p* < 0.01**	*p* = 0.03	*p* = 0.07	*p* = 0.08	*p* = 0.14	*p* = 0.14
French fries	arrogant	get	beach	mystery	coffee
greasy	haughty	understanding	sea	solve	tea
fryer	haughtily	insight	sun	puzzle	bag
mayonnaise	conceited	understand	holidays	question	cup
fat	snob	awareness	summer	reflect	chocolate milk
unhealthy	unsympathetic	understanding	sand	answer	warm
ketchup	pride	realize	sunbathing	solution	milk
hamburger	vain	see	coast	ask	cocoa
roll	pretension	realize	parasol	problem*	mug
sauce	patronizing	notion	wind	think	tea time
fastfood	look down	know	warm	problem	teapot
fryhouse	superior	conscious	sandcastle	difficult	tea-bag
snack	arrogance	clue	tan	question mark	tableware
croquette	inferior	sink in	bikini	sudoku	cocoa
fries	egocentric	know	sunbathe	quiz	filter
stall	pedantic	click	shell	quiz*	thermos
snack	contempt		terrace	challenge	cappucino
ground beef	spoiled		surf	crossword	coffee
mustard	elitist		dune	guess	visit
sausage	pleased with		Australia	assignment	
kebab	mundane		sea breeze	questionnaire	
...	...		...	...	

Macroscopic Level

Global network structure with implications for efficiency and robustness

Macroscopic Structure

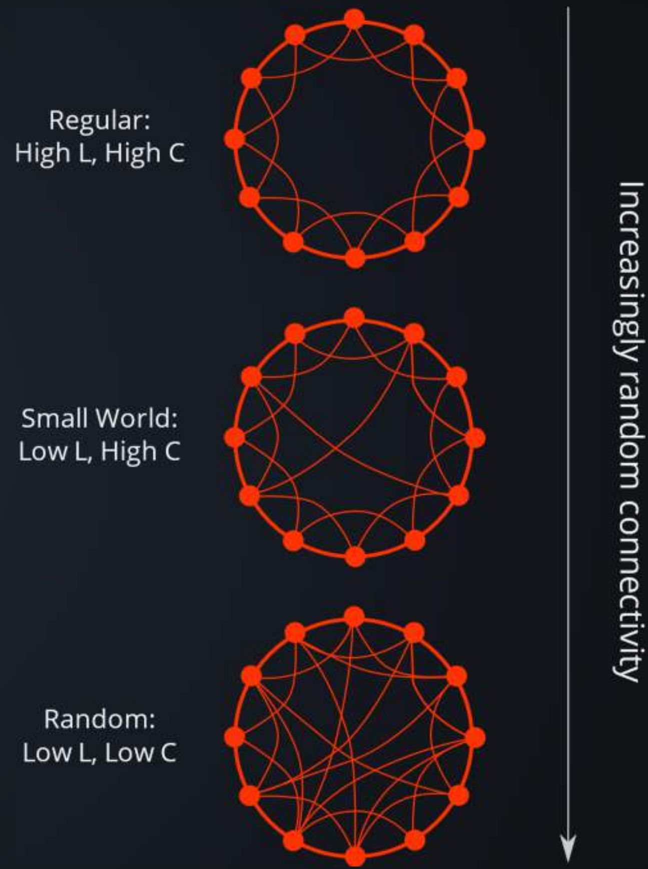
Density and Average Path Length

- G_1 : d = .22, L = 4.14 steps
- G_{12}: d = .43, L = 3.38 steps
- G_{123}: d = .64, L = 3.06 steps

