Computer-assisted approaches to semantic maps
A qualitative approach to large-scale lexical datasets

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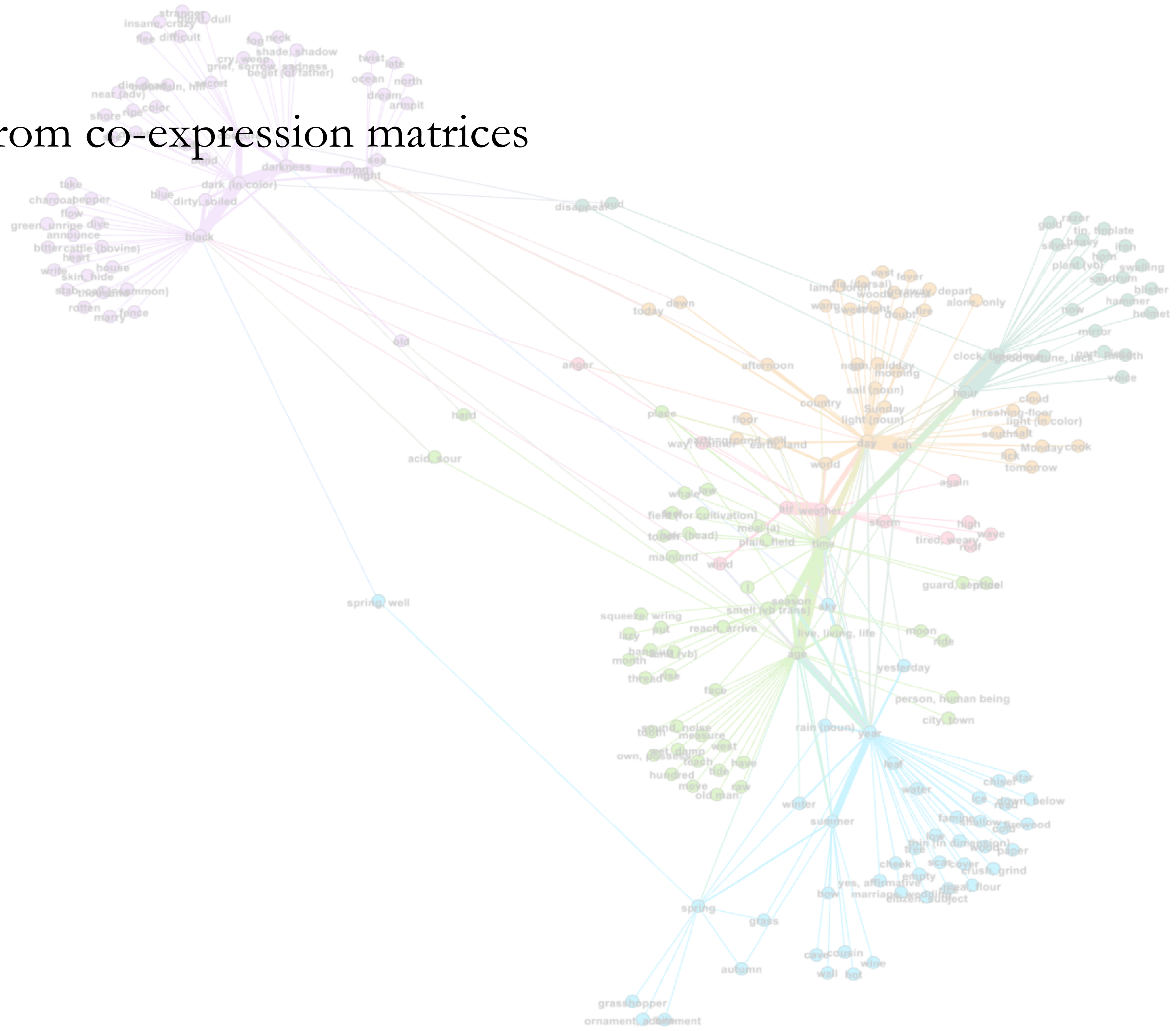
Outline of the talk

- (Classical) semantic maps
  - Basic principles
  - Inferring semantic maps from co-expression matrices



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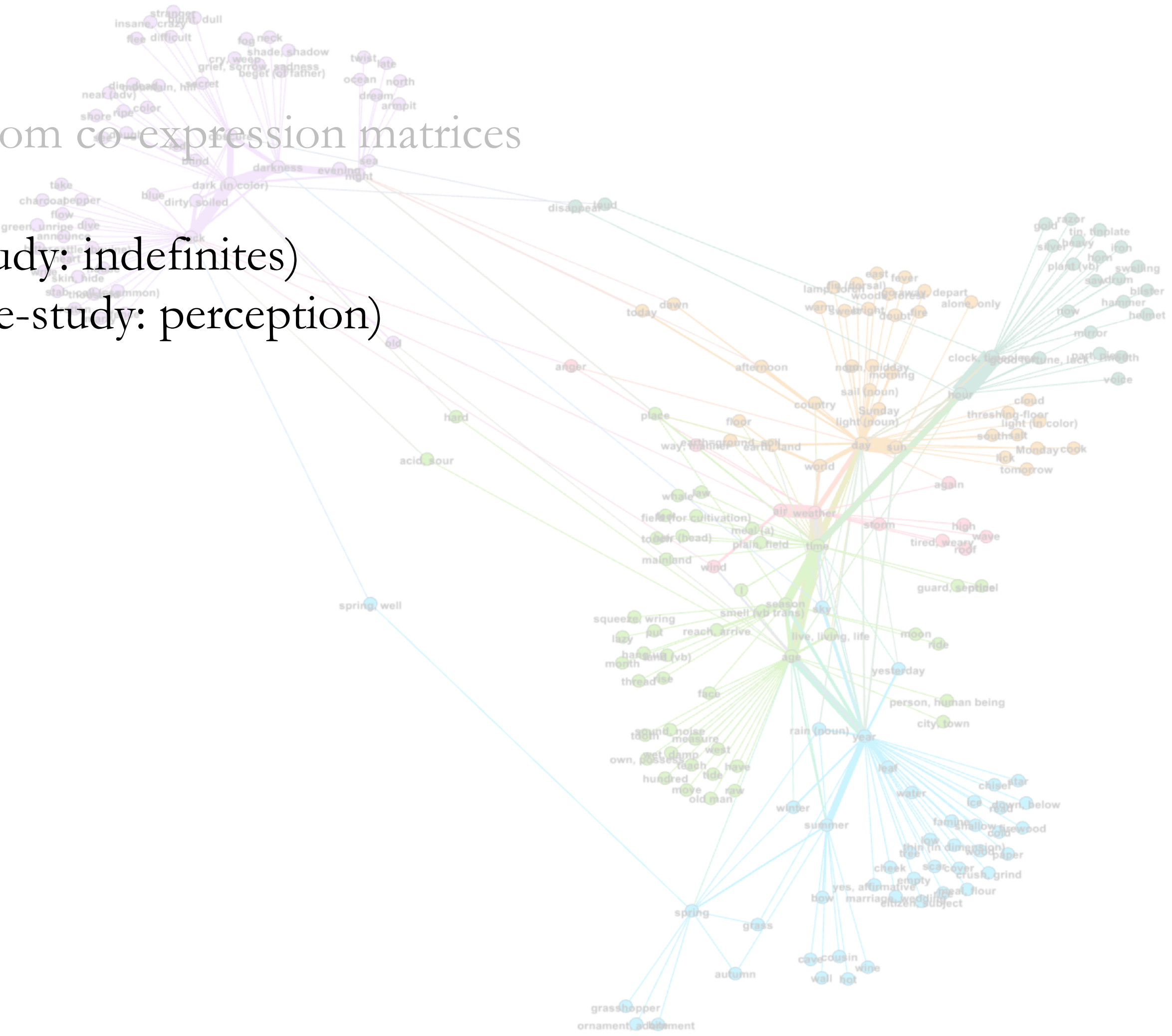
- Tool: pros and cons
  - Can we do better? (case-study: indefinites)
  - Unsolvable inferences (case-study: perception)



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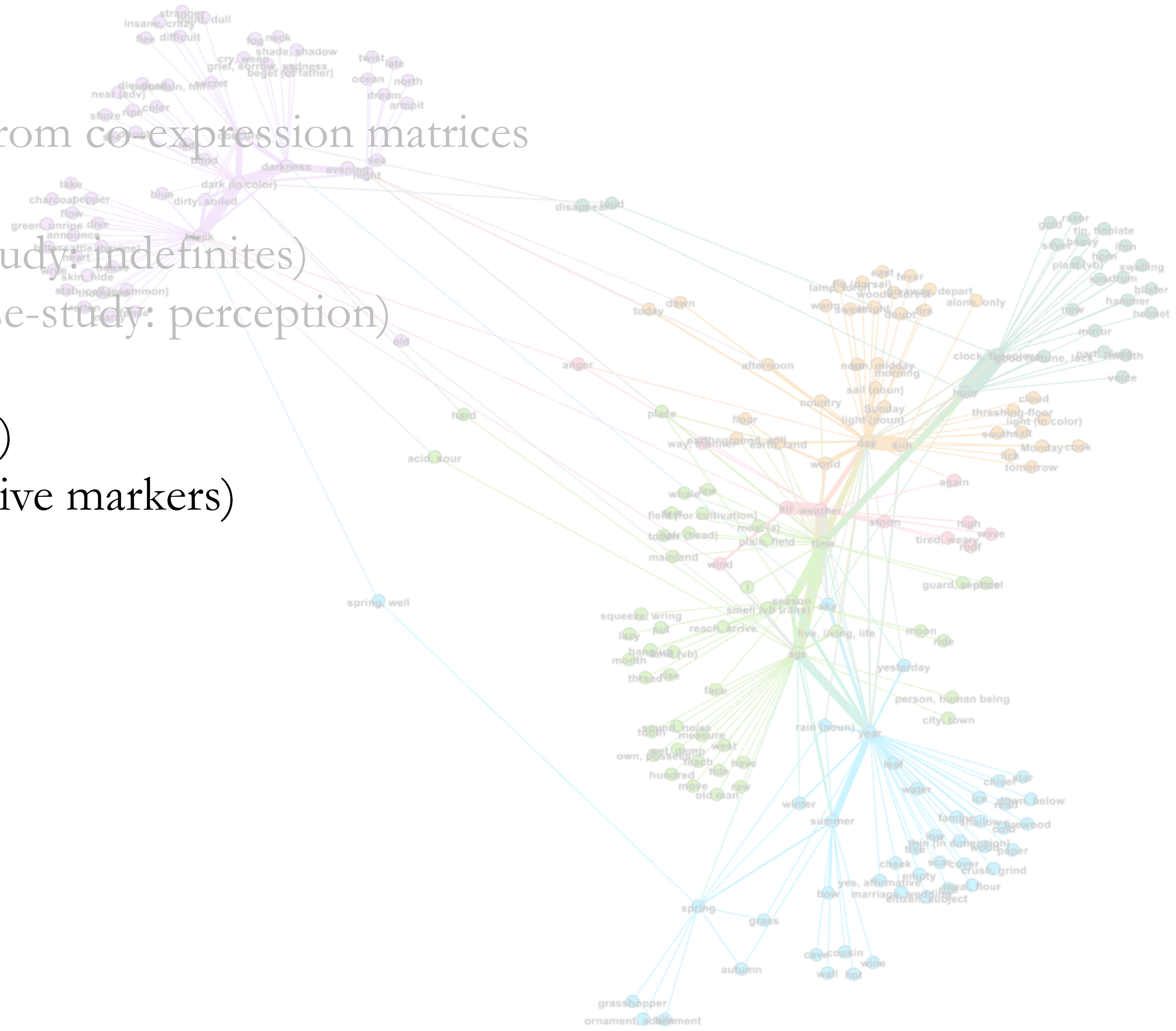
  - Size (case-study: emotions)
  - Structure (case-study: allative markers)



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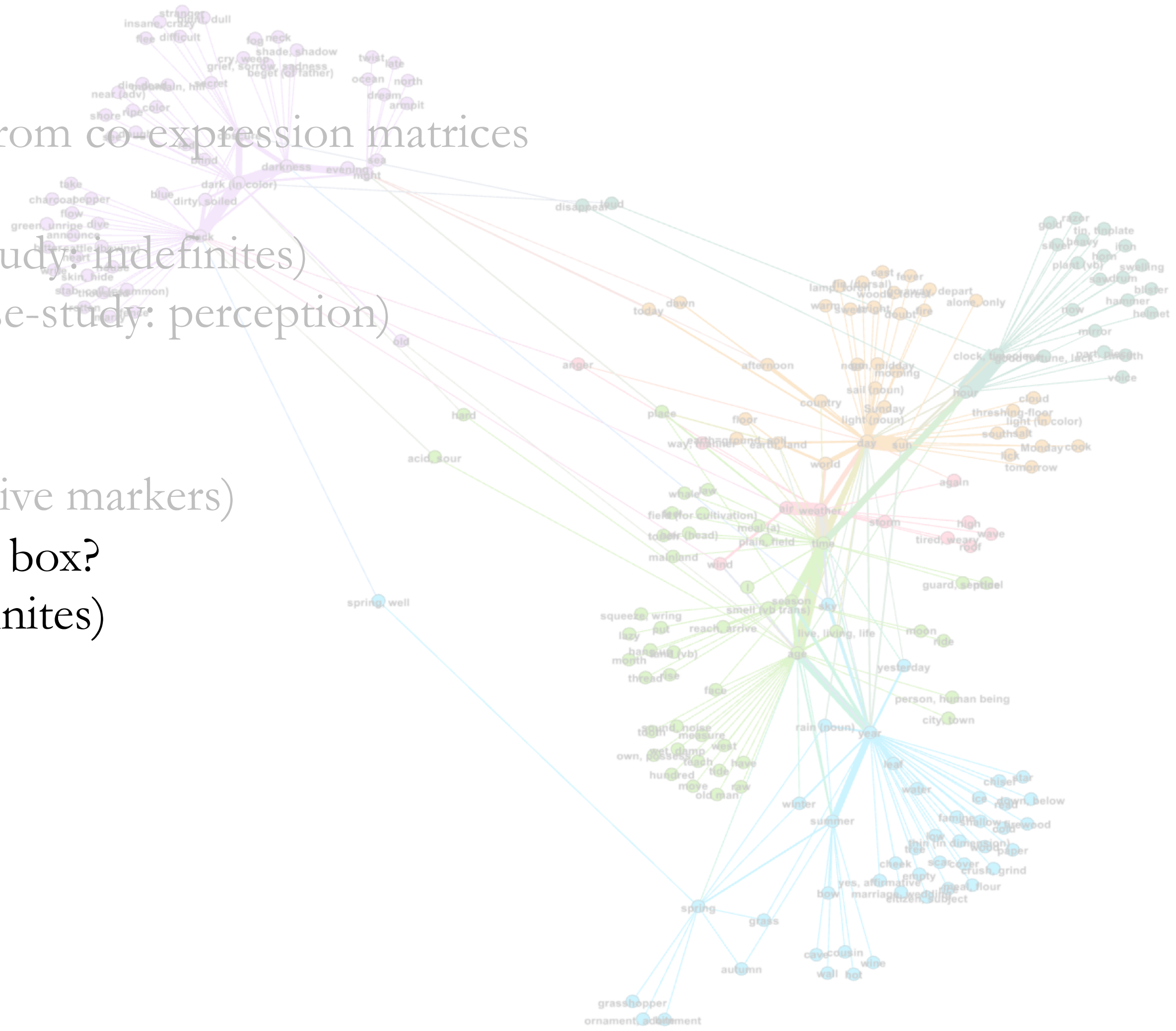
  - Lattices (case-study: indefinites)



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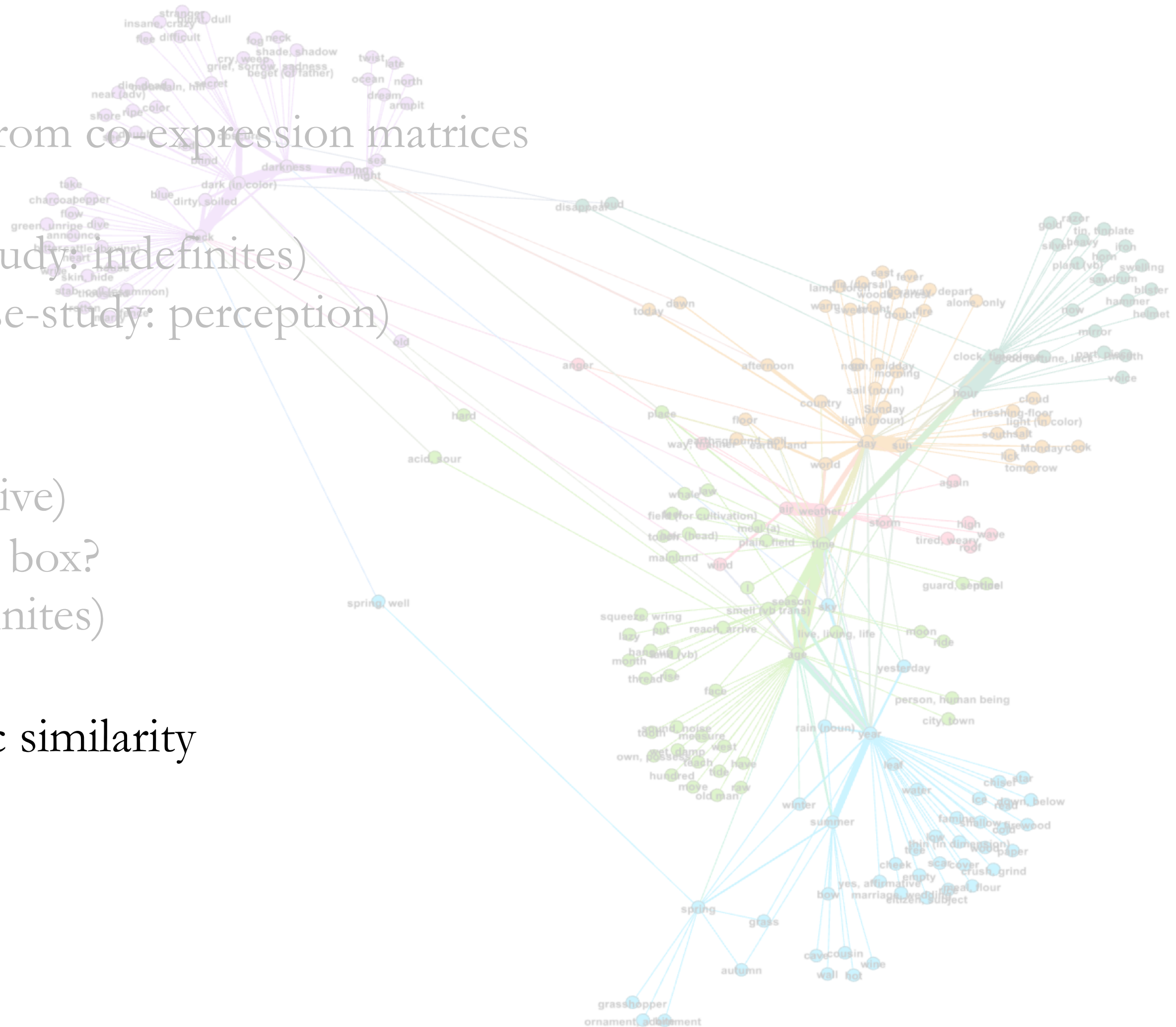
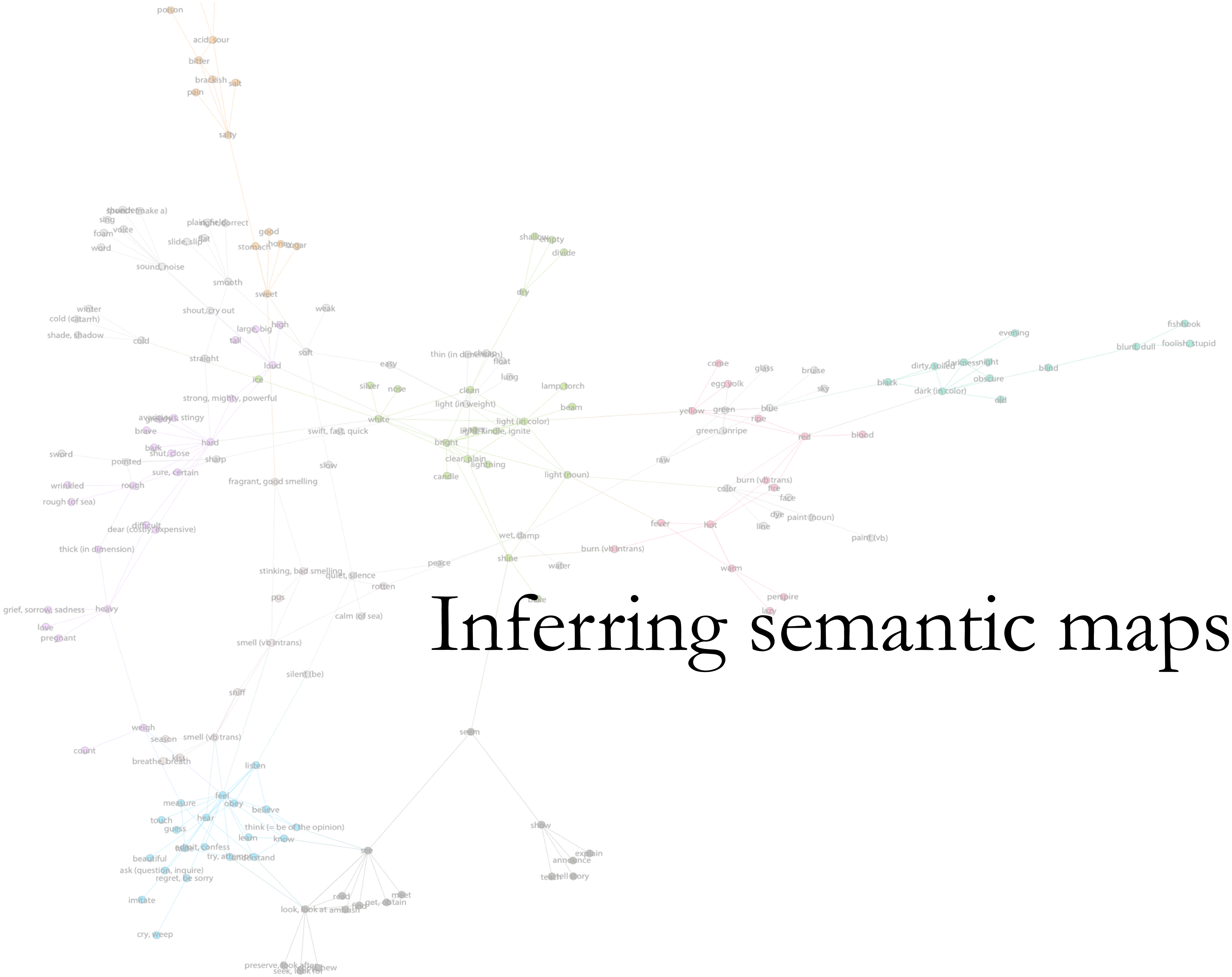
- Conclusions
  - Co-expression vs semantic similarity