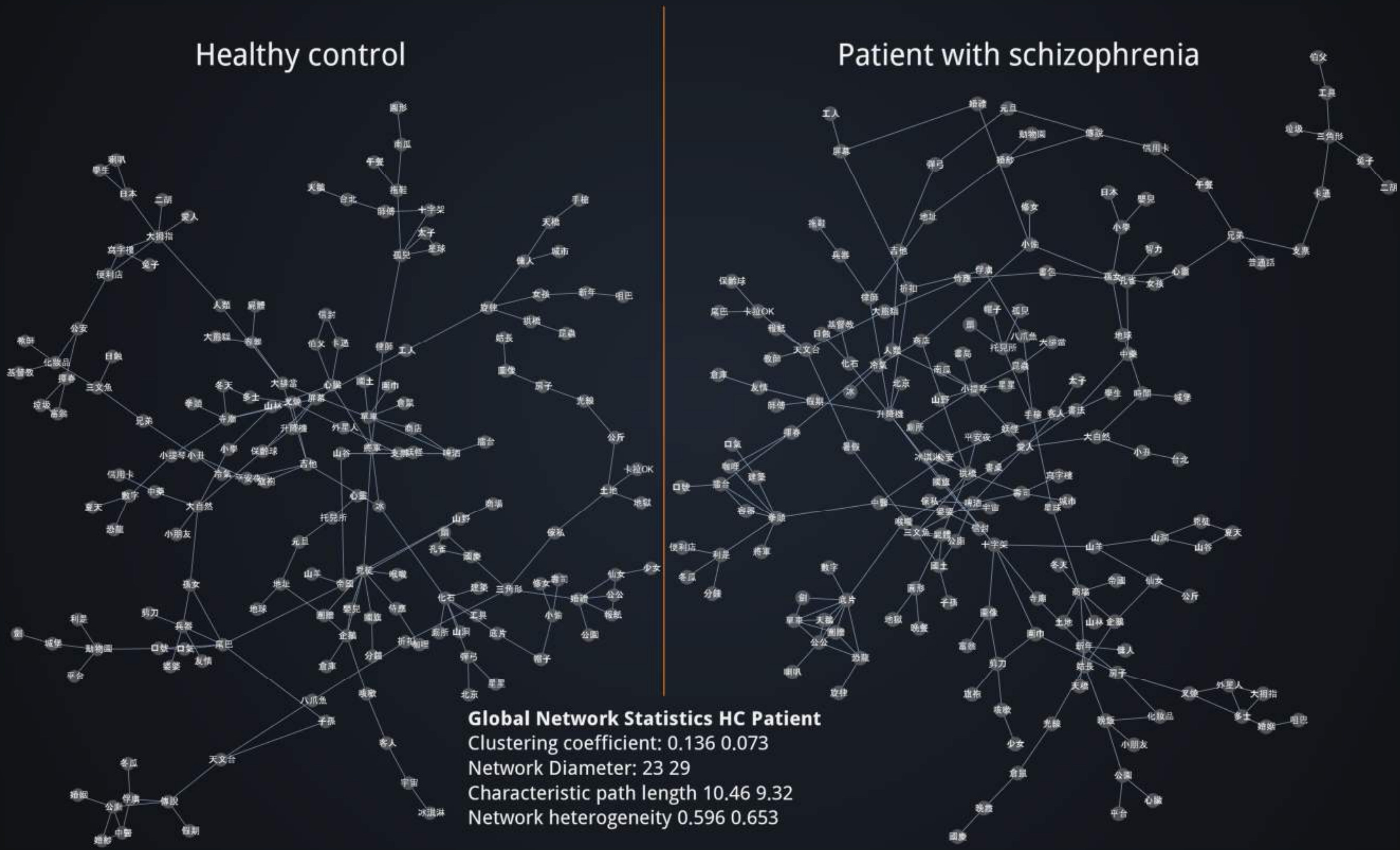
Small-World properties of G_{123}

Strong interconnected regions

- (CC = .331 vs CC_{rand} =.045)



Applications to language disorders

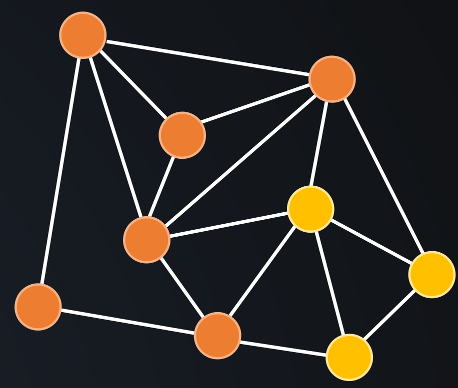


De Deyne, Elvevåg, Hui, Poon, & Chen (2017)

Connecting Micro, Meso & Macro

1. The case of assortative mixing

Node Assortativity



Assortative mixing

"Likes like like"

- Age, race in social networks
- Measure ≈ correlation coef.
- Different from bias

What word properties determine the presence of an associative link?

Discrete lexical covariates

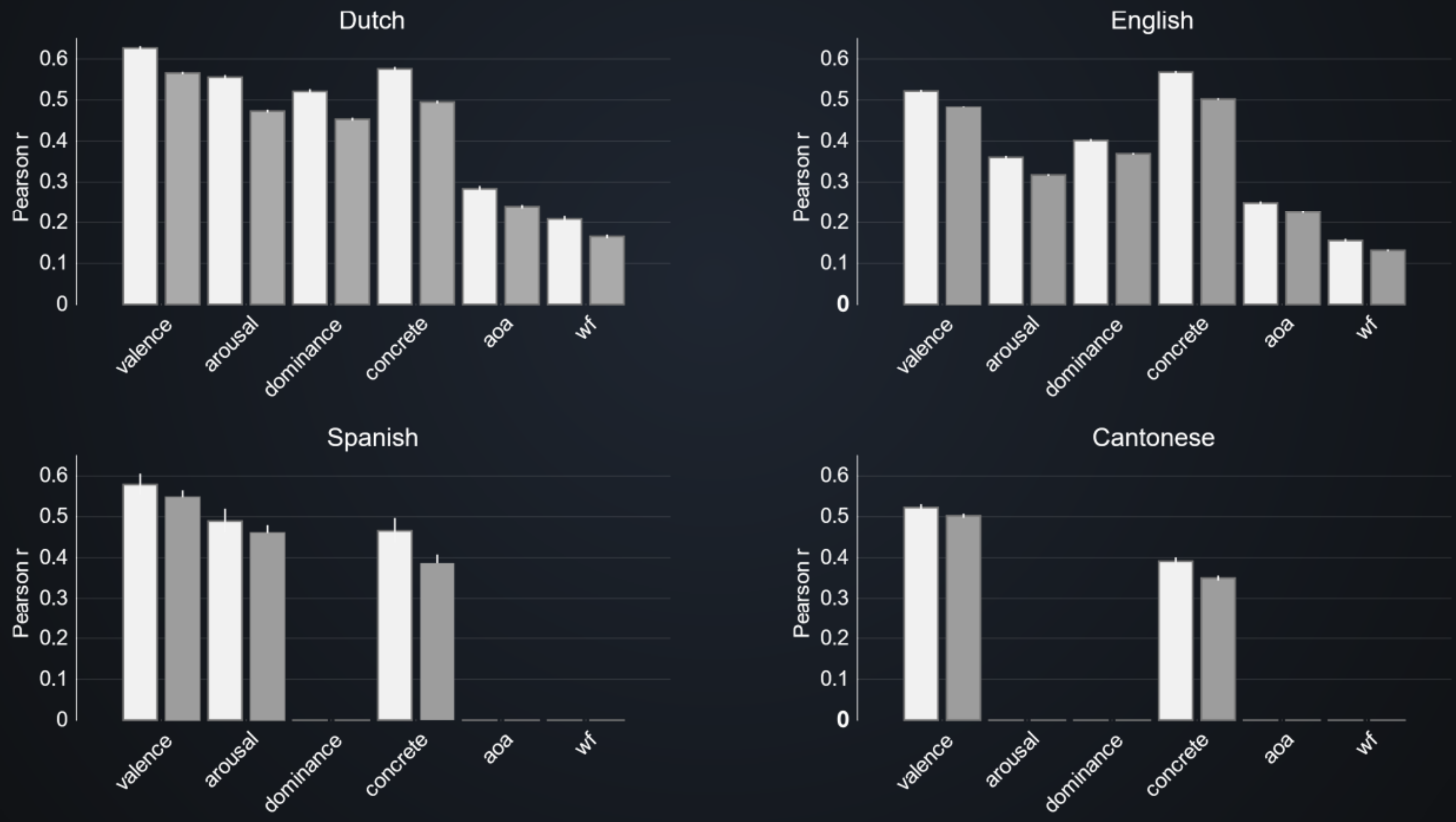
POS: Noun, Verb, Adj
Assortative: paradigmatic
Disassortative: syntagmatic