Inferring semantic maps

Inferring semantic maps

- 'A semantic map is a geometrical representation of functions (…) that are linked by connecting lines and thus constitute a network'

  (Haspelmath 2003)

- A semantic map is a method for visually representing cross-linguistic regularity in semantic structure based on patterns of co-expression

  (Georgakopoulos & Polis 2018)

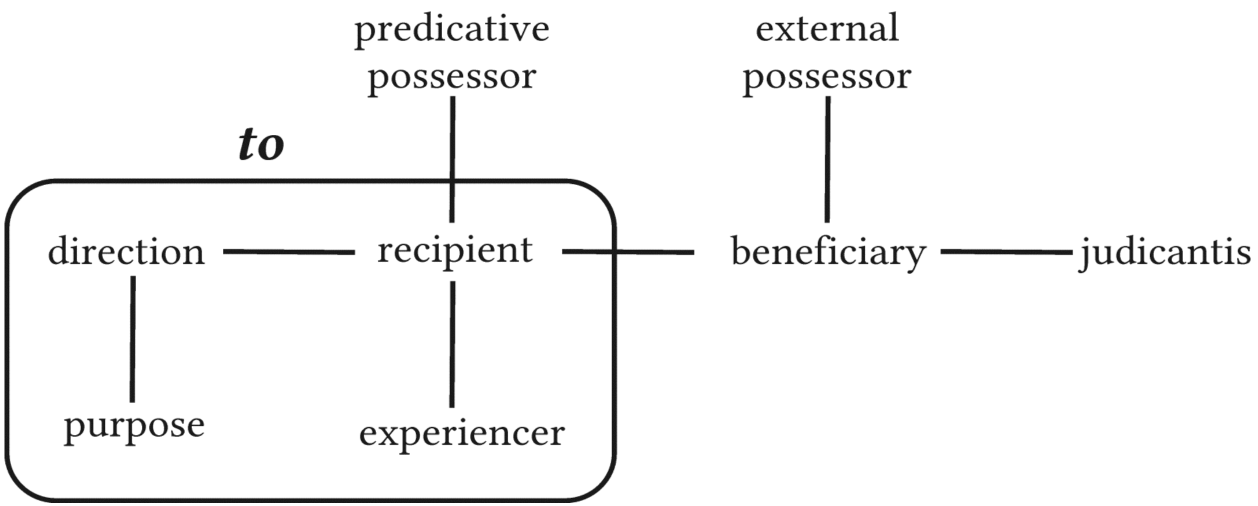


FIGURE 1. A semantic map of typical dative functions / the boundaries of English *to* (based on Haspelmath 2003: 213)

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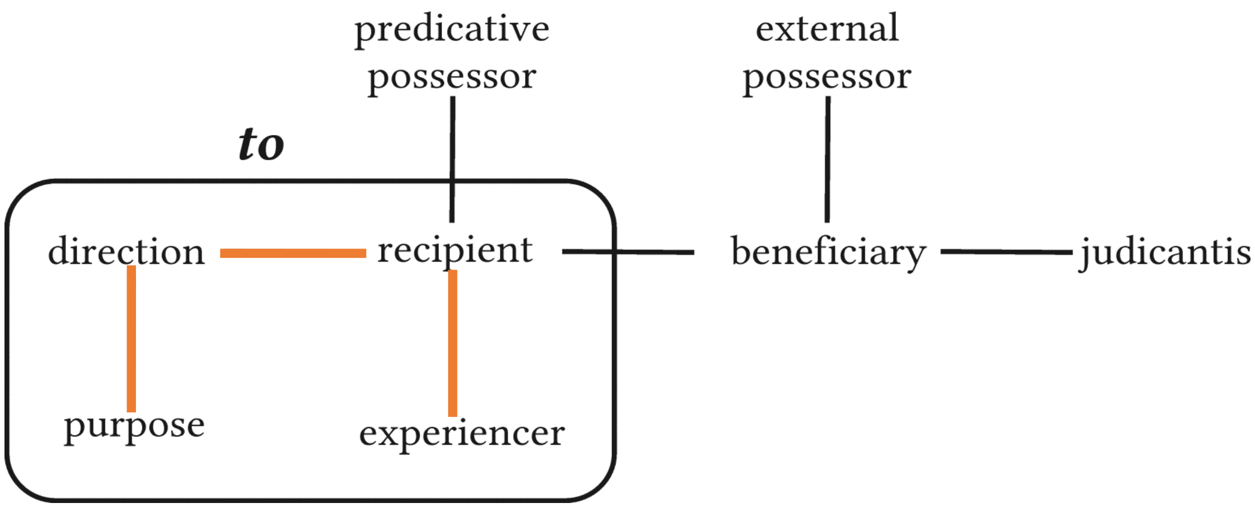

Connectivity hypothesis

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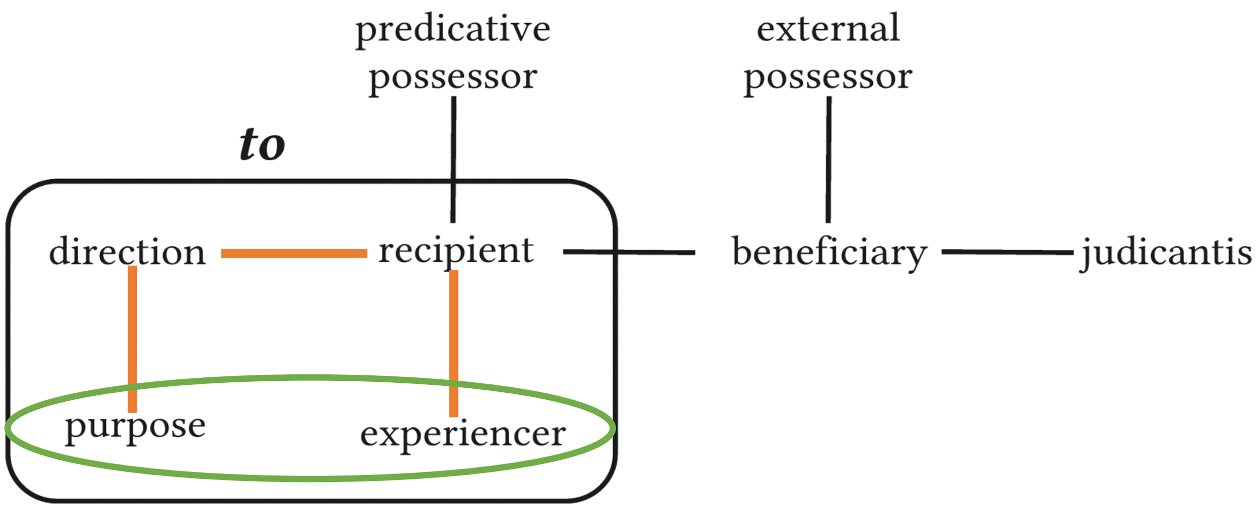

Connectivity hypothesis

Economy principle

FIGURE 1. A semantic map of typical dative functions / the boundaries of English *to* (based on Haspelmath 2003: 213)

Inferring semantic maps

“ideally (…) it should be possible to generate semantic maps automatically on the basis of a given set of data”
(Narrog & Ito 2007: 280)

Inferring semantic maps

Limitation of the (classical) semantic map method: practically, it is impossible to handle large-scale crosslinguistic datasets manually

"not mathematically well-defined or computationally tractable, making it impossible to use with large and highly variable crosslinguistic datasets"

(Croft & Poole 2008: 1)

Inferring semantic maps

- Dimensionality reduction
  - **Points** = meanings (or contexts)
  - **Proximity** = similarity between meanings (or contexts)

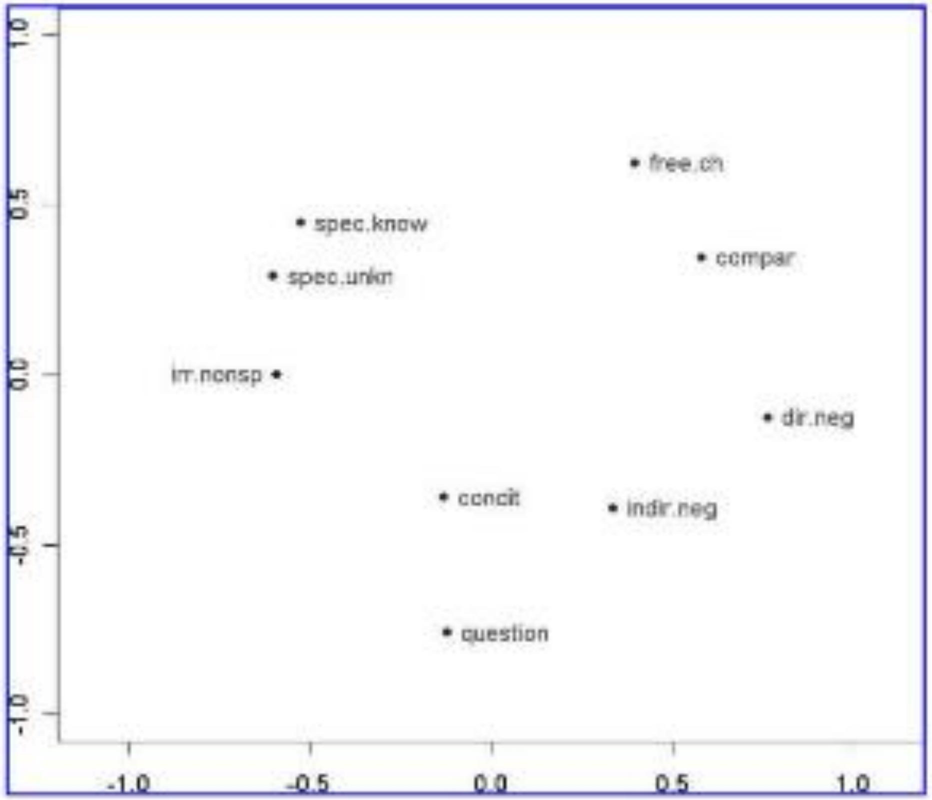

FIGURE 2. MDS analysis of Haspelmath's (1997) data on indefinite pronouns
(Croft & Poole 2008: 15)

Inferring semantic maps

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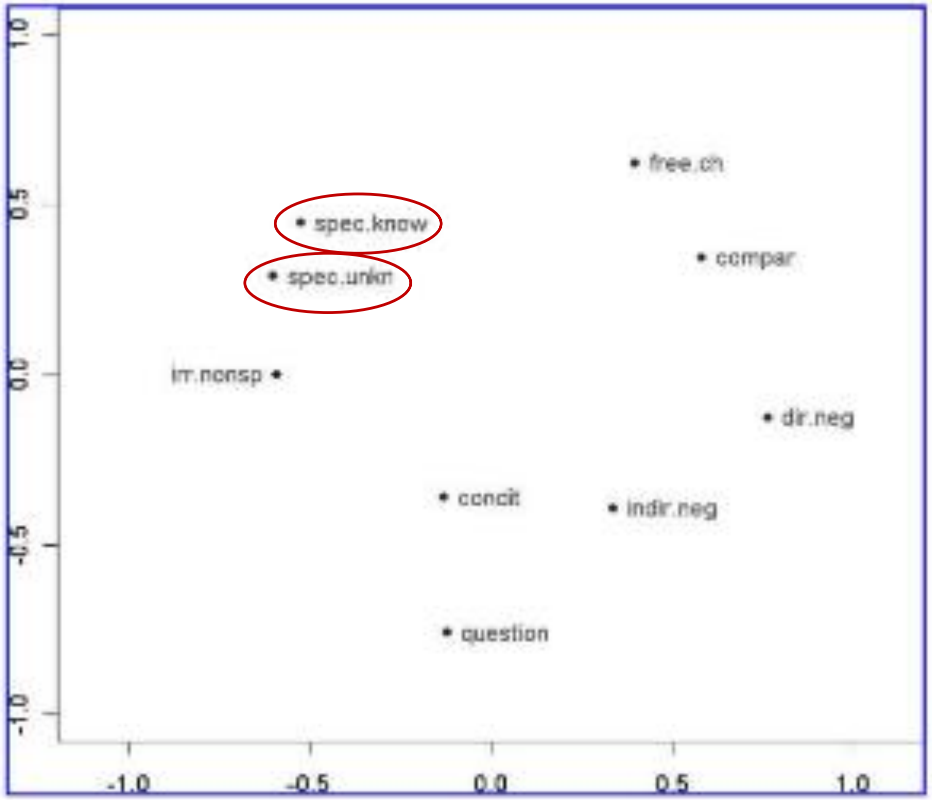
1. **Specific known**
   Somebody called you, guess who

2. **Specific unknown:**
   Somebody called you, but I don't know who



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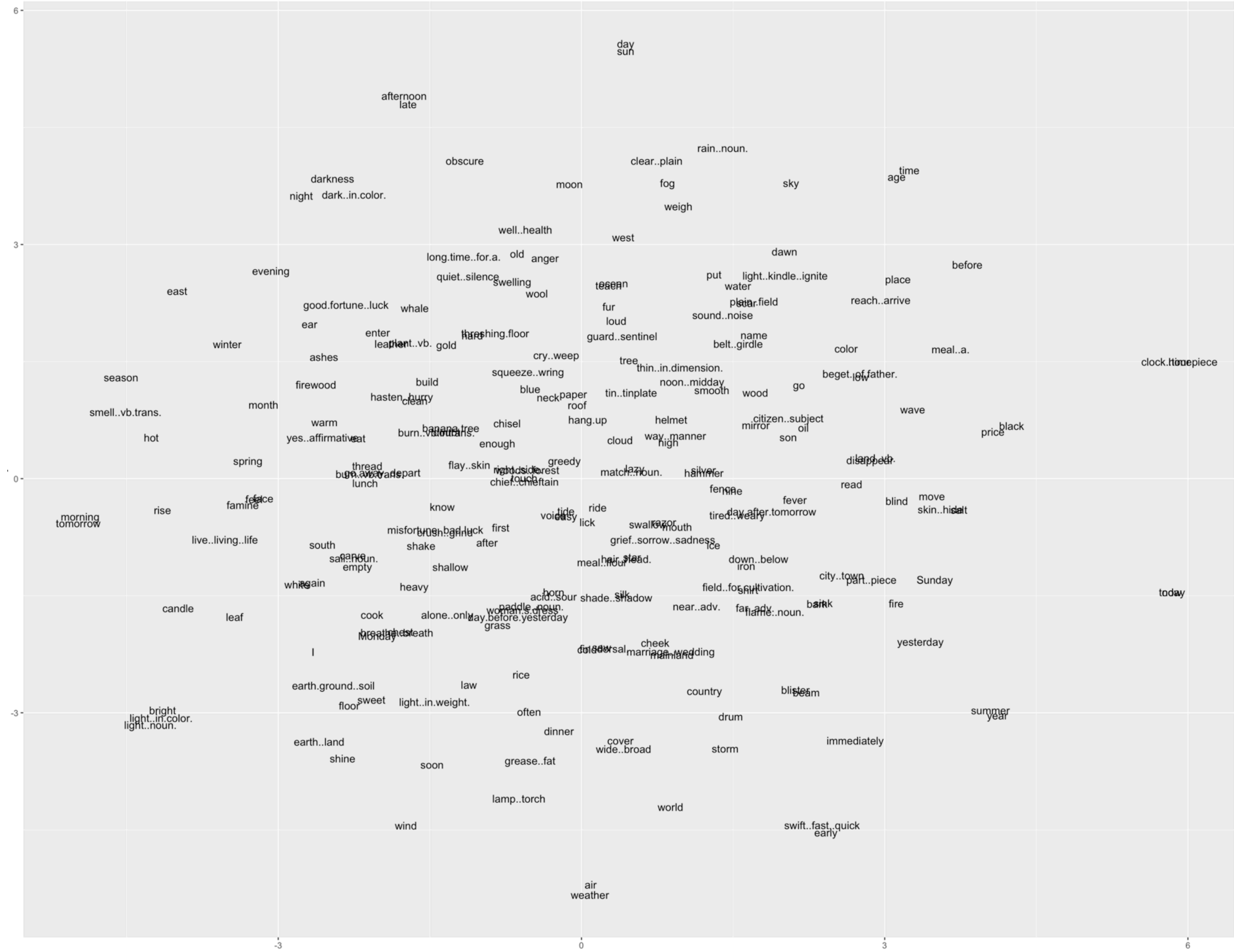

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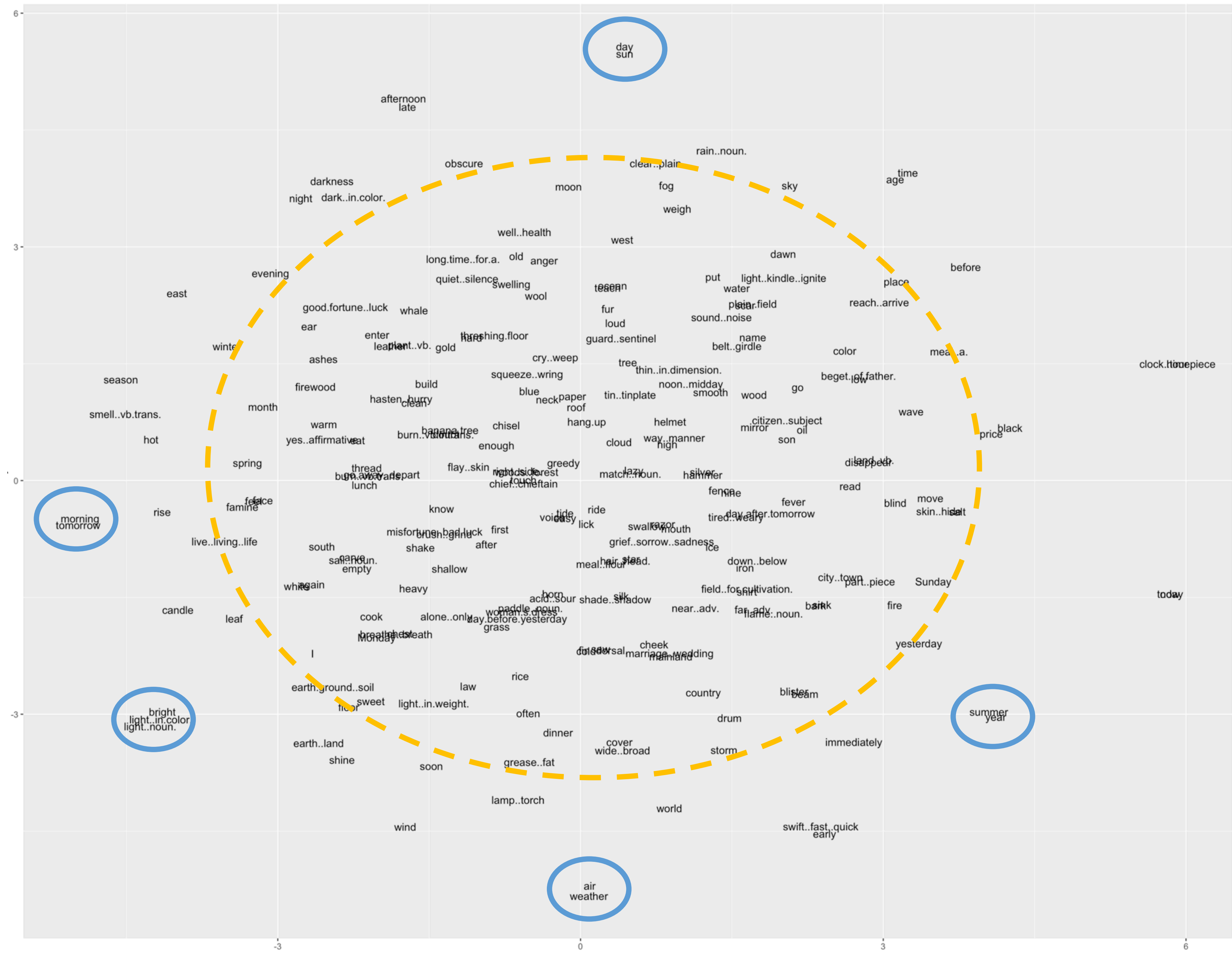
6
day
sun
afternoon
late
rain..noun.
obscure
clear..plain
darkness
moon
fog
sky
time
age
night
dark..in.color.
weigh
well..health
west
dawn
long.time..for.a.
old
anger
before
evening
quiet..silence
swelling
put
light..kindle..ignite
place
east
wool
water
good.fortune..luck
whale
fur
plain..field
reach..arrive
sound..noise
ear
loud
enter
threshing.floor
guard..sentinel
name
winter
gold
belt..girdle
color
meal..a.
ashes
cry..weep
tree
thin..in.dimension.
clock..timepiece
season
squeeze..wring
beget..of.father.
low
build
noon..midday
go
firewood
blue
smooth
wood
hasten..hurry
neck
paper
tin..tinplate
month
roof
wave
smell..vb.trans.
warm
chisel
hang.up
helmet
citizen..subject
mirror
black
oil
price
hot
yes..affirmative
enough
cloud
way..manner
son
high
spring
greedy
flay..skin
disappear
thread
depart
match..noun.
lunch
chief..chieftain
read
fence
fever
move
blind
rise
famine
know
ride
day.after.tomorrow
morning
tomorrow
lick
skin..hide
tired..weary
mouth
first
live..living..life
south
shake
after
grief..sorrow..sadness
ice
empty
shallow
down..below
iron
city..town
part..piece
Sunday
heavy
again
field..for.cultivation.
today
shade..shadow
candle
near..adv.
leaf
cook
alone..only
day.before.yesterday
flame..noun.
fire
grass
Monday
cheek
yesterday
marriage..wedding
I
rice
law
earth.ground..soil
sweet
country
light..in.weight.
floor
often
bright
light..in.color.
light..noun.
drum
summer
year
dinner
cover
wide..broad
earth..land
immediately
storm
shine
soon
grease..fat
lamp..torch
world
wind
swift..fast..quick
early
air
weather