Scalar lexical covariates

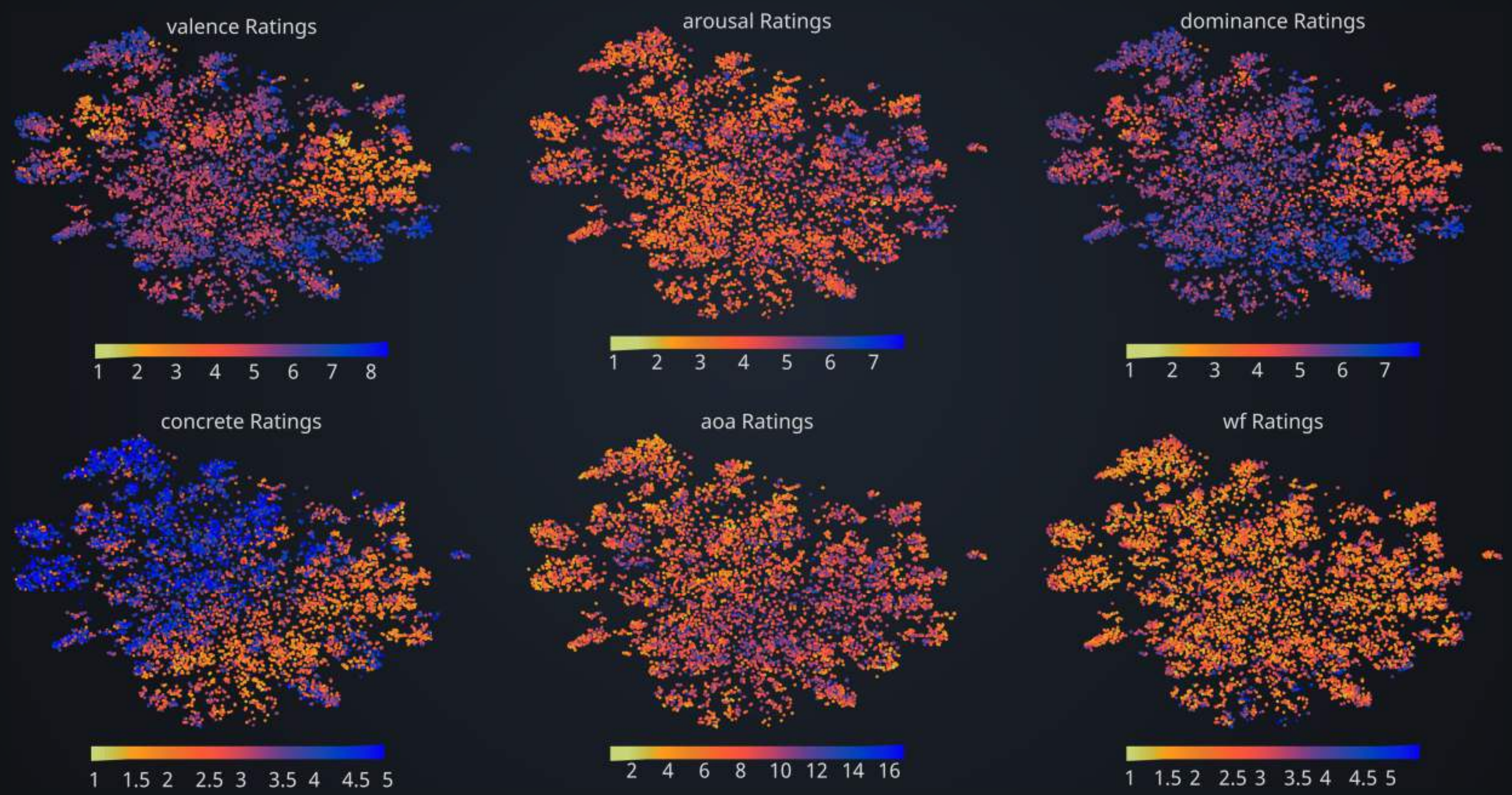
Psycho-affective: Valence, Arousal, Dominance
Semantic: Concreteness, Age-of-Acquisition
Distributional: Word Frequency, Contextual Diversity

Local Assortativity

To what degree do cues and responses exhibit assortativity?



Macroscopic Assortative structure



Implications

1. Local assortativity determines a graph's global structure

2. Global emergent pattern suggests two main organising factors:
    - Valence
    - Concreteness

3. Provides a basis for inferring psycholinguistic properties using near-neighbor methods

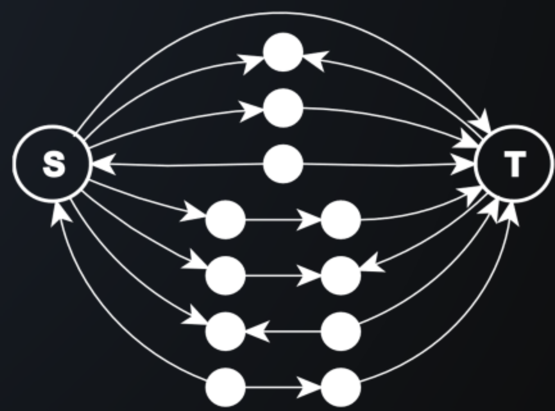
4. Extends Osgoods' findings for nouns to entire lexicon

5. Issue of scale: including all words (not just emotive ones) shows novel contribution of concreteness

Van Rensbergen, Storms & De Deyne, 2016
De Deyne, Navarro & Perfors, in preparation