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east
wool
water
place
good.fortune..luck
whale
fur
sound..noise
reach..arrive
ear
loud
enter
threshing.floor
guard..sentinel
name
winter
gold
belt..girdle
color
mea..a.
ashes
cry..weep
tree
thin..in.dimension.
clock..timepiece
season
squeeze..wring
beget..of.father.
firewood
build
noon..midday
go
blue
smooth
wood
month
neck
paper
tin..tinplate
hasten..hurry
clean
roof
smell..vb.trans.
wave
warm
chisel
hang.up
helmet
citizen..subject
mirror
black
price
oil
hot
yes..affirmative
eat
enough
cloud
way..manner
son
high
spring
greedy
disappear
thread
flay..skin
lunch
chief..chieftain
read
fence
fever
move
blind
rise
famine
know
ride
tired..weary
day.after.tomorrow
skin..hide
morning
tomorrow
lick
live..living..life
first
grief..sorrow..sadness
south
shake
after
ice
down..below
empty
shallow
iron
city..town
part..piece
Sunday
today
again
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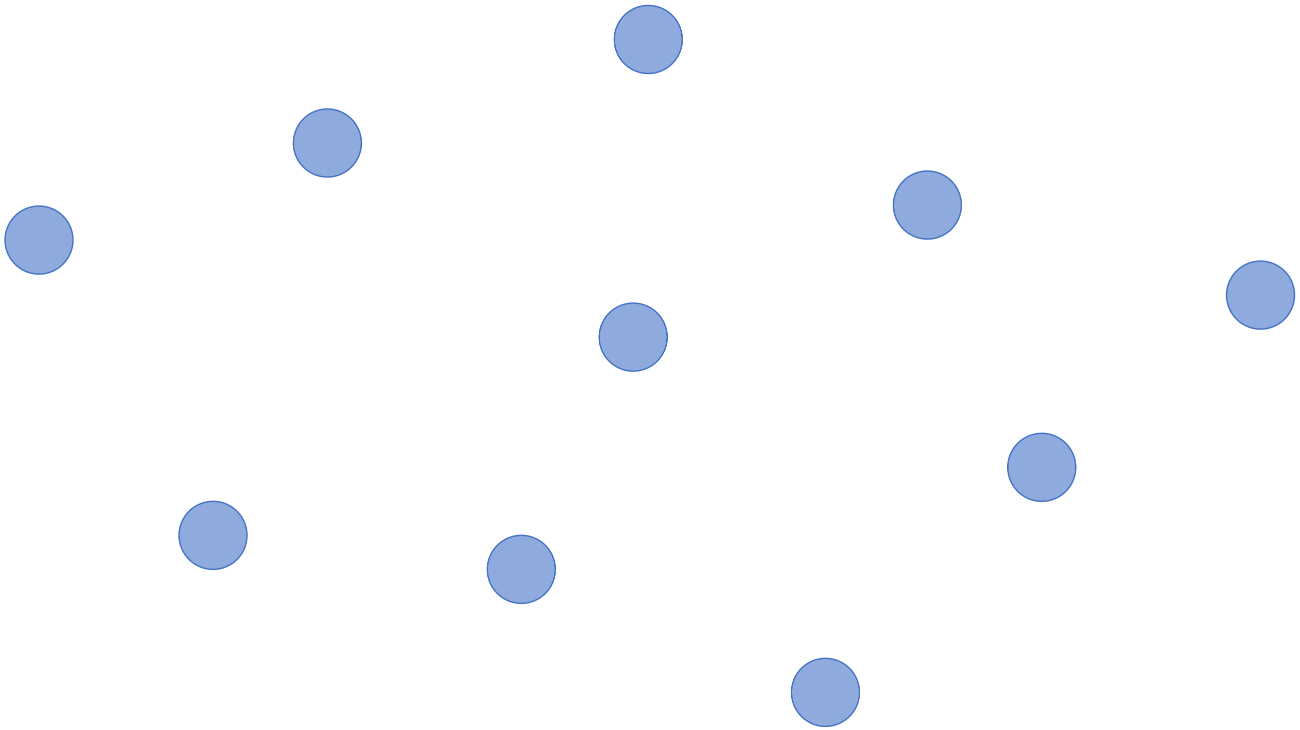
Inferring semantic maps

Regier, Khetarpal, and Majid showed that the semantic map inference problem is “formally identical to another problem that superficially appears unrelated: inferring a social network from outbreaks of disease in a population” (Regier *et al*. 2013: 91)

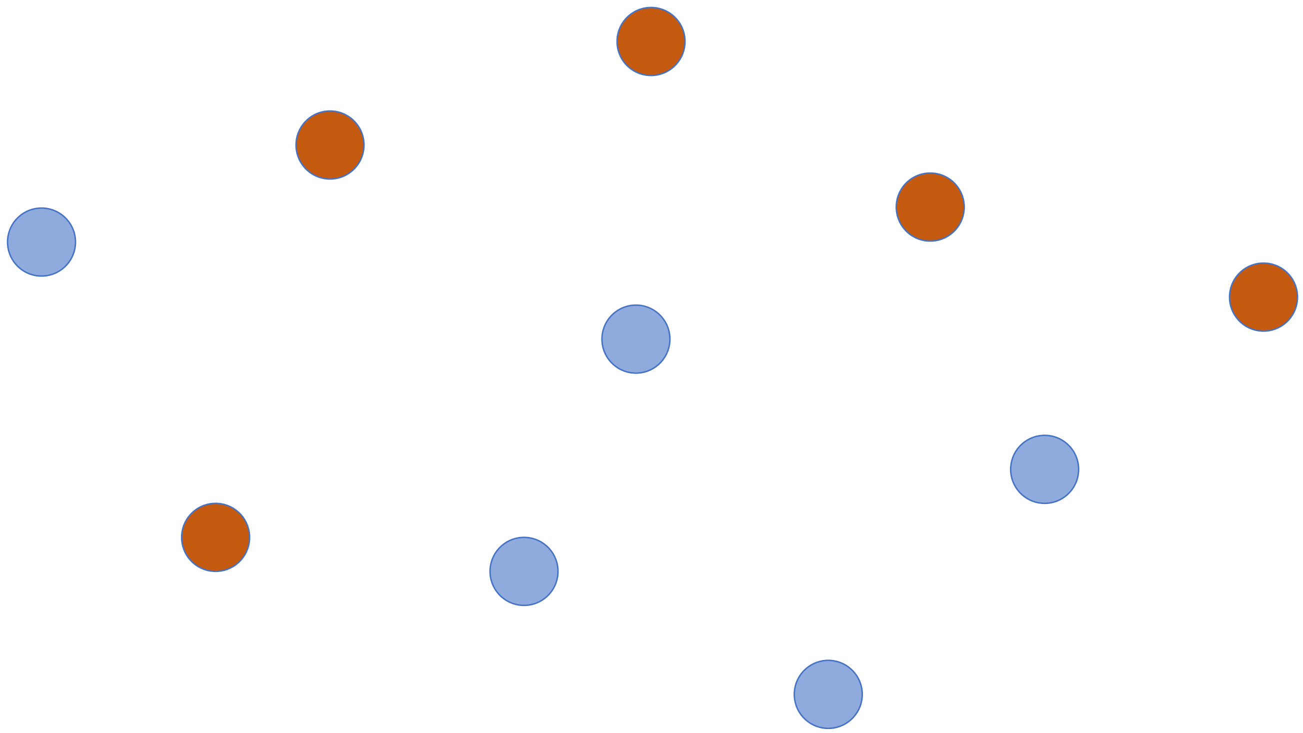
Inferring semantic maps

- What's the idea?
  - Consider a group of social agents (represented by the nodes of a potential graph)



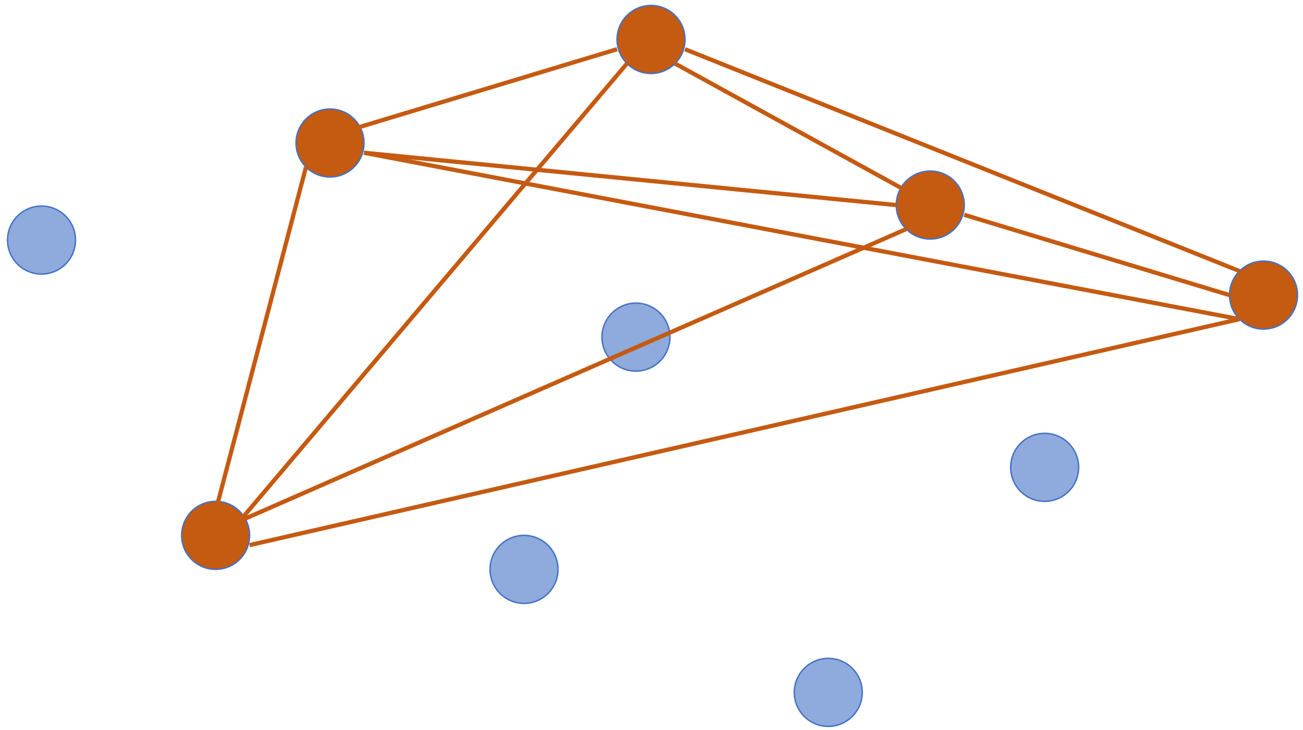
Inferring semantic maps

- What's the idea?
  - If one observes the same disease for five of these agents (technically called a constraint on the nodes of the graph)



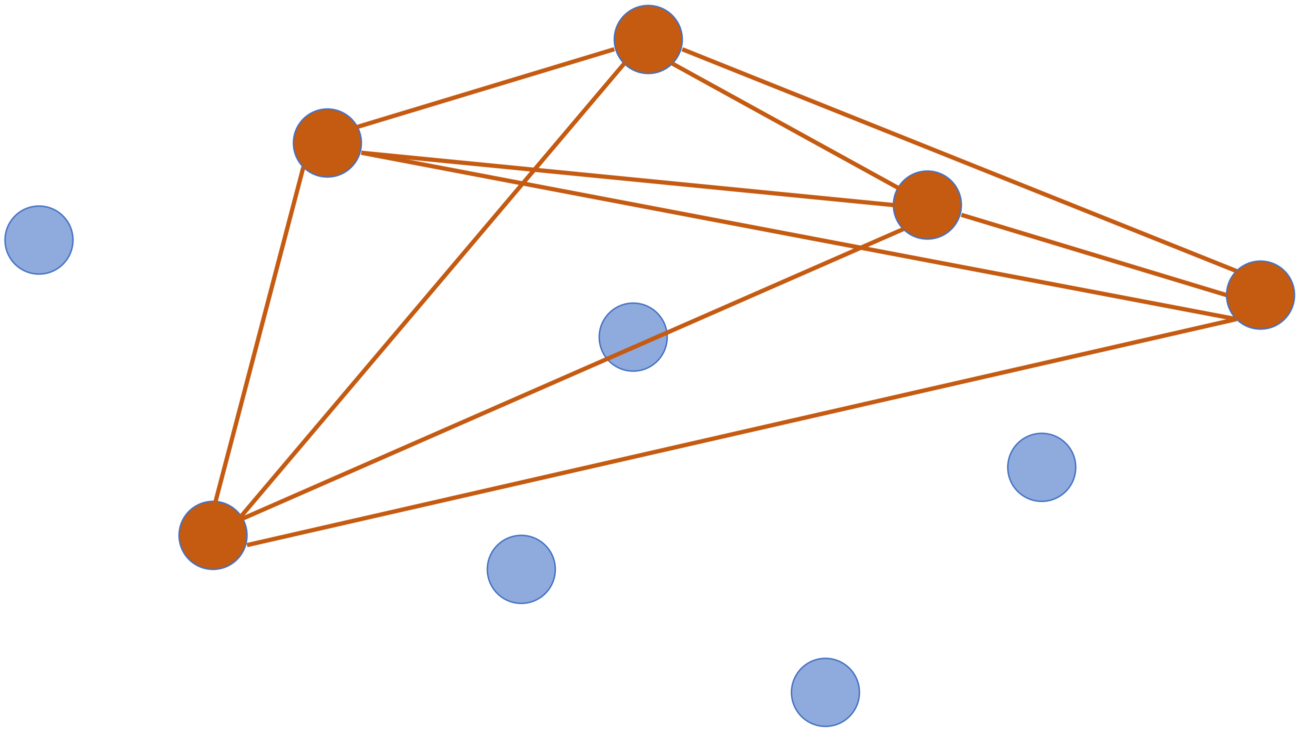
Inferring semantic maps

- What's the idea?
  - One can postulate that all the agents met, so that all the nodes of the graph are connected (10 edges between the 5 nodes)



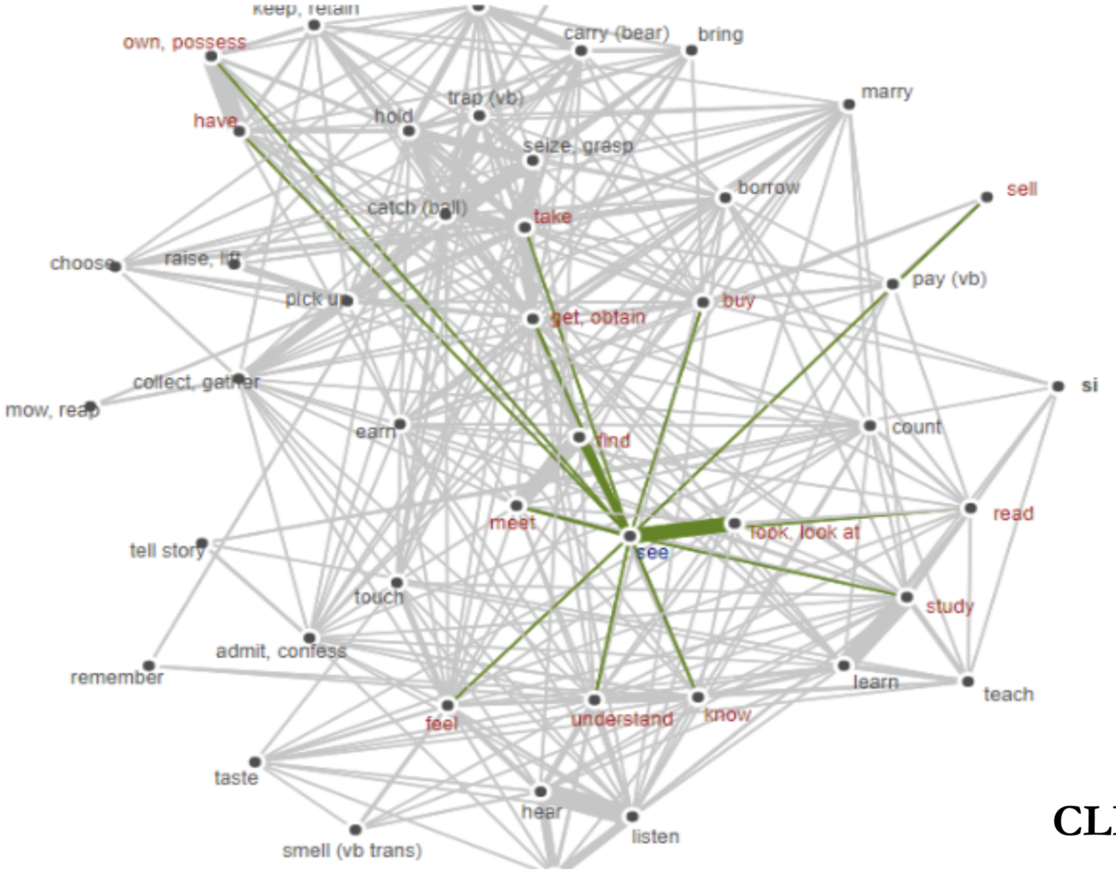
Inferring semantic maps

- What's the idea?
  - This is neither a very likely, nor a very economic explanation



Inferring semantic maps

- What's the idea?
  - But this is precisely what a colexification network does



CLICS² (https://clics.clld.org)

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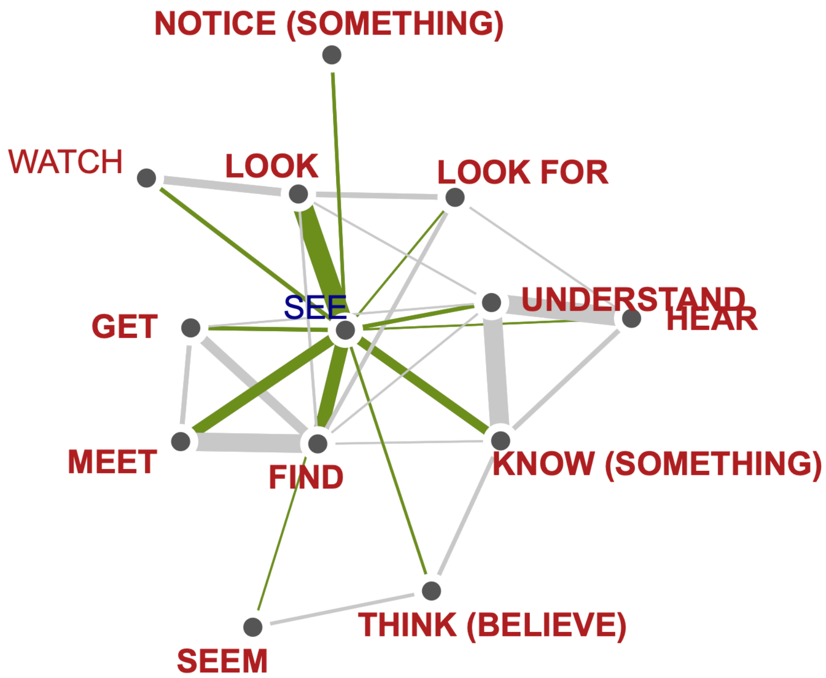

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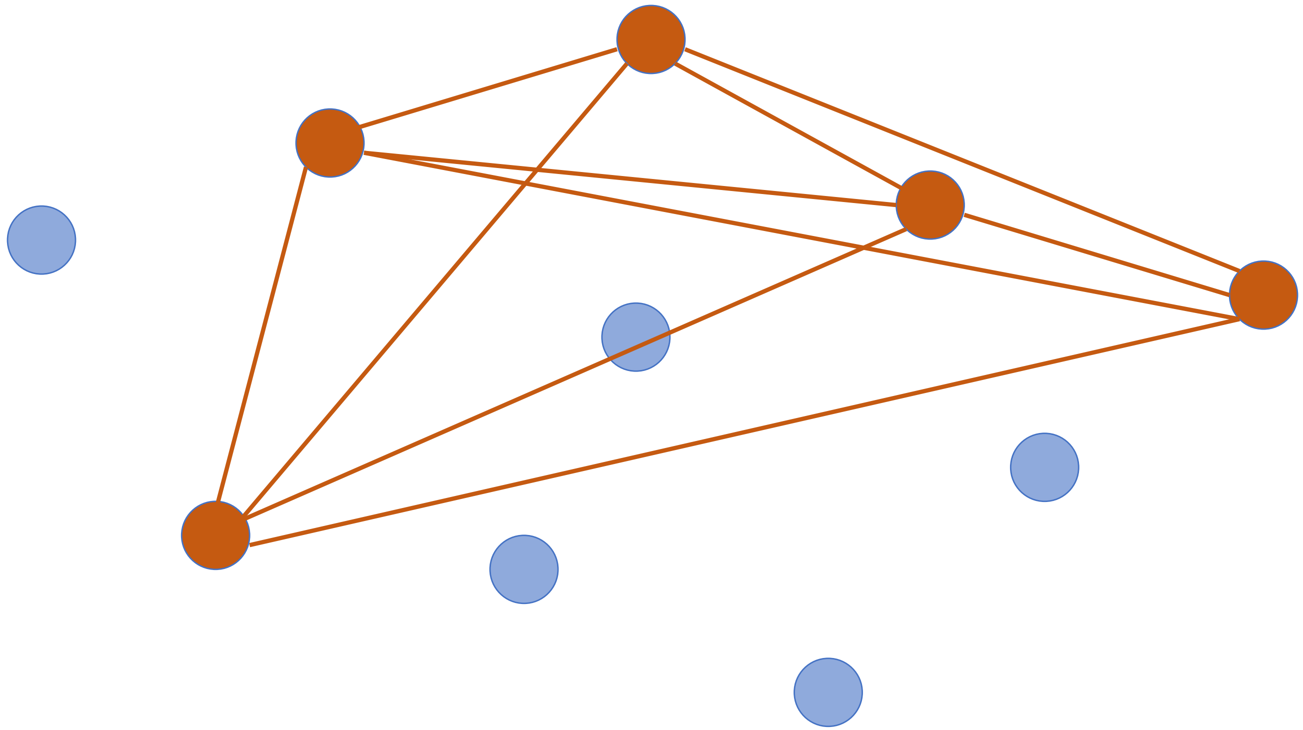
- What's the idea?
  - The goal would be to find a more economical solution and to have all the social agents connected with as few edges as possible, but still accounting for all the observations



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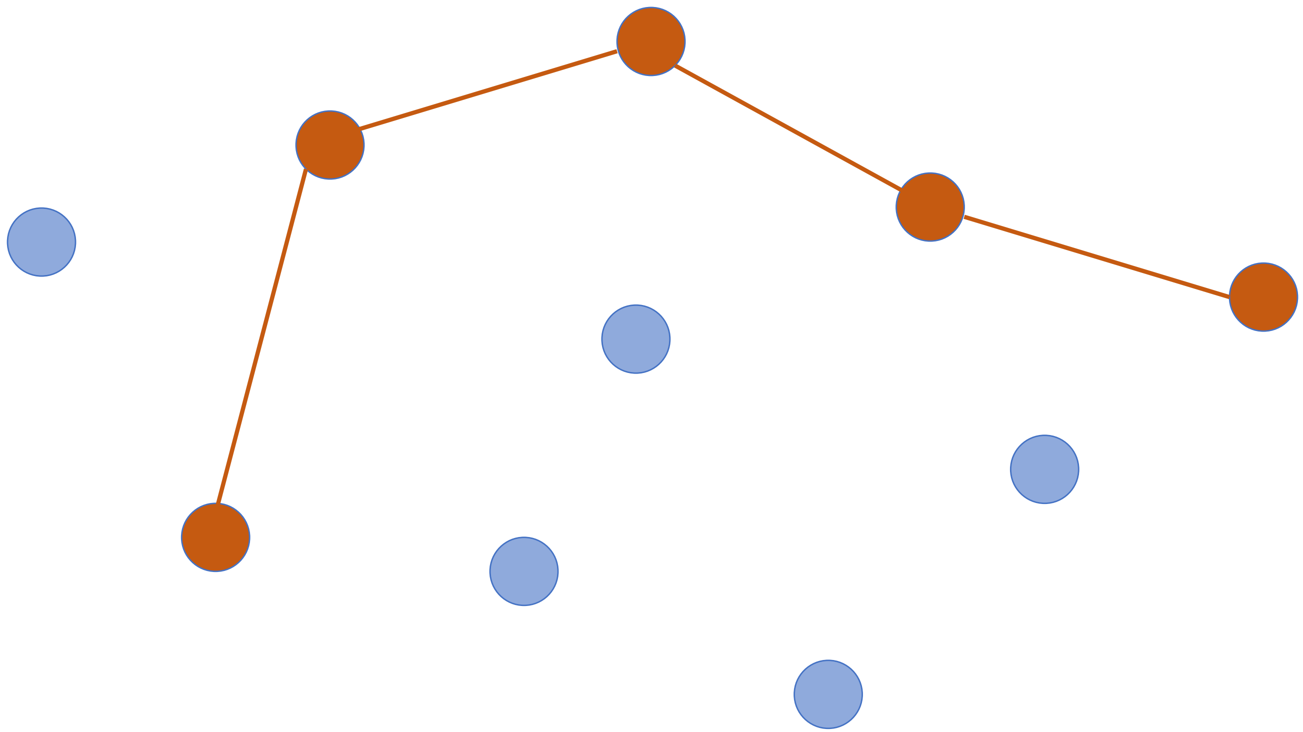

Inferring semantic maps

- How does it transfer to semantic maps?

Inferring semantic maps

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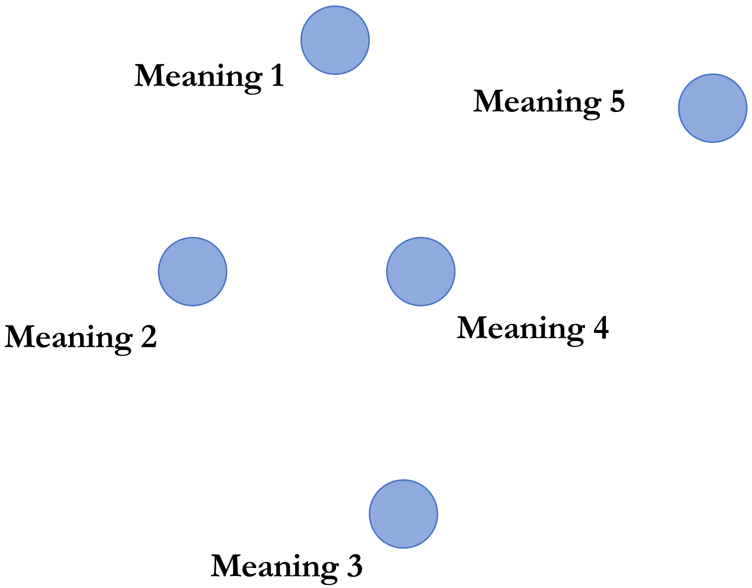
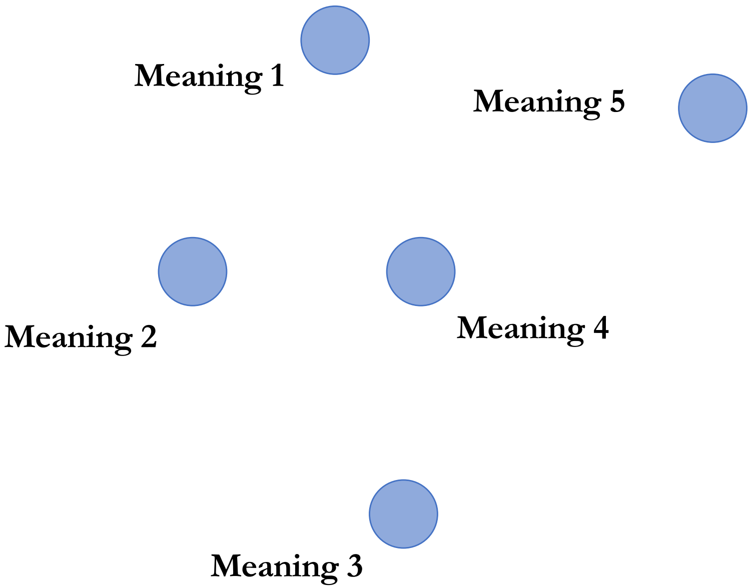
  - Nodes are meanings



Meaning	1	2	3	4	5

Inferring semantic maps

- How does it transfer to semantic maps?
  - Nodes are meanings
  - Constraints are patterns of co-expression (connectivity hypothesis)



Meaning	1	2	3	4	5
Polysemic item A	√	√			
Polysemic item B		√	√	√	
Polysemic item C			√	√	√

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- How does it transfer to semantic maps?
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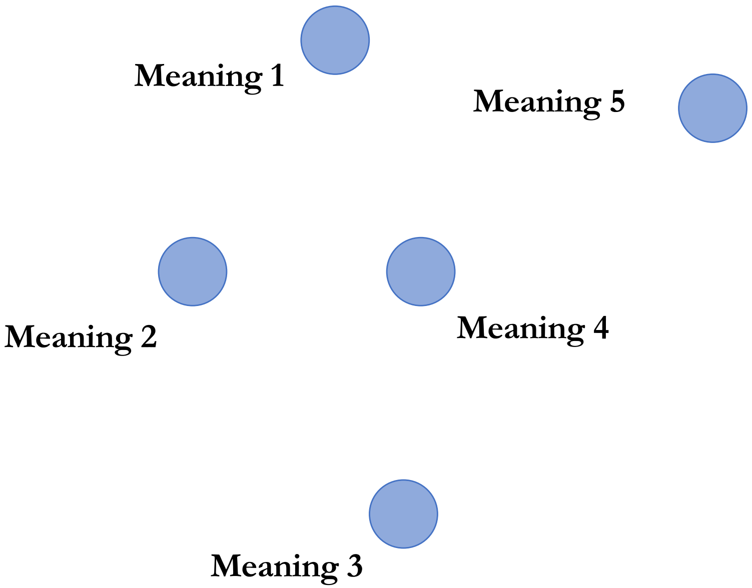
  - One connects the nodes economically based on these constraints (economy principle)



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- How does it transfer to semantic maps?
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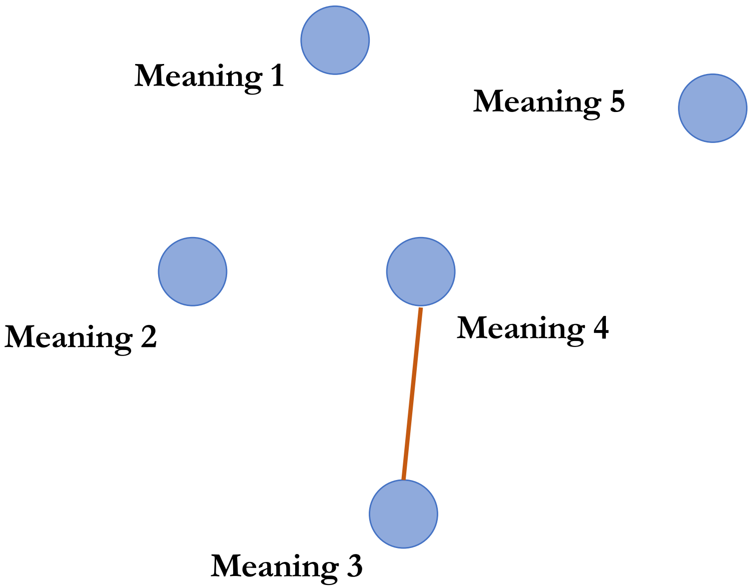

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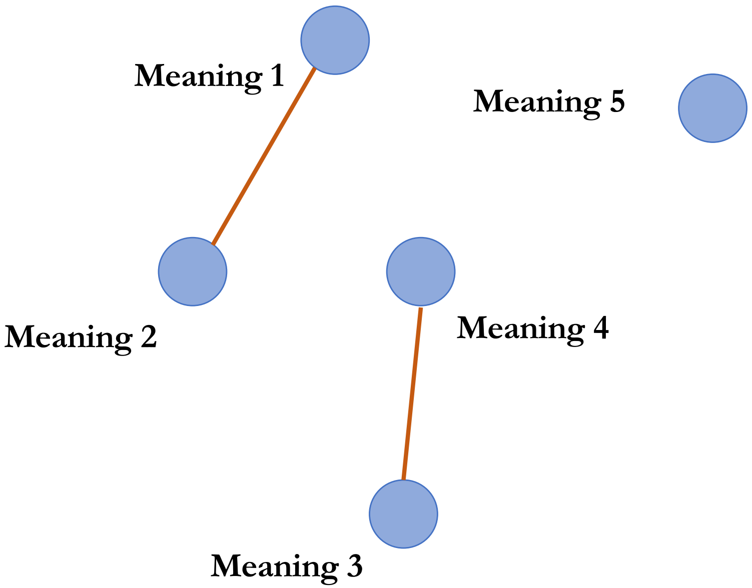

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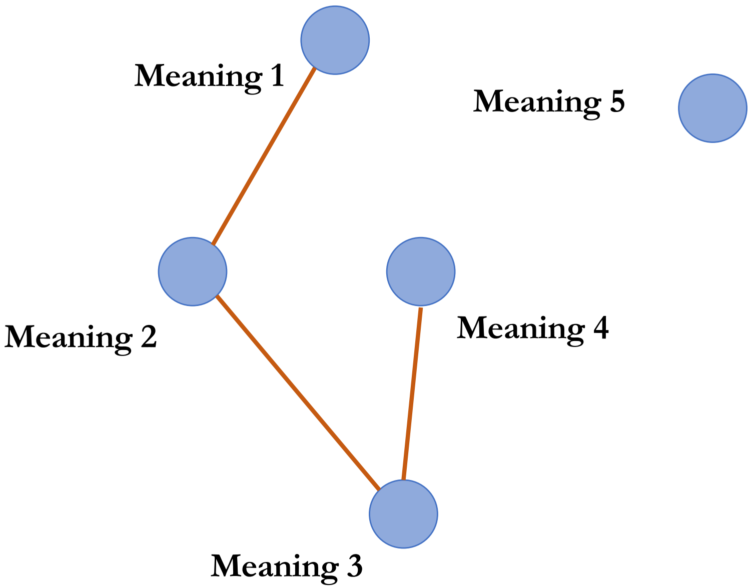

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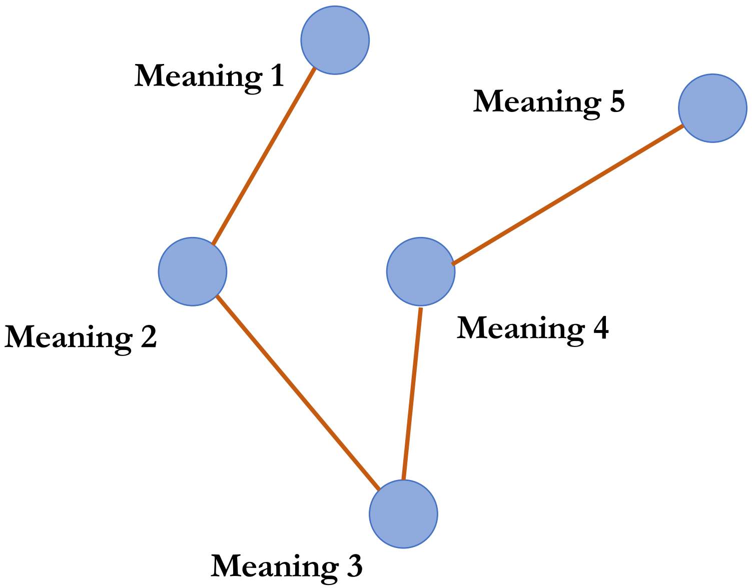

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Polysemic item C			√	√	√

Inferring semantic maps

- Regier et al. (2013) observed that the approximations produced by this algorithm (Angluin et al. 2010) are of high quality
  - Tested on the crosslinguistic data of Haspelmath (1997) and Levinson et al. (2003)

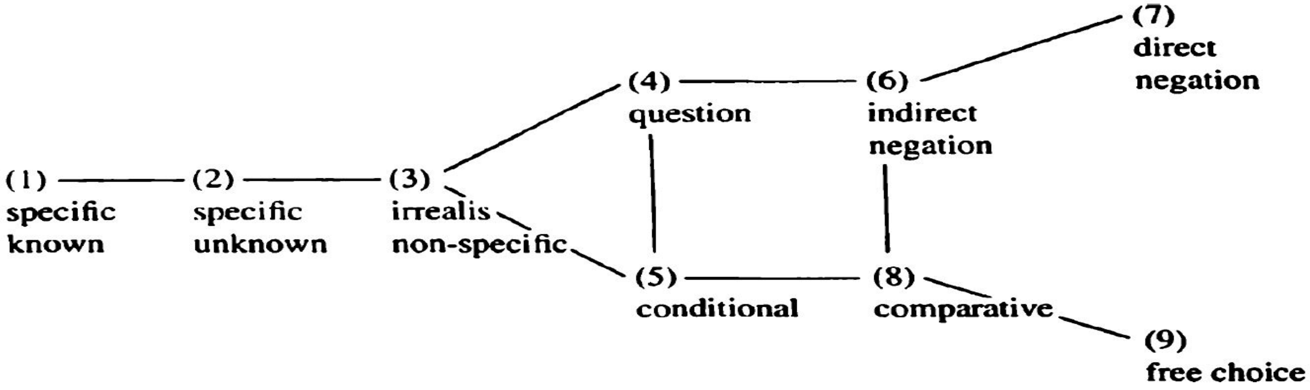

Figure. Haspelmath's (1997: 4) original semantic map of the indefinite pronouns functions

Inferring semantic maps

INPUT
(lexical matrix)

Language	*Word*	Specific Known **SK**	Specific Unknown **SU**	Irrealis Non-specific **IR**	Question **QN**	Conditional **CD**	Indirect Negation **IN**
German	"etwas"	1	1	1	1	1	1
German	"irgend"	0	1	1	1	1	1
German	"je"	0	0	0	1	1	1
German	"jeder"	0	0	0	0	0	1
German	"n-"	0	0	0	0	0	0
Dutch	"dan ook"	0	0	1	1	1	1
Dutch	"enig"	0	0	0	1	1	1
Dutch	"iets"	1	1	1	1	1	1
Dutch	"niets"	0	0	0	0	0	0
English	"any"	0	0	0	1	1	1
English	"ever"	0	0	0	1	1	1
English	"no"	0	0	0	0	0	0
English	"some"	1	1	1	1	1	0

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English	"no"	0	0	0	0	0	0
English	"some"	1	1	1	1	1	0

ALGORITHM
(python script)

```
# MAIN LOOP
objfn = C(G,T)
while (objfn < 0):
    print ("objective fn is currently", objfn,)
    max_score = 0
    # choose next edge greedily: the one that increases objfn the most
    for e in PossE:
        # temporarily add e to graph G
        G.add_edge(*e)
        score = C(G,T) - objfn
        G.remove_edge(*e)
        if (score > max_score):
            max_score = score
            max_edge = e
```

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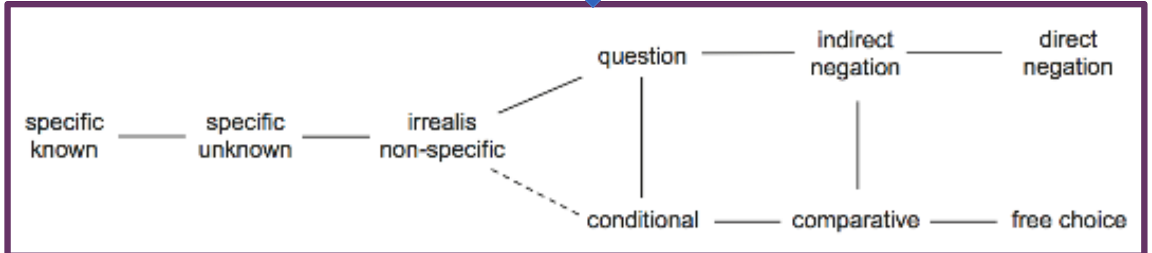
German	"irgend"	0	1	1	1	1	1
German	"je"	0	0	0	1	1	1
German	"jeder"	0	0	0	0	0	1
German	"n-"	0	0	0	0	0	0
Dutch	"dan ook"	0	0	1	1	1	1
Dutch	"enig"	0	0	0	1	1	1
Dutch	"iets"	1	1	1	1	1	1
Dutch	"niets"	0	0	0	0	0	0
English	"any"	0	0	0	1	1	1
English	"ever"	0	0	0	1	1	1
English	"no"	0	0	0	0	0	0
English	"some"	1	1	1	1	1	0