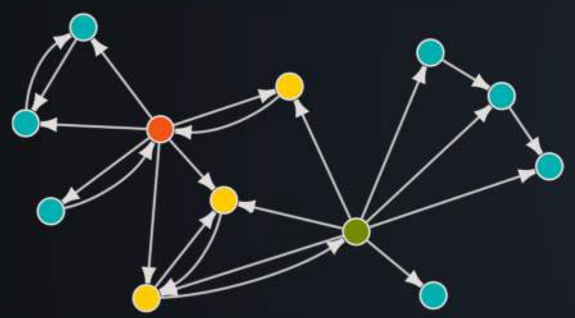
Connecting Micro, Meso & Macro

2. Local and Global Similarity



Spreading activation model

Local Similarity Measure
Neighbour distributional overlap
Cosine: Degree of sharing immediate neighbours



Weights

$$\max\left(0, \log_2 \frac{P(resp|cue)n}{P(resp)}\right)$$

Graph-based global similarity
Random walk based measure similar to **Katz Index**
Similar nodes share neighbours that are also similarz

Procezdure
G converted to a row-normalized transition matrix

$$G_{rw(1)} = I$$

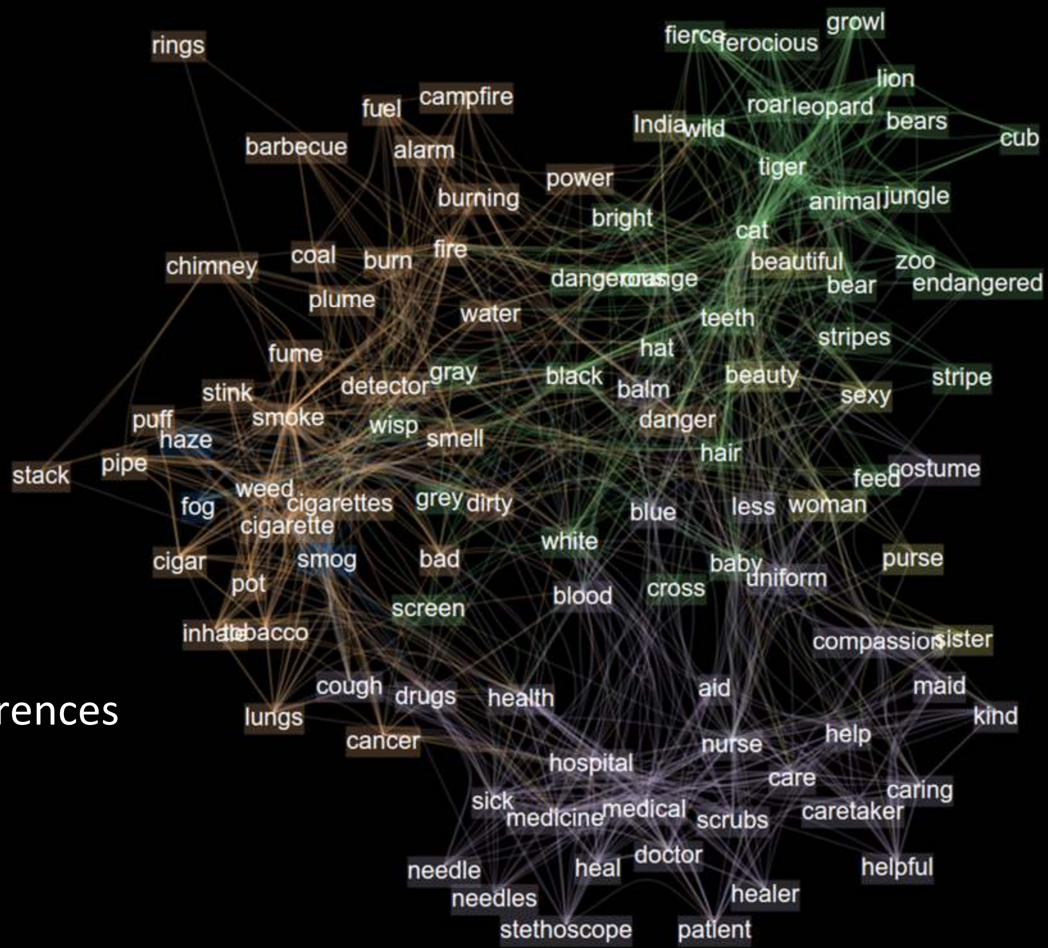
$$G_{rw(2)} = I + \alpha G$$

$$G_{rw(3)} = I + \alpha G + \alpha^2 G$$

$$in\ the\ limit\ \mathrm{G}_\infty = \sum_{r=0}^{\infty} (\alpha G)^r$$

α determines contribution of short over longer paths
➔ limits spread of activation

Illustration tiger – nurse - smoke



The meaning of a word:

Direct and indirect associations or co-occurrences

Spreading activation example

Example of new paths for *tiger*

α = 0.25	**α = 0.50**	**α = 0.75**	**α = 0.95**
leopard	leopard	leopard	lioness
safari	safari	hyena	hyena
bear	hyena	lioness	cougar
zebra	lioness	safari	leopard
giraffe	zebra	zebra	devour
fox	giraffe	devour	jungle
	devour	pheasant	Jerry can
	pheasant	carnivore	carbine
	carnivore	cougar	pheasant
	jaguar	bird of prey	bird of prey
D = 0.01	D = 0.03	D = 0.08	D = 0.10

De Deyne, S., Navarro, D.J., Perfors, A. and Storms, G. (2016), Structure at every scale: A semantic network account of the similarities between unrelated concepts. *Journal of Experimental Psychology: General*.

Similarity plays an important role in organizing the semantic system. However, given that similarity cannot be defined on purely logical grounds, it is important to understand how people perceive similarities between different entities. Despite this, the vast majority of studies focus on measuring similarity between very closely related items. When considering concepts that are very weakly related, little is known. In this article, we present 4 experiments showing that there are reliable and systematic patterns in how people evaluate the similarities between very dissimilar entities. We present a semantic network account of these similarities showing that a spreading activation mechanism defined over a word association network naturally makes correct predictions about weak similarities, whereas, though simpler, models based on direct neighbors between word pairs derived using the same network cannot.

Keywords: word associations, similarity, semantic networks, random walks

Relatedness across the lexicon

Behavioural

Common categories
fruit, insects, tools, …

Domains
artifacts, animals

Arbitrary concepts
nouns

High similarity / inter-subject agr. → Low similarity / inter-subject agr.

Explanations

Psychologically small, finite number of features shared among individuals (Medin & Ortony, 1989)

Infinite number of ways two concepts can be similar (Goodman, '72, Medin, Goldstone & Gentner, '93)

⇕ ⇕

Lexico-semantic view

Humans continuously track weak linguistic contingencies lead to stable structure shared among individuals across a range of concept relations

Empirically no clear evidence, and issue of sparsity of the input

Structure in remote, domain and basic level triads

REMOTE

Stimuli

- 100 randomly generated triads
- Same frequency concreteness range
- Mostly weakly related pairs

Sunday - vitamin - idiot

dark - heat - shot

DOMAIN TRIADS

Stimuli

- Animals, Artifacts, Food, Activities
- Words occur only once

pigeon - sardine - butterfly

jeep - gun - sweater

deer - peacock - salmon

BASIC LEVEL TRIADS

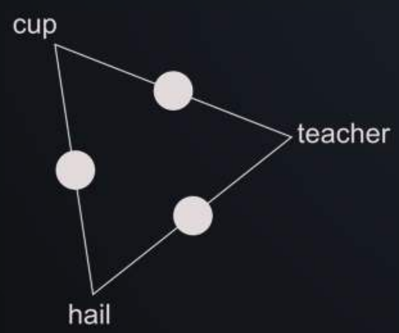
Stimuli

- taken from De Deyne et al. (08)
- 4 x Animals, 6 x Artifacts
  2 x Food, 2 x Activities