ALGORITHM
(python script)

```
# MAIN LOOP
objfn = C(G,T)
while (objfn < 0):
    print ("objective fn is currently", objfn,)
    max_score = 0
    # choose next edge greedily: the one that increases objfn the most
    for e in PossE:
        # temporarily add e to graph G
        G.add_edge(*e)
        score = C(G,T) - objfn
        G.remove_edge(*e)
        if (score > max_score):
            max_score = score
            max_edge = e
```

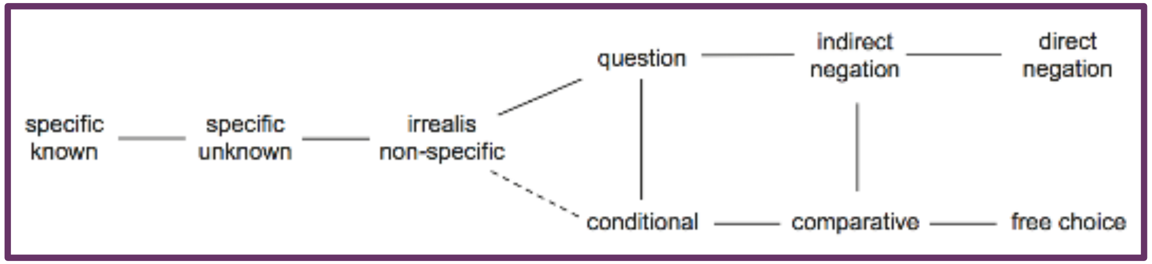
RESULT
(semantic map)



Tool:
pros & cons

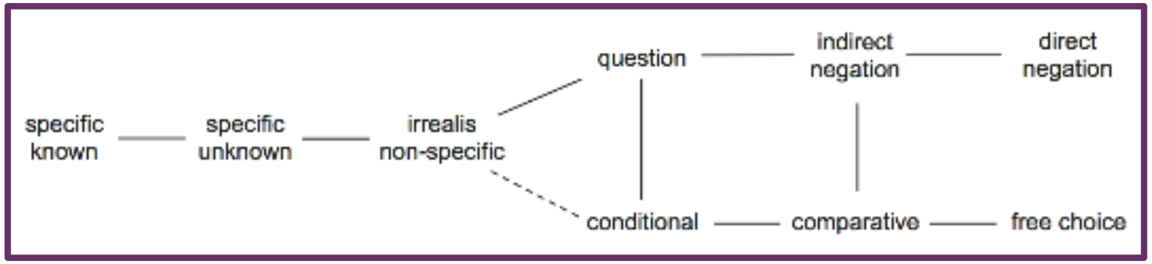
Tool: pros and cons

RESULT
(semantic map)



Tool: pros and cons

RESULT
(semantic map)



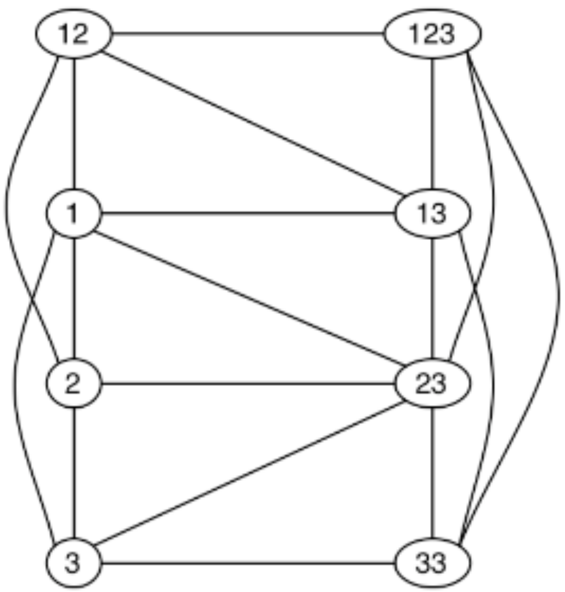


FIGURE 4a. A simple semantic map of person marking (Cysouw 2007: 231)

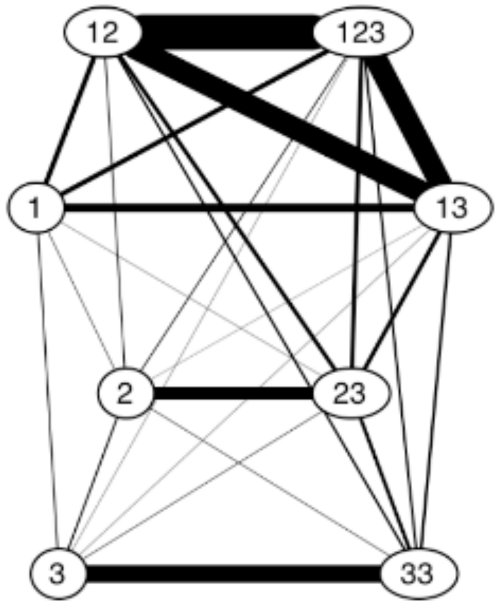


FIGURE 4b. A weighted semantic map of person marking (Cysouw 2007: 233)

Tool: pros and cons

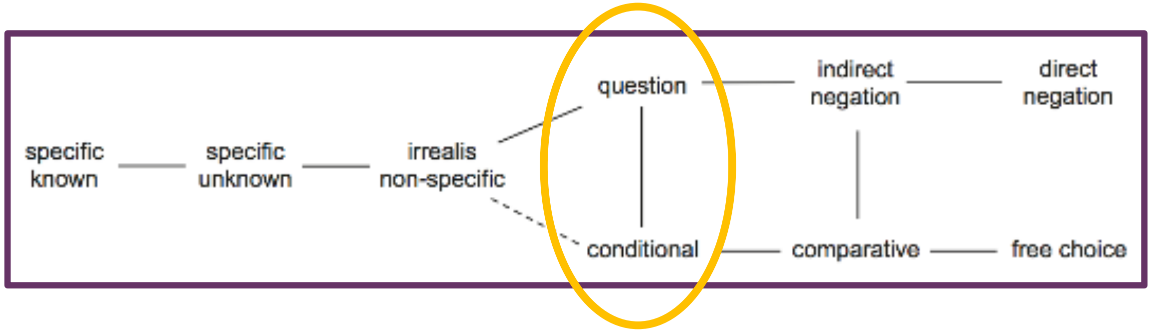
Towards weighted semantic maps

- Generate the map with a modified version of the algorithm of Regier et al. (2013)
    - PRINCIPLE: for each edge that is being added between two meanings of the map, we know the number of constraints that it satisfy (`max_score` in the `#main loop`), which can be used directly as weight for the edge.

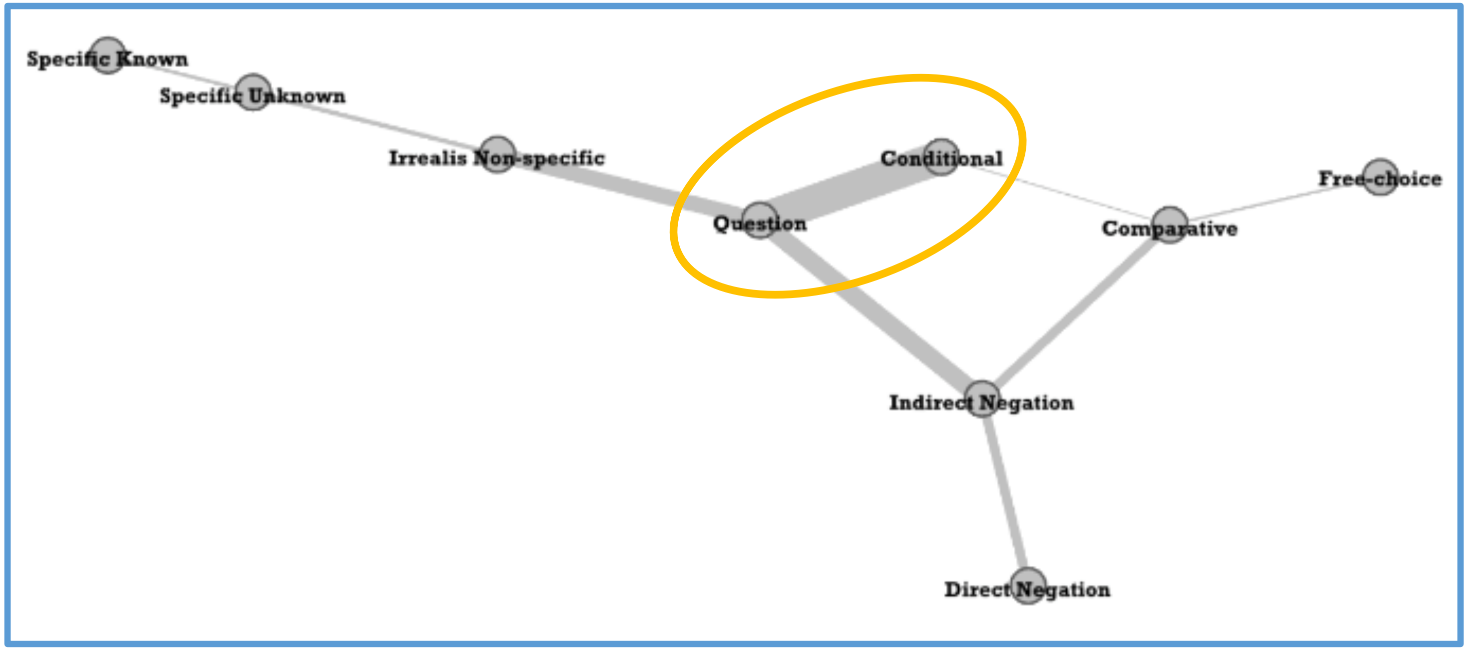
```
G.add_edge(*max_edge, weight=max_score)
```

Tool: pros and cons

Towards weighted semantic maps



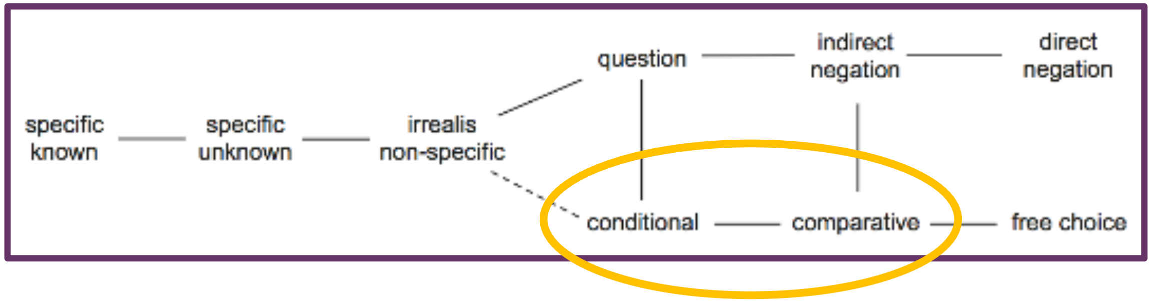
Automatically plotted semantic maps: non-weighted vs. weighted (data from Haspelmath 1997)



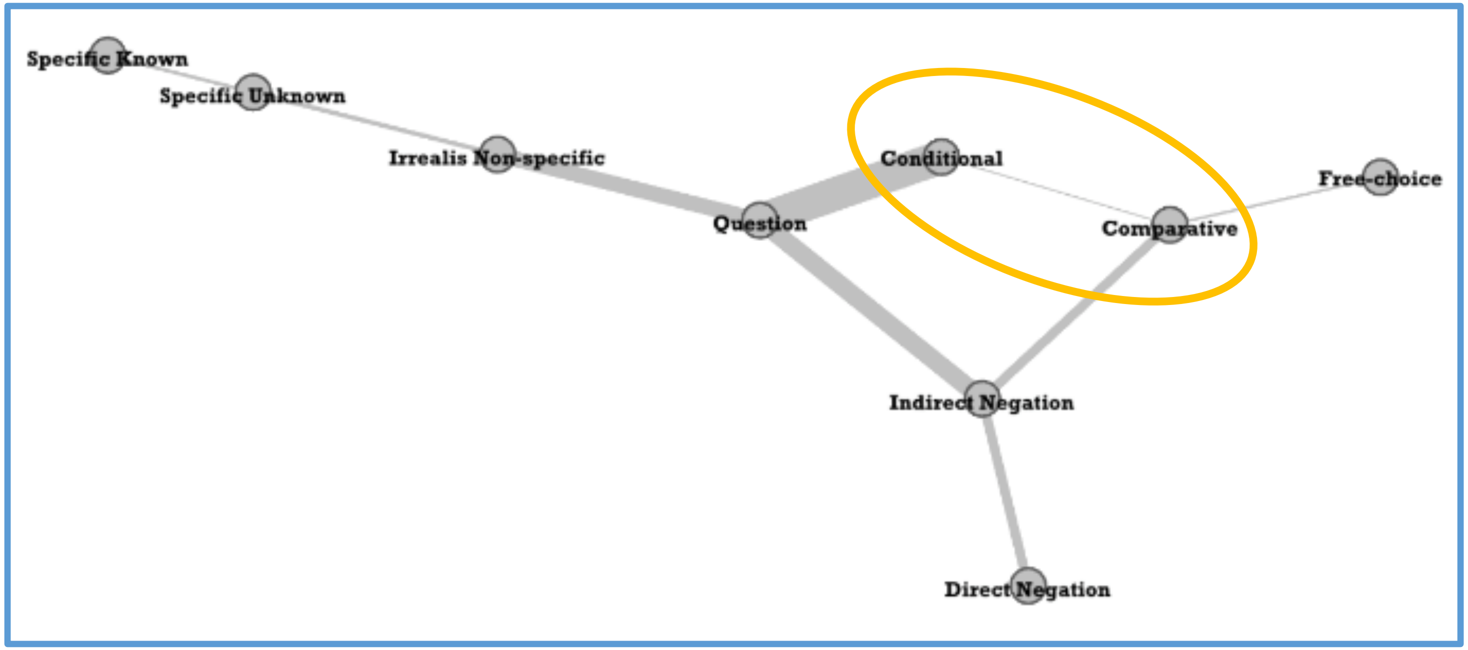
The graph is visualized in Gephi® with the *Force Atlas* algorithm

Tool: pros and cons

Towards weighted semantic maps



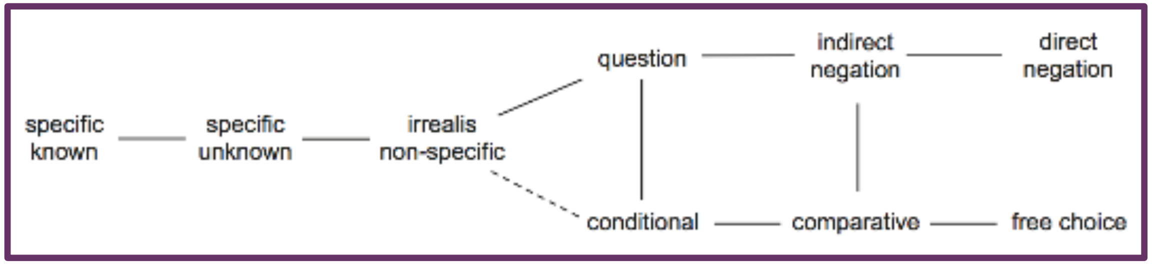
Automatically plotted semantic maps:
non-weighted vs. weighted
(data from Haspelmath 1997)



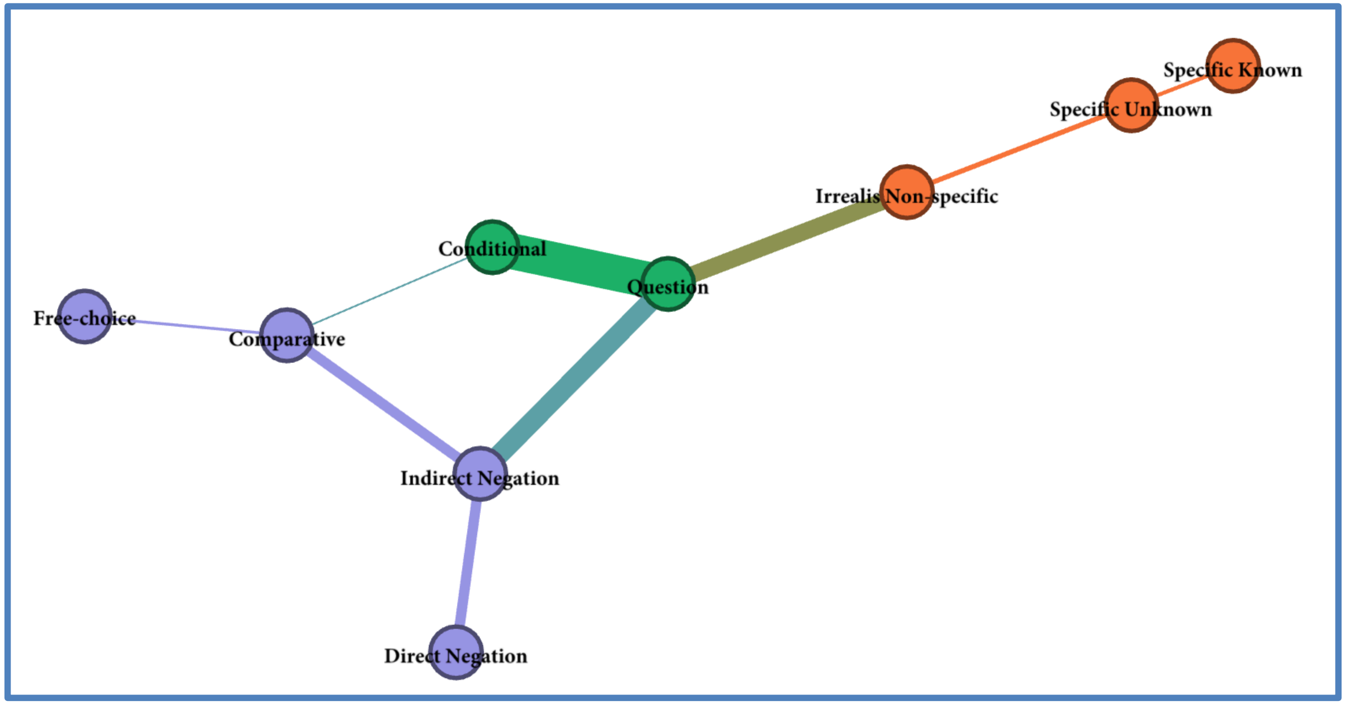
The graph is visualized in Gephi® with the *Force Atlas* algorithm

Tool: pros and cons

Towards weighted semantic maps



Automatically plotted semantic maps: non-weighted vs. weighted (data from Haspelmath 1997)



The graph is visualized in Gephi® with the *Force Atlas* algorithm and modularity analysis (Lambiotte et al. 2009)

Tool: pros and cons

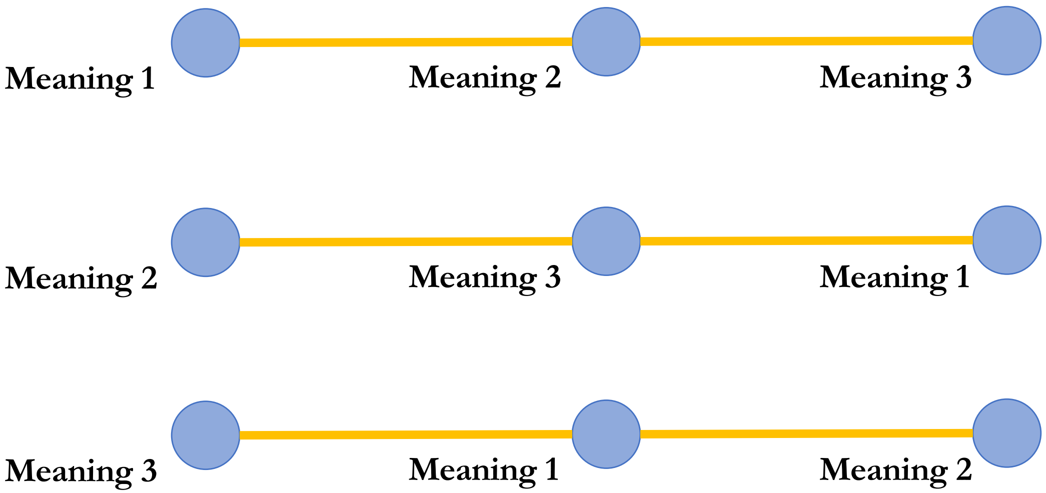
Unsolvable inferences

Meaning	1	2	3
Polysemic item A	√	√	√
Polysemic item B	√	√	√

Tool: pros and cons

Unsolvable inferences

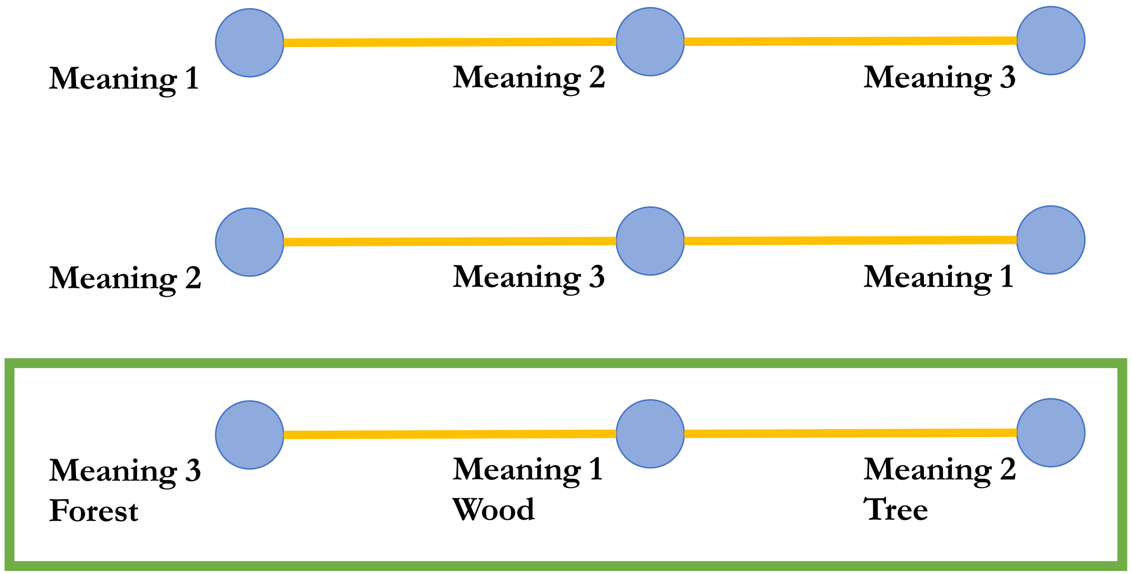
Meaning	1	2	3
Polysemic item A	√	√	√
Polysemic item B	√	√	√



Tool: pros and cons

Unsolvable inferences

Meaning	1 Wood	2 Tree	3 Forest
Polysemic item A	√	√	√
Polysemic item B	√	√	√

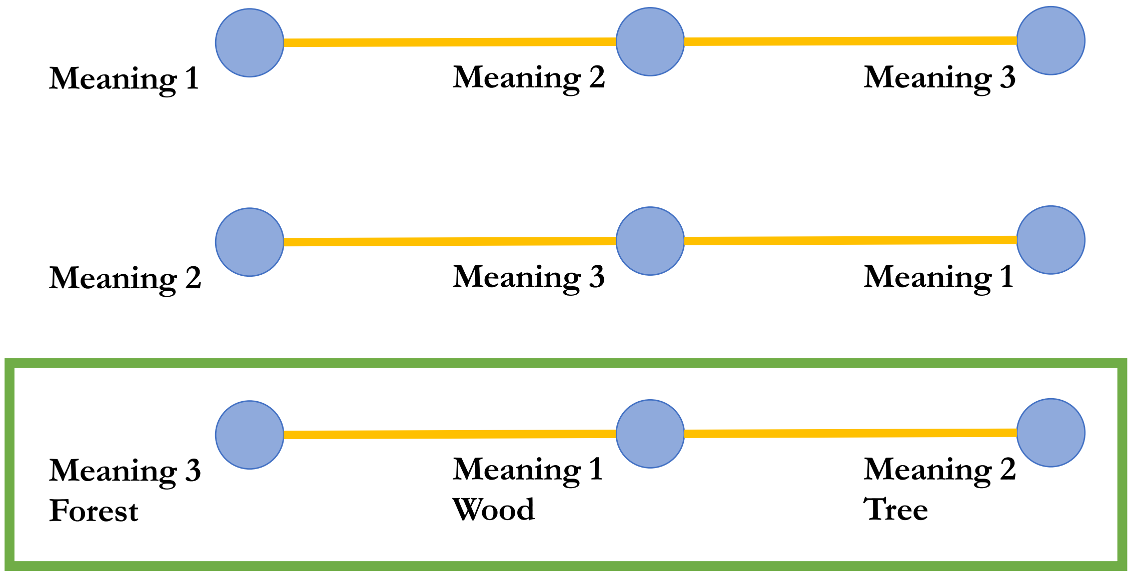


- Qualitative semantic analysis

Tool: pros and cons

Unsolvable inferences

Meaning	1 Wood	2 Tree	3 Forest
Polysemic item A	√	√	√
Polysemic item B	√	√	√



- ➢ Qualitative semantic analysis
- ➢ More typological data
  ⇒ more constraints

Tool: pros and cons

Unsolvable inferences

Form	Language	SMELL (PERCEIVE)	HEAR	LISTEN	FEEL	SEE	TASTE (SOMETHING)	UNDERSTAND
thin55	Changsha	1	1	0	0	0	0	0
ak	Gurdjar	1	1	0	0	1	0	0
sentire	Italian	1	1	0	1	0	0	0
clywed	Welsh	1	1	0	0	0	0	0
nenglengay	Sanapaná	1	1	0	0	0	0	0
lingaiyi	Lengua	1	1	0	1	0	1	0
dai3n@n6	Nung-Ninbei	1	1	0	0	0	0	0
klevet	Breton	1	1	0	0	0	0	0
hnov	White Hmong	1	1	0	1	0	0	0
eta	Kali'na	1	1	0	0	0	0	1
indr	Moresada	1	1	0	0	0	0	0
theng5	Mulam	1	0	1	0	0	0	0
ka31ngiet33	Bulang	1	0	1	0	0	0	0
zu21	Tujia	1	0	1	0	0	0	0

Tool: pros and cons

Unsolvable inferences

Form	Language	SMELL (PERCEIVE)	HEAR	LISTEN	FEEL	SEE	TASTE (SOMETHING)	UNDERSTAND
thin55	Changsha	1	1	0	0	0	0	0
ak	Gurdjar	1	1	0	0	1	0	0
sentire	Italian	1	1	0	1	0	0	0
clywed	Welsh	1	1	0	0	0	0	0
nenglengay	Sanapaná	1	1	0	0	0	0	0
lingaiyi	Lengua	1	1	0	1	0	1	0
dai3n@n6	Nung-Ninbei	1	1	0	0	0	0	0
klevet	Breton	1	1	0	0	0	0	0
hnov	White Hmong	1	1	0	1	0	0	0
eta	Kali'na	1	1	0	0	0	0	1
indr	Moresada	1	1	0	0	0	0	0
theng5	Mulam	1	0	1	0	0	0	0
ka31ngiet33	Bulang	1	0	1	0	0	0	0
zu21	Tujia	1	0	1	0	0	0	0

Tool: pros and cons

Unsolvable inferences

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sentire	Italian	1	1	0	1	0	0	0
clywed	Welsh	1	1	0	0	0	0	0
nenglengay	Sanapaná	1	1	0	0	0	0	0
lingaiyi	Lengua	1	1	0	1	0	1	0
dai3n@n6	Nung-Ninbei	1	1	0	0	0	0	0
klevet	Breton	1	1	0	0	0	0	0
hnov	White Hmong	1	1	0	1	0	0	0
eta	Kali'na	1	1	0	0	0	0	1
indr	Moresada	1	1	0	0	0	0	0
theng5	Mulam	1	0	1	0	0	0	0
ka31ngiet33	Bulang	1	0	1	0	0	0	0
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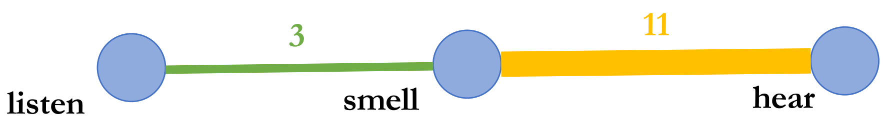

Tool: pros and cons

Unsolvable inferences

Form	Language	SMELL (PERCEIVE)	HEAR	LISTEN	FEEL	SEE	TASTE (SOMETHING)	UNDERSTAND
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sentire	Italian	1	1	0	1	0	0	0
clywed	Welsh	1	1	0	0	0	0	0
nenglengay	Sanapaná	1	1	0	0	0	0	0
lingaiyi	Lengua	1	1	0	1	0	1	0
dai3n@n6	Nung-Ninbei	1	1	0	0	0	0	0
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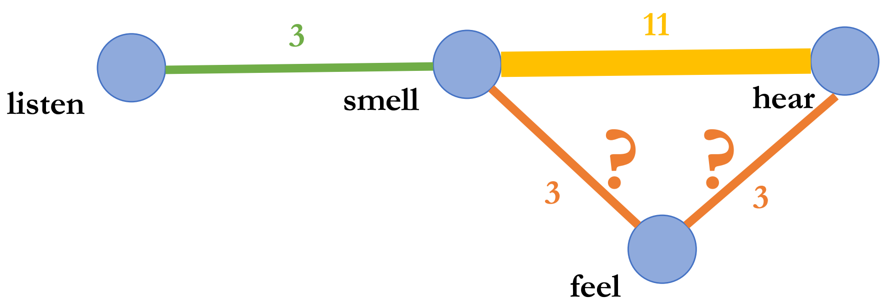
theng5	Mulam	1	0	1	0	0	0	0
ka31ngiet33	Bulang	1	0	1	0	0	0	0
zu21	Tujia	1	0	1	0	0	0	0



Tool: pros and cons

Unsolvable inferences

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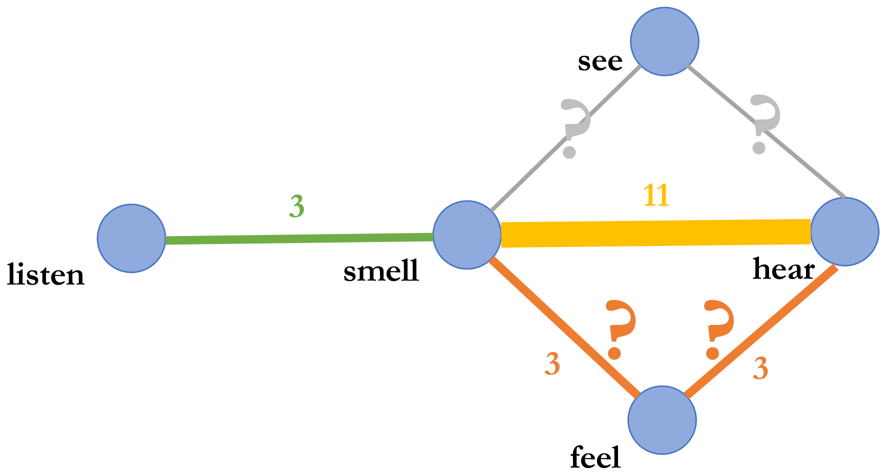
klevet	Breton	1	1	0	0	0	0	0
hnov	White Hmong	1	1	0	1	0	0	0
eta	Kali'na	1	1	0	0	0	0	1
indr	Moresada	1	1	0	0	0	0	0
theng5	Mulam	1	0	1	0	0	0	0
ka31ngiet33	Bulang	1	0	1	0	0	0	0
zu21	Tujia	1	0	1	0	0	0	0



Tool: pros and cons

Unsolvable inferences

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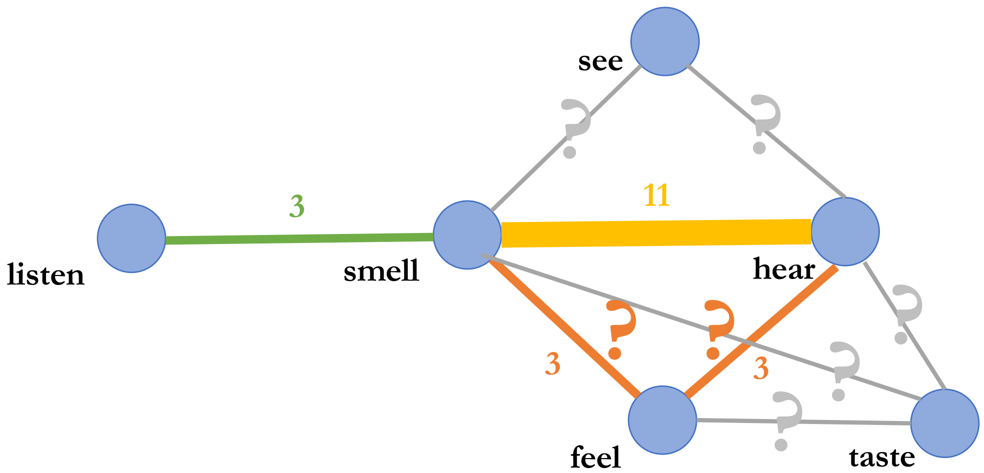
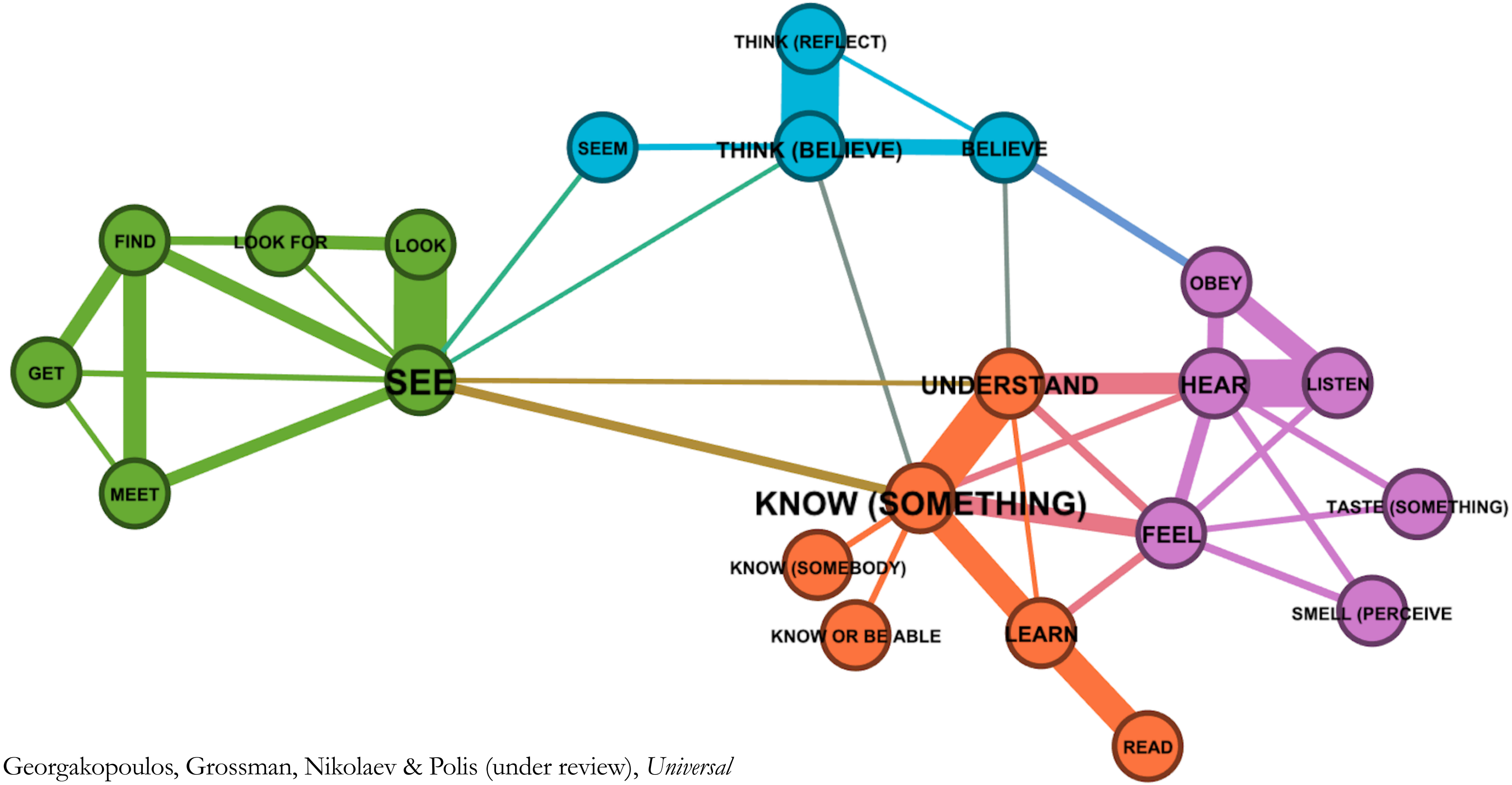
indr	Moresada	1	1	0	0	0	0	0
theng5	Mulam	1	0	1	0	0	0	0
ka31ngiet33	Bulang	1	0	1	0	0	0	0
zu21	Tujia	1	0	1	0	0	0	0



- More typological data
  ⇒ more constraints

Tool: pros and cons

Unsolvable inferences



Georgakopoulos, Grossman, Nikolaev & Polis (under review), *Universal and macro-areal patterns in the lexicon. A case-study in the perception-cognition domain*, in: *LT*.

Datasets: what do we need?

Datasets: what do we need?

Size

Emotions (properties) in CLICS^2 (colexifications in 1220 languages)

Cf. Joshua Conrad Jackson, Joseph Watts, Teague Henry, Johann-Mattis List, Robert Forkel, Simon Greenhill, Russell Gray, Kristen Lindquist, *Variability and Universality in Human Emotion Across 1156 Languages*,

Datasets: what do we need?

Size

Emotions (properties) in CLICS[2] (colexifications in 1220 languages)

AMAZING	GREEDY
ANGRY	HAPPY
ASHAMED	HONEST
ASTONISHED	IMPORTANT
BAD	INSOLENT
BEAUTIFUL	KEEN
BORING	KIND OR POLITE
BRAVE	LOVELY
CLEVER	MERRY
CONTEMPTIBLE	PASSIONATE
CORRECT (RIGHT)	PROUD
CRUEL	RUDE
CUNNING	SAD
DEAR	SHY
DILIGENT	SORROWFUL
DREADFUL	SURPRISED
EVIL	TRUE
EXACT	UGLY
FAITHFUL	UNPLEASANT
GENTLE	VULGAR
GLOOMY	WRONG
GOOD	

43

Concepticon (https://concepticon.clld.org)

Datasets: what do we need?

Size

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GOOD	

43

Concepticon (https://concepticon.clld.org)

ANGRY	TRUE
ASHAMED	UGLY
BAD	WRONG
BEAUTIFUL	
BRAVE	
CLEVER	
CORRECT (RIGHT)	
CUNNING	
DEAR	
DILIGENT	
EVIL	
FAITHFUL	
GENTLE	
GOOD	
GREEDY	
HAPPY	
HONEST	
MERRY	
PROUD	
SAD	
SHY	
SURPRISED	

25 (attested)

Clics² (https://clics.clld.org)

Datasets: what do we need?

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43

Concepticon (https://concepticon.clld.org)

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Clics[2] (https://clics.clld.org)

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SAD
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TRUE
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WRONG

20 (colexified)

Clics[2] (https://clics.clld.org)

Datasets: what do we need?

Size

Emotions (properties) in CLICS^2 (colexifications in 1220 languages)

ANGRY
BAD
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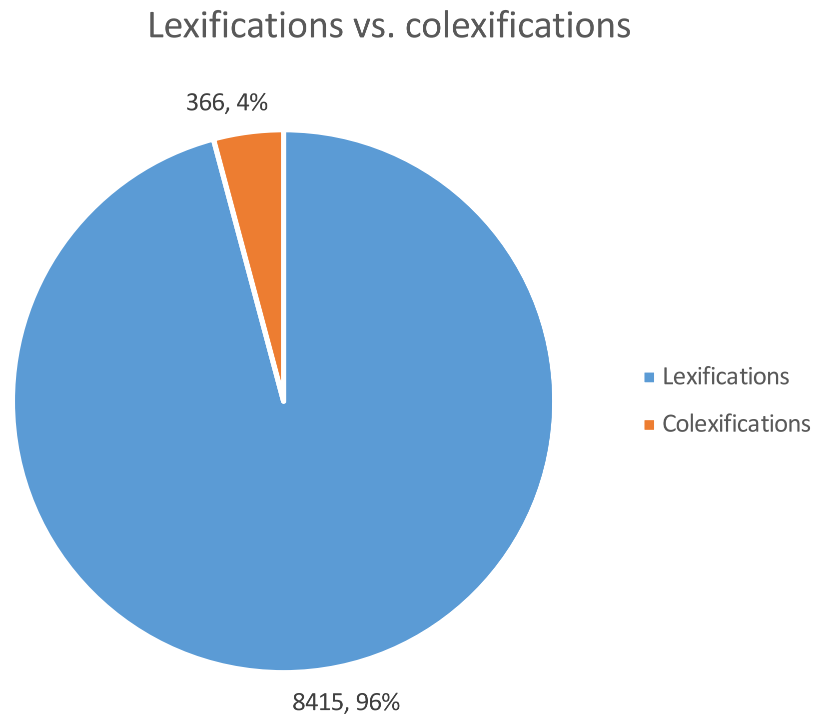

20 (colexified)

Clics^2 (https://clics.clld.org)

Datasets: what do we need?

Size

Emotions (properties) in CLICS² (colexifications in 1220 languages)

ANGRY
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BEAUTIFUL
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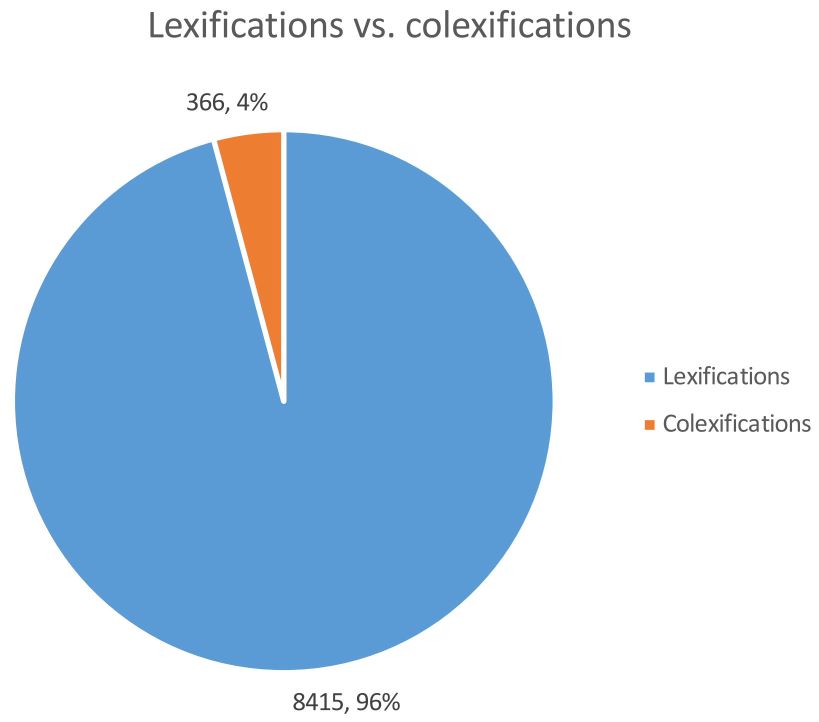
Clics² (https://clics.clld.org)



20 meanings

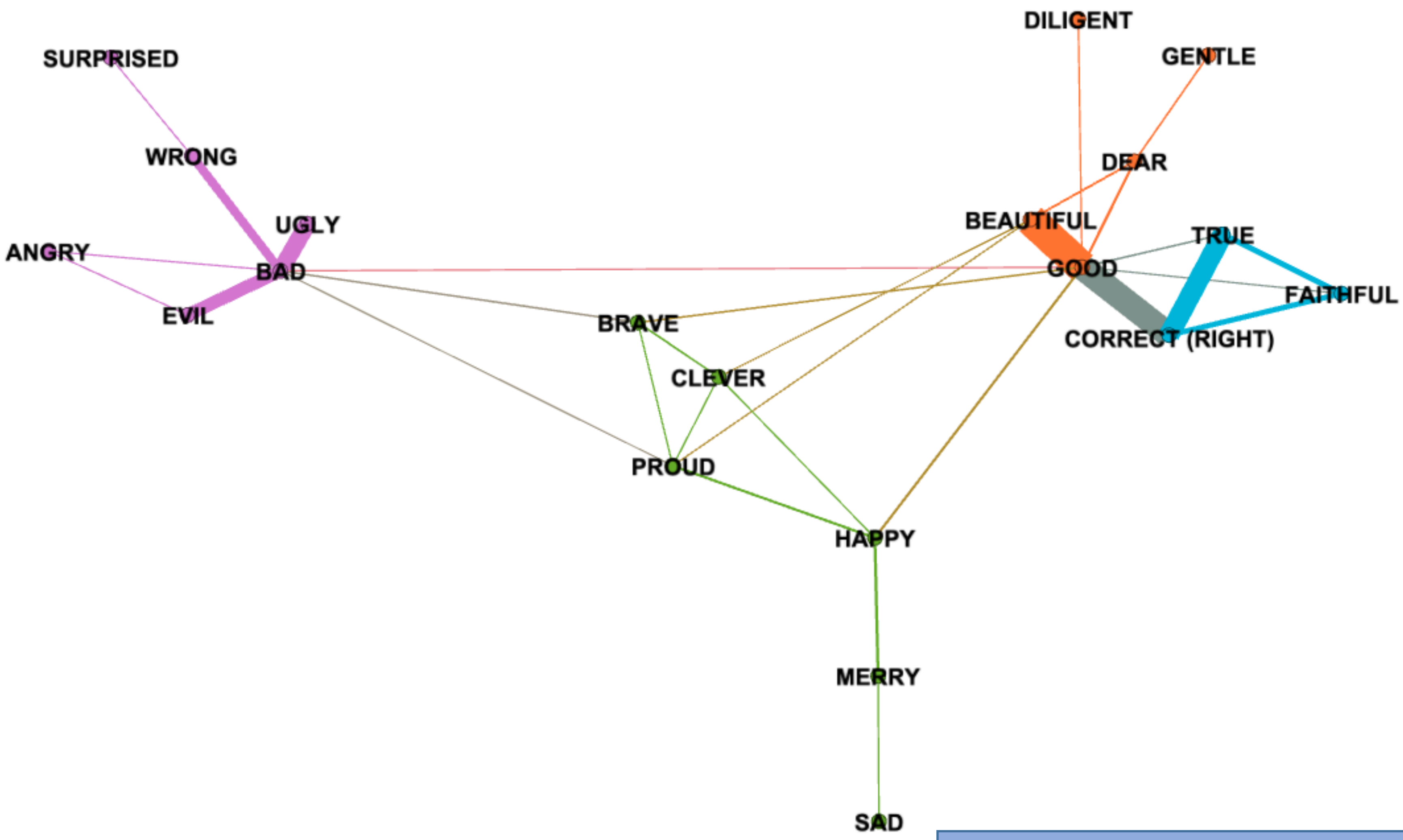
366 constraints

31 edges

Datasets: what do we need?

Size

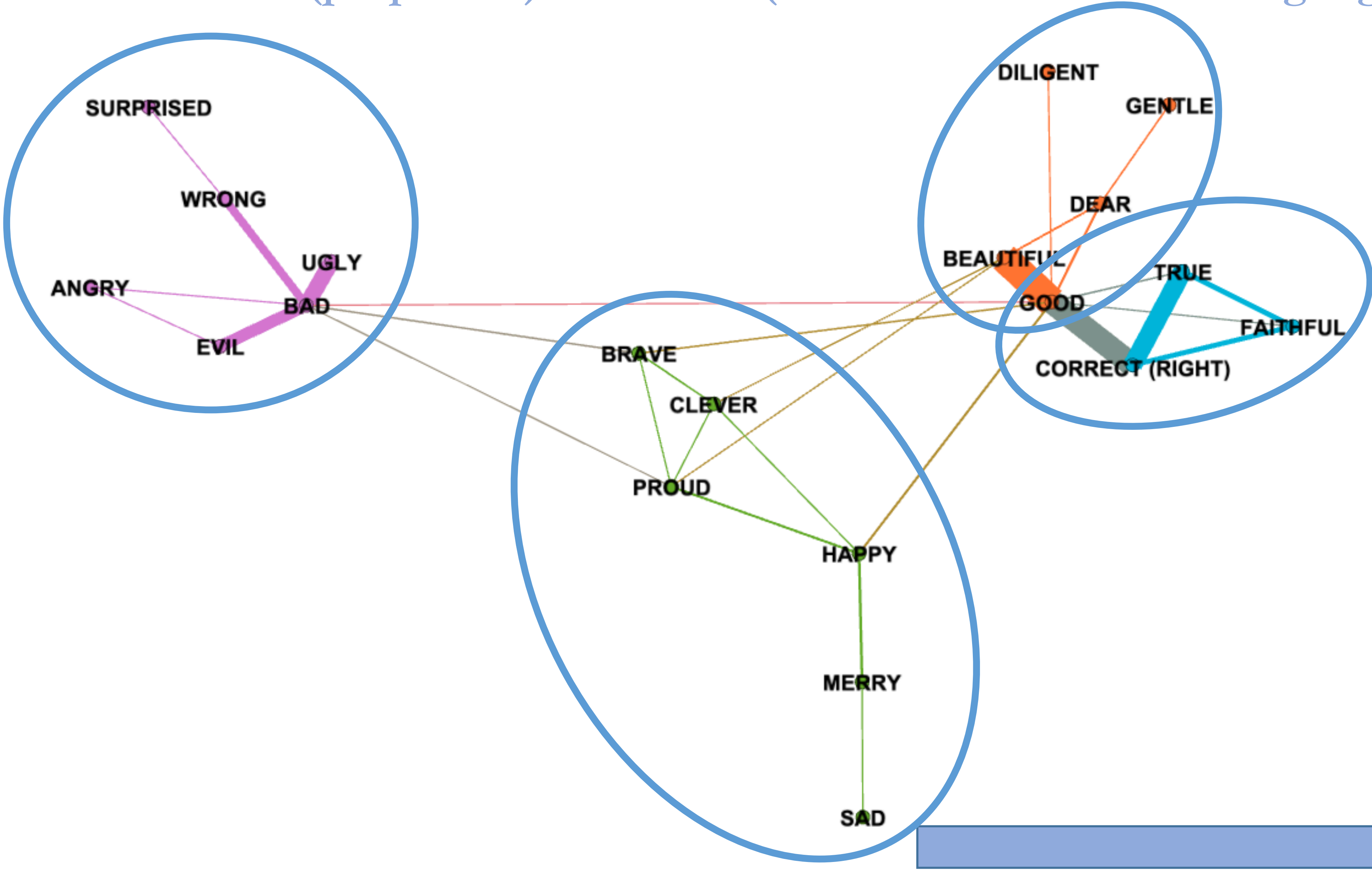
Emotions (properties) in CLICS² (colexifications in 1220 languages)



Datasets: what do we need?

Size

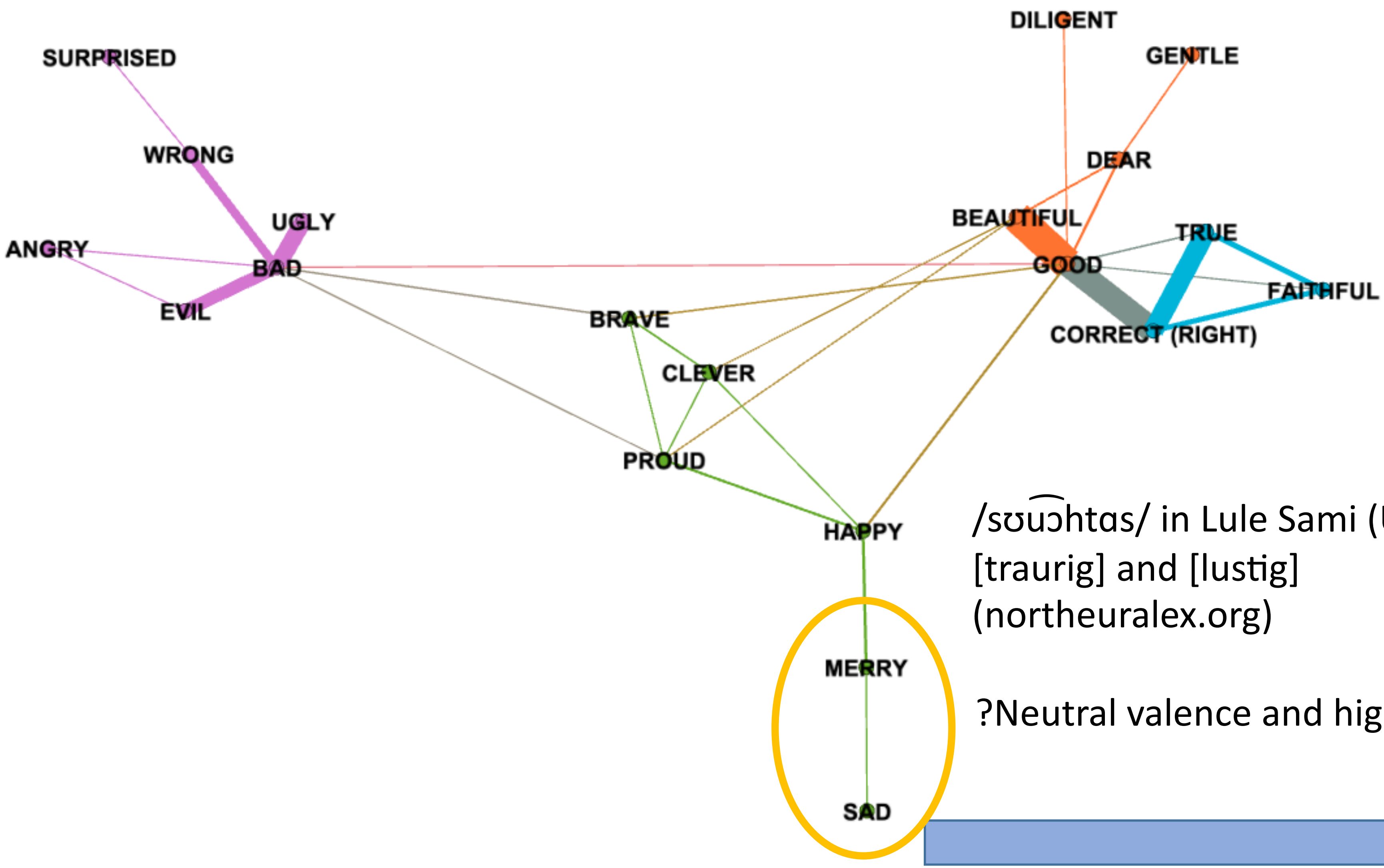
Emotions (properties) in CLICS^2 (colexifications in 1220 languages)



Datasets: what do we need?

Size

Emotions (properties) in CLICS^2 (colexifications in 1220 languages)



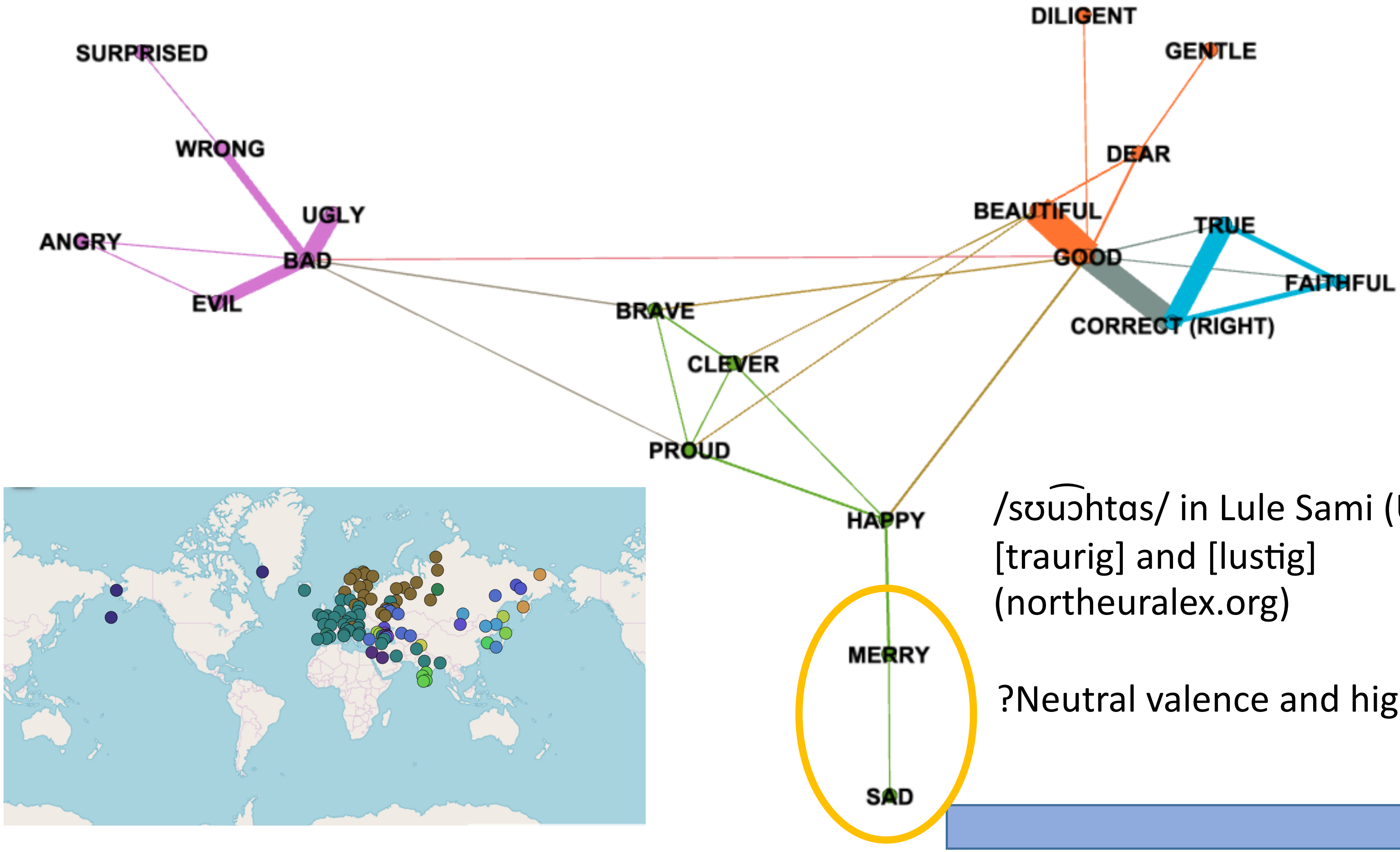
/sʊu͡ɔhtɑs/ in Lule Sami (Uralic)
[traurig] and [lustig]
(northeuralex.org)

?Neutral valence and high arousal?

Datasets: what do we need?

Size

Emotions (properties) in CLICS[2] (colexifications in 1220 languages)



/sʊu͡ɔhtɑs/ in Lule Sami (Uralic)
[traurig] and [lustig]
(northeuralex.org)

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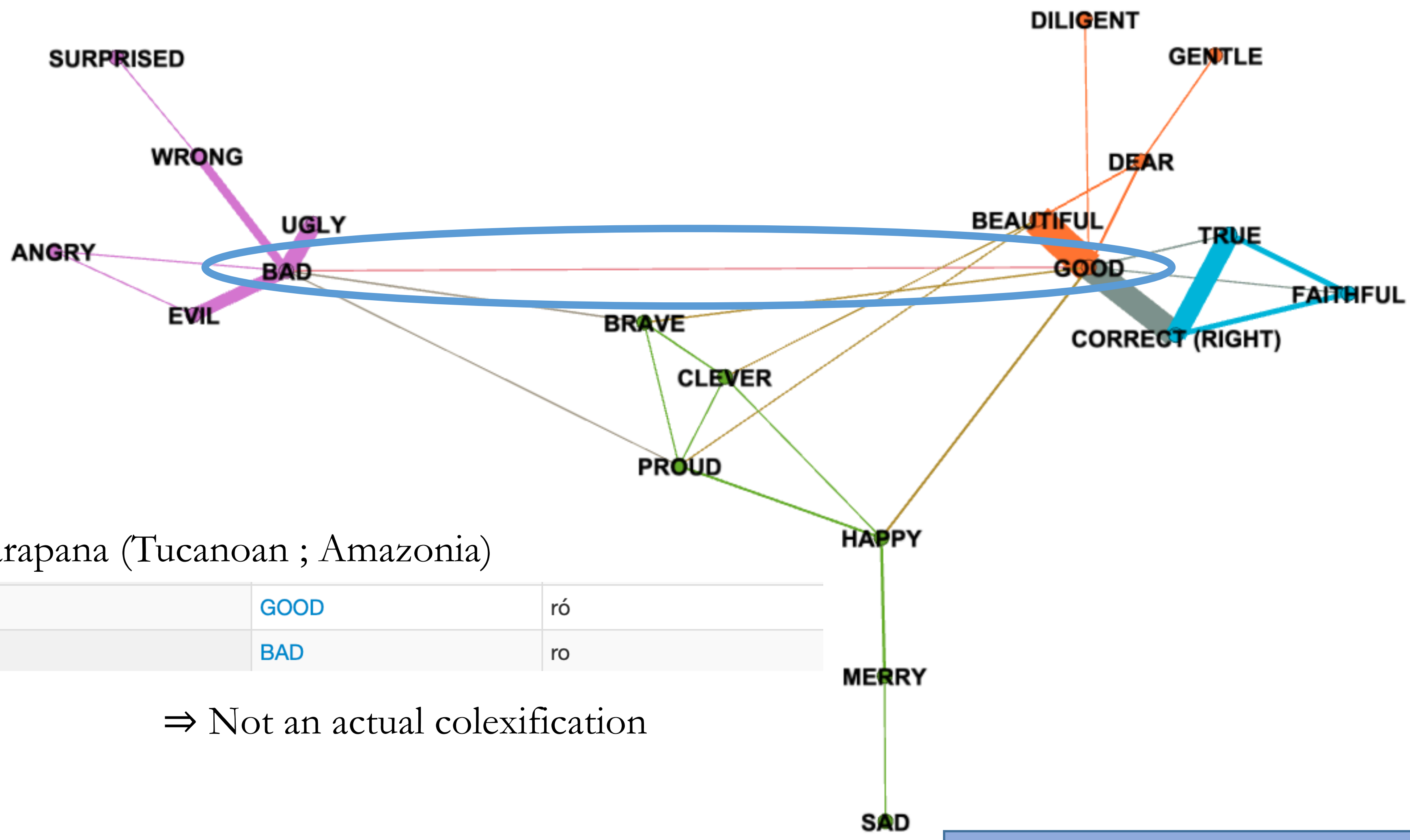
Datasets: what do we need?