goldfish - shark - pike

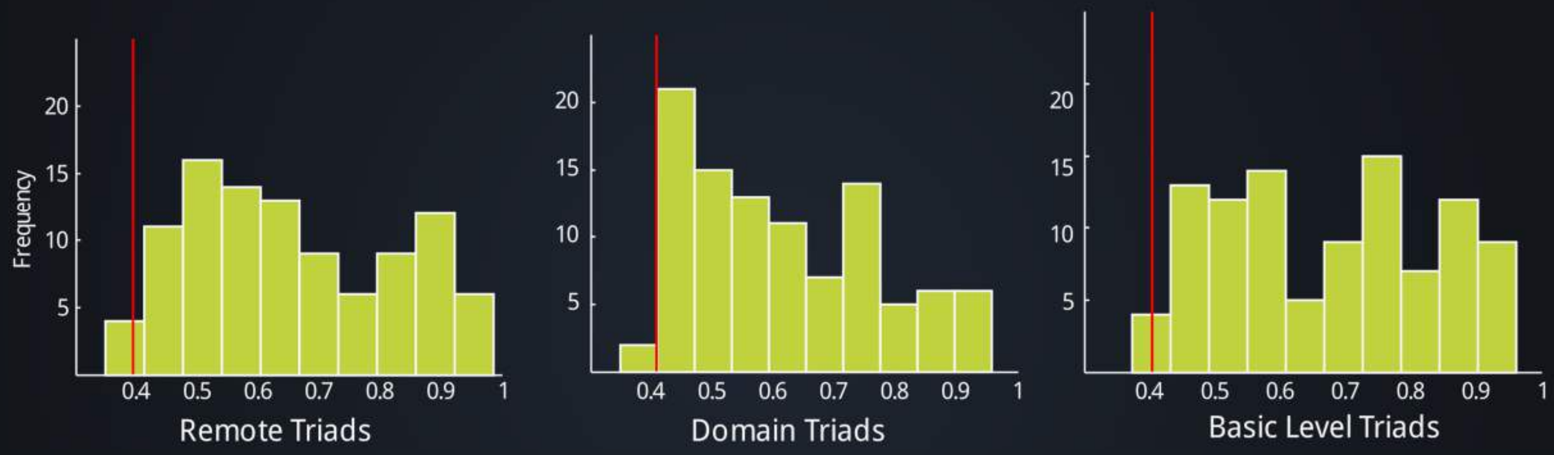
donkey - horse - zebra

onion - cauliflower - parsley



"Choose strongest related pair"

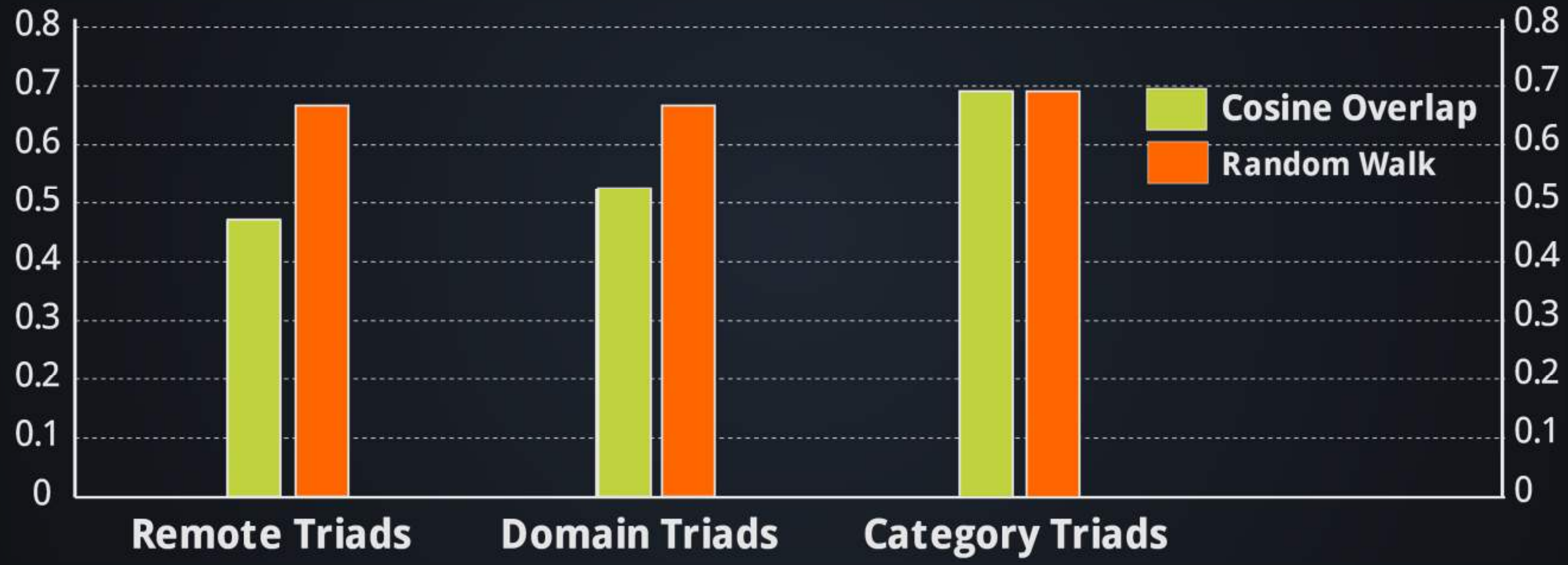
Do participants agree about remote, domain and basic triads?