Size

Emotions (properties) in CLICS² (colexifications in 1220 languages)



Carapana (Tucanoan ; Amazonia)

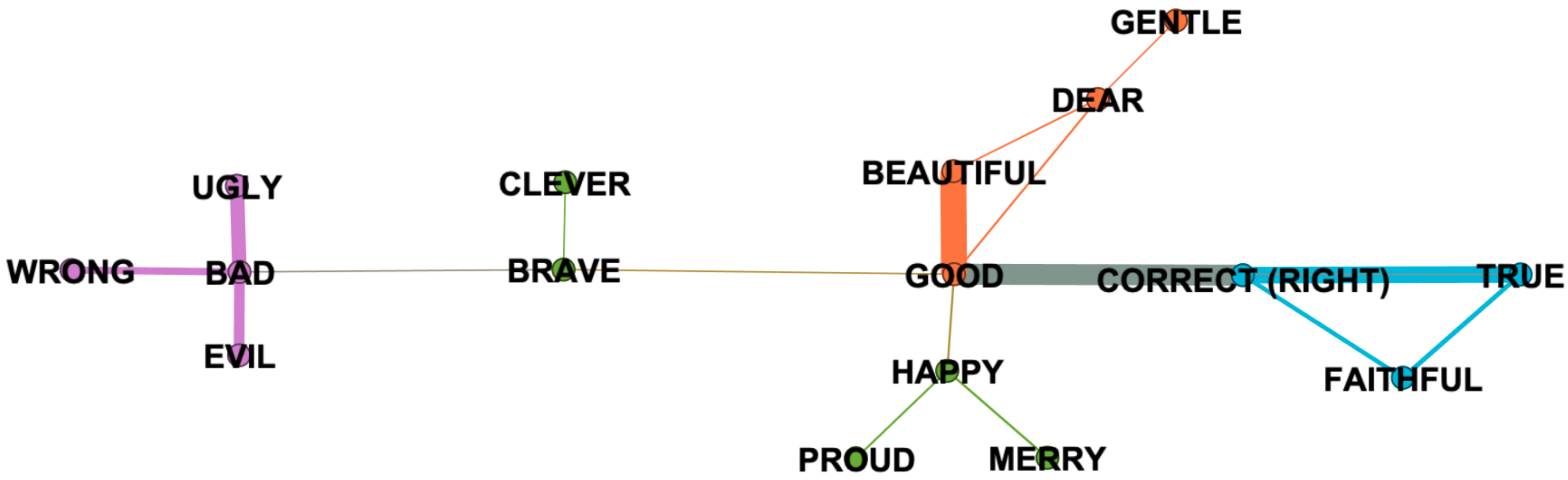
ro	GOOD	ró
ro	BAD	ro

⇒ Not an actual colexification

Datasets: what do we need?

Size

Emotions (properties) in CLICS² (colexifications in 1220 languages)



Semantic map based on colexification patterns attested in more than 1 language variety

Datasets: what do we need?

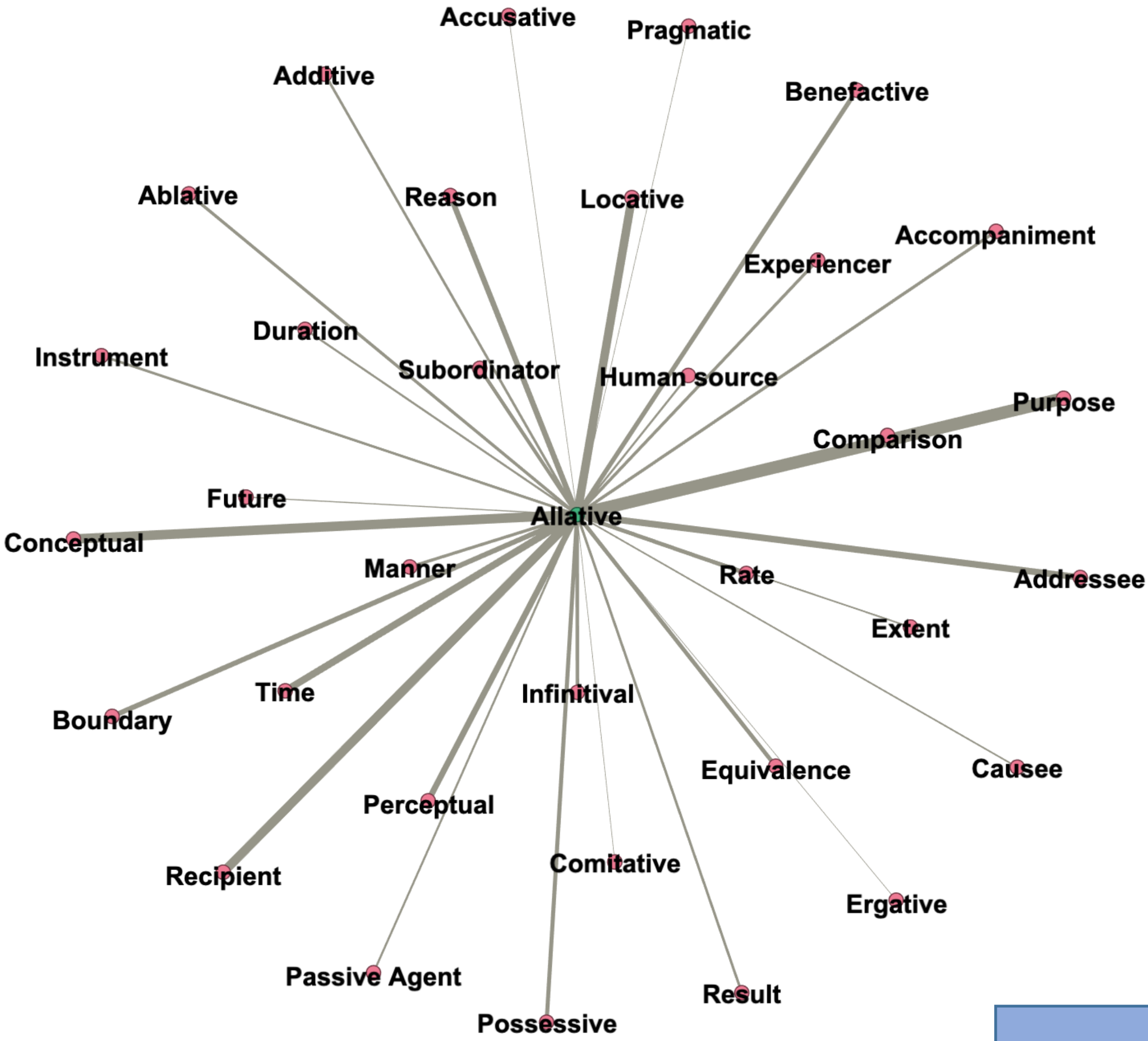
Structure

Allative markers (based on Rice & Kabata 2007)

Language	Japanese	English	French	Korean	Maori	Spanish	German	Lezgi	Tibetan	Tagalog	English	Hawai'ian	Ik	Swahili	Tamil	Polish	Russian	Kanuri	Bidyara	Acholi	Bella Coola	Hopi	Korean	Ika	Persian	Yoruba	Acholi	Mandarin	North Slavey	Polish
ALLATIVE	*ni*	*to*	*à*	*ey*	*ki*	*a*	*zu*	*z*	*la*	*sa*	*for*	*ia*	*ke*	*kwa*	*iku*	*na*	*v*	*ro*	*gu*	*kà*	*ʔuɬ*	*mi*	*ulo*	*seʔ*	*be*	*si*	*bòót*	*dào*	*ts'ę́*	*do*
ALLATIVE	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
LOCATIVE	+		+	+		+	+		+	+		+	+	+		+	+		+	+				+		+				
ABLATIVE										+		+		+			+			+							+			
TIME	+		+	+		+	+	+	+						+	+	+	+		+										
BOUNDARY		+				+											+				+	+						+	+	+
DURATION				+							+				+	+														
RECIPIENT	+	+	+	(+)	+	+		+	+	+		+			+						+			+	+		+		+	
ADDRESSEE	+	+	+	(+)	+		+	+	+				+								+	+			+				+	
BENEFACTIVE	+				+			+	+	+	+		+						+											
POSSESSIVE	+		+					+	+	+			+		+				+											
PASSIVE AGENT	+		+	(+)								+																		
HUMAN SOURCE	+			(+)		+																		+						
CAUSEE	+			(+)	+																									
COMITATIVE																											+			
CONCEPTUAL	+	+	+	+	+		+	+	+	+				+							+	+				+		+		
PERCEPTUAL	+	+			+	+		+			+	+										+			+			+		
EXPERIENCER	+	+		(+)		+		+			+										+									
PURPOSE	+	+	+		+	+	+		+	+	+		+	+	+	+	+	+	+	+		+								+
REASON	+			+						(+)	+	+	+	+		+		+	+				+							
RATE	+	+	+	+		+	+								+	+														
EQUIVALENCE	+	+	+		+						+				+					+			+							
MANNER	+												+	+		+		+					+							
COMPARISON	+	+								+							+	+												
RESULT	+	+					+										+						+							

Datasets: what do we need?

Allative markers (based on Rice & Kabata 2007)



- 34 meanings
- 33 edges

Datasets: what do we need?

Structure

Allative markers (based on Rice & Kabata 2007)

```
Initial graph created
objective fn is currently -254
adding ('Allative', 'Purpose') with score 25
objective fn is currently -229
adding ('Allative', 'Conceptual') with score 19
objective fn is currently -210
adding ('Allative', 'Recipient') with score 18
objective fn is currently -192
adding ('Allative', 'Locative') with score 17
objective fn is currently -175
adding ('Allative', 'Time') with score 14
objective fn is currently -161
adding ('Allative', 'Addressee') with score 13
objective fn is currently -148
adding ('Allative', 'Perceptual') with score 12
objective fn is currently -136
adding ('Allative', 'Reason') with score 11
objective fn is currently -125
adding ('Allative', 'Boundary') with score 10
objective fn is currently -115
adding ('Allative', 'Benefactive') with score 9
objective fn is currently -106
adding ('Allative', 'Possessive') with score 8
objective fn is currently -98
adding ('Allative', 'Rate') with score 8
objective fn is currently -90
adding ('Allative', 'Equivalence') with score 8
objective fn is currently -82
adding ('Allative', 'Subordinator') with score 7
objective fn is currently -75
adding ('Allative', 'Infinitival') with score 7
objective fn is currently -68
adding ('Allative', 'Experiencer') with score 6
objective fn is currently -62
adding ('Allative', 'Manner') with score 6
objective fn is currently -56
adding ('Allative', 'Accompaniment') with score 6
objective fn is currently -50
```

Ln: 88 Col: 4

Datasets: what do we need?

Structure

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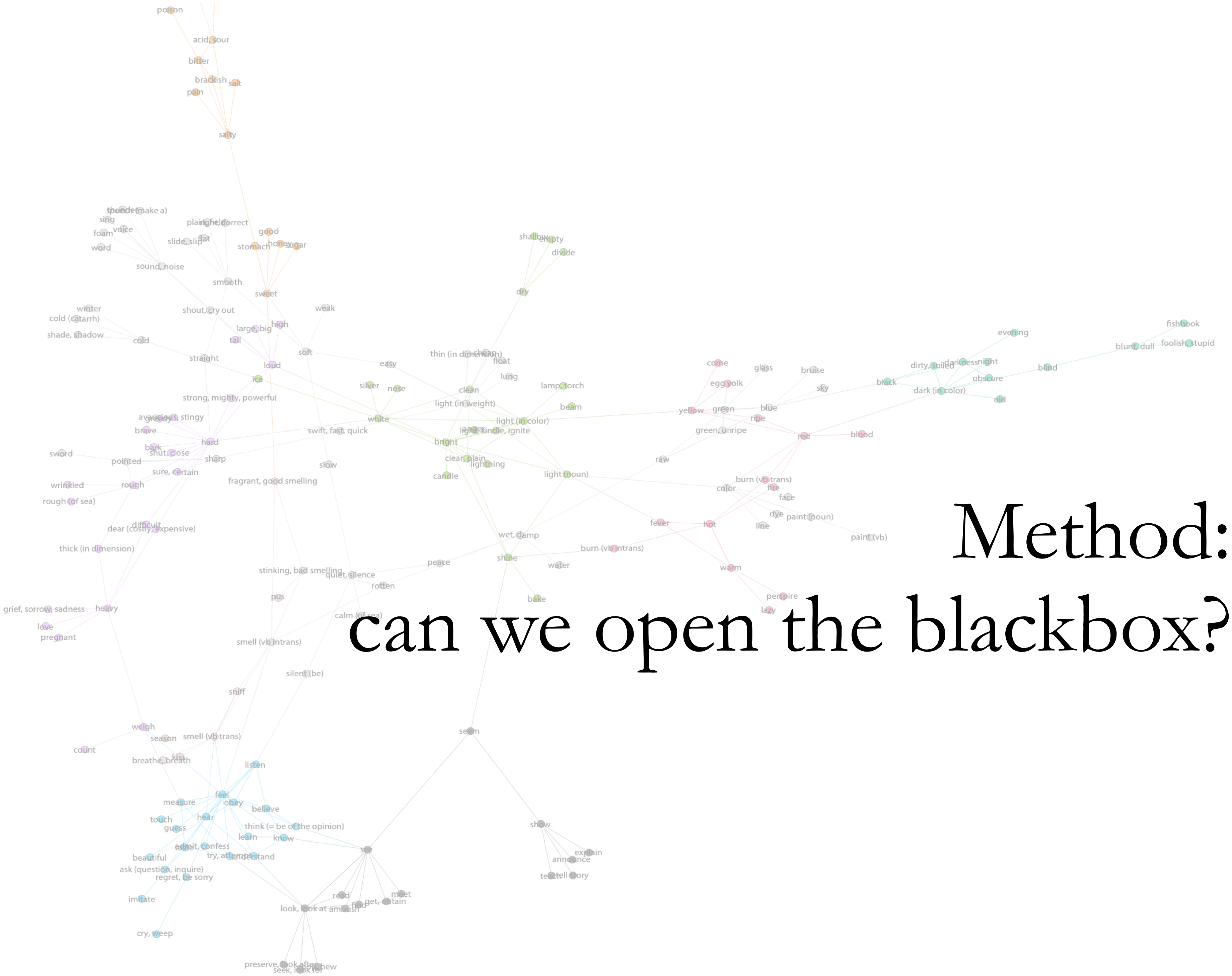
```

Ln: 88 Col: 4

Data should be structured around several meanings

Method: can we open the blackbox?



Method: can we open the black-box?

Formal Concept Lattices (hierarchical graphs)

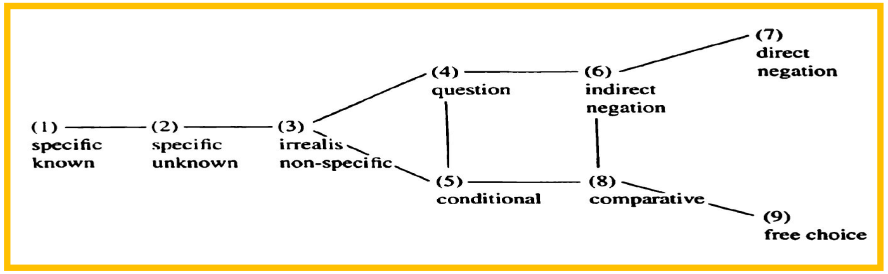
Formal Concept Lattices as Semantic Maps

Daria Ryzhova and Sergei Obiedkov

National Research University Higher School of Economics,
Moscow, Russia
daria.ryzhova@mail.ru sergei.obj@gmail.com

2017

Method: can we open the black-box?



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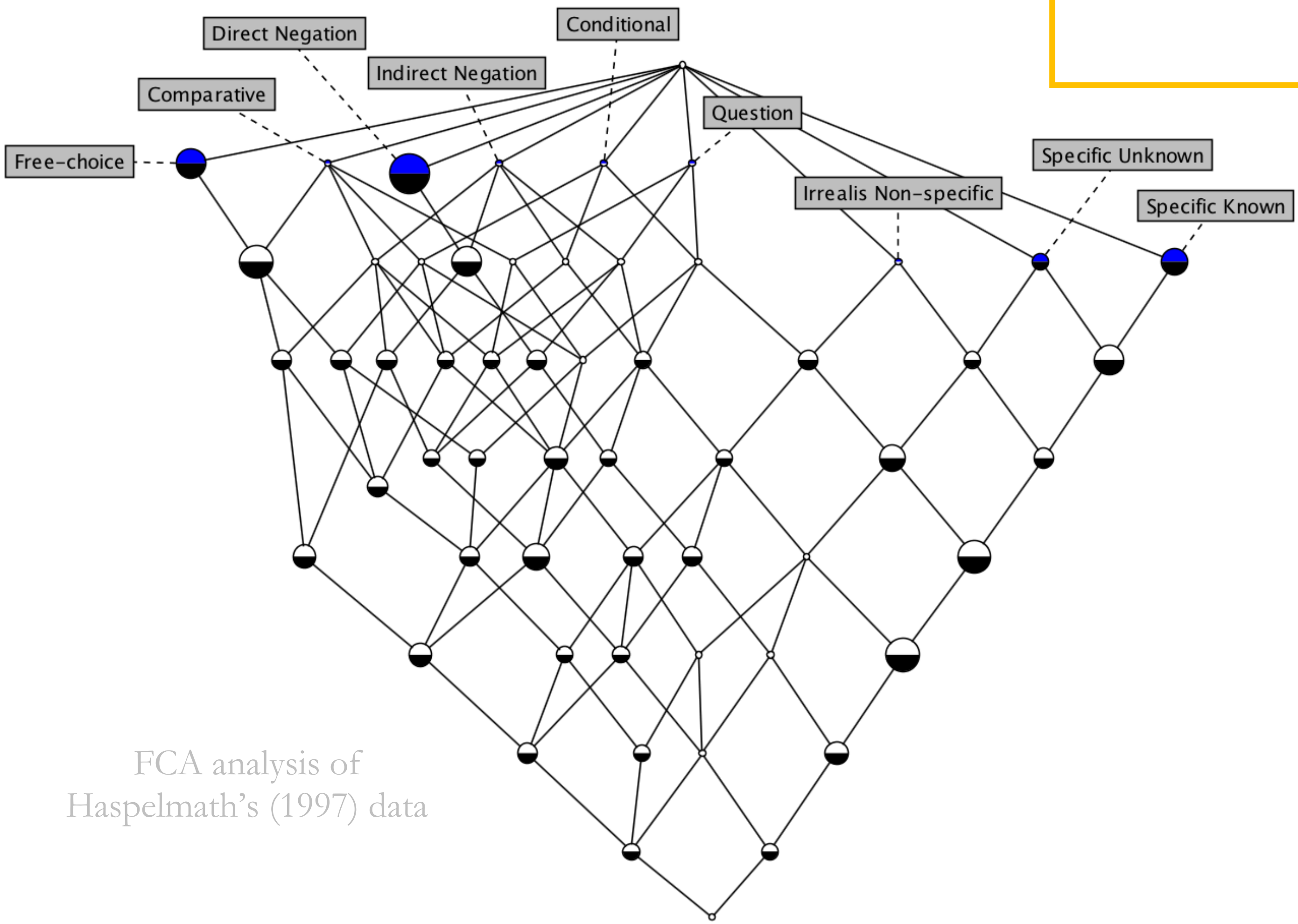

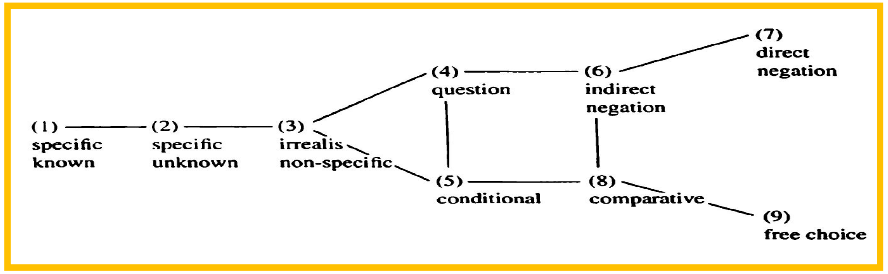

FCA solves the problem of form/meaning mapping

FCA analysis of Haspelmath's (1997) data

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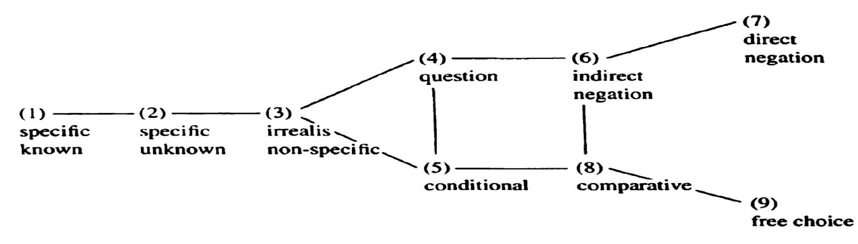