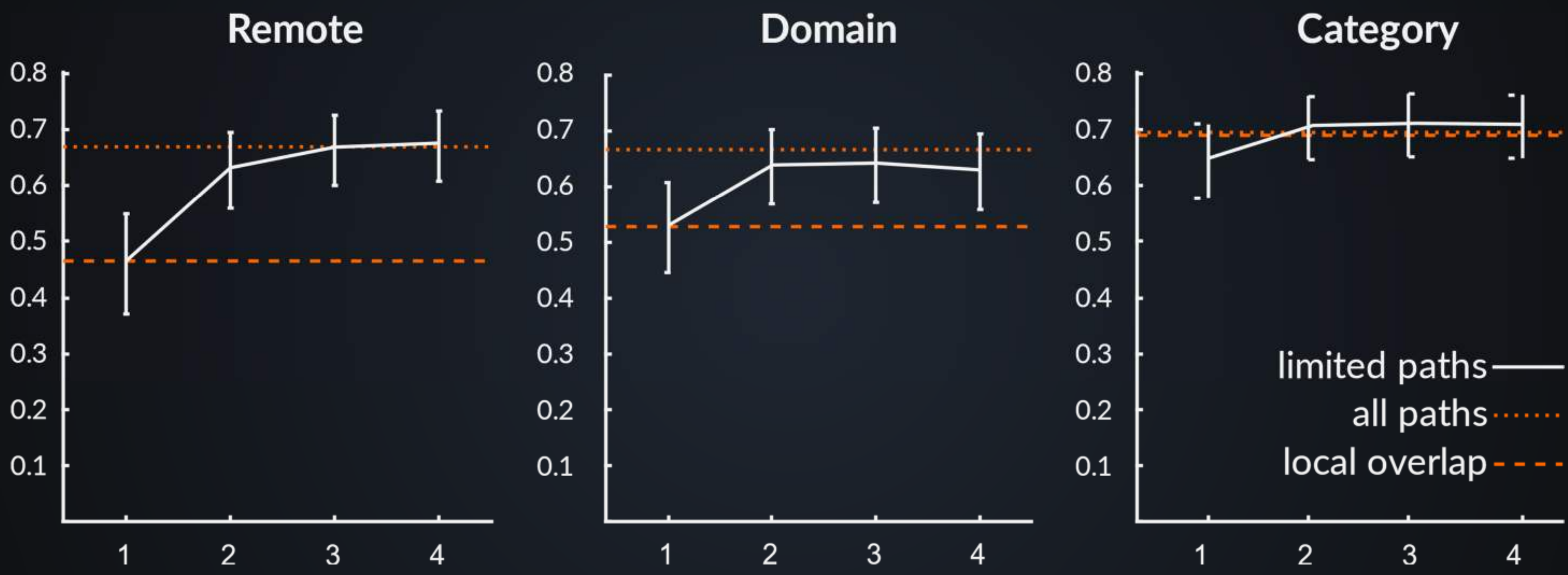
Dominant choice probability and 95% confidence boundary for random choice (N=100)

Agreement among participants preferences for majority of triads

Overview model findings



The role of path length



How do they compare?

	n	n(overlap)	**Linguistic Model**		**Word Association Model**	
			Count	w2v	Count	RW
Similarity Judgements						
WordSim-353B	203	175	.74	.79	.84	.87
SimLex-999	998	927	.37	.43	.70	.68
Relatedness Judgements						
WordSim-353A	252	207	.67	.70	.77	.82
MTURK-711	778	771	.67	.71	.81	.83
Radinsky2011	287	137	.75	.78	.74	.79
RG1965	65	52	.78	.83	.93	.95
MEN	3000	2611	.75	.79	.85	.87
Remote relatedness judgments						
Remote triads	300	300	.65	.52	.62	.74
Average			**.67**	**.69**	**.78**	**.82**

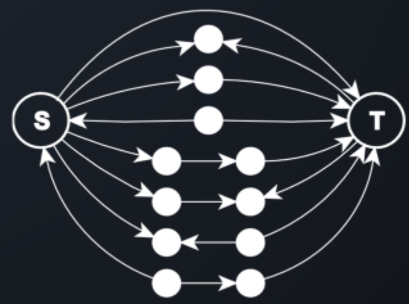
Interim conclusions

Methodological

- Random walk: interesting way to model spreading activation, using little heuristics
- Improvements across a range of relations (remote, domains, basic)
- Limited walks address concerns by extent of spreading activation throughout network
- Strong test for inference in lexico-semantic models

Theoretical

- Similarity:
  Sufficiently constrained between remote pairs
- A connected homogeneous view of lexicon bridging associative and semantic meaning



Tutorial

Entirely optional: You can follow along in RStudio.

Download or close the repository at https://github.com/SimonDeDeyne/wellington2023

Software and Packages

- You will need to have R and Rstudio installed.
- igraph package for network analysis
- A list of additional packages can be found in the setup.R file on Github.

Note: some of these packags are continuously developed, and older versions might not provide the same results

Selected readings

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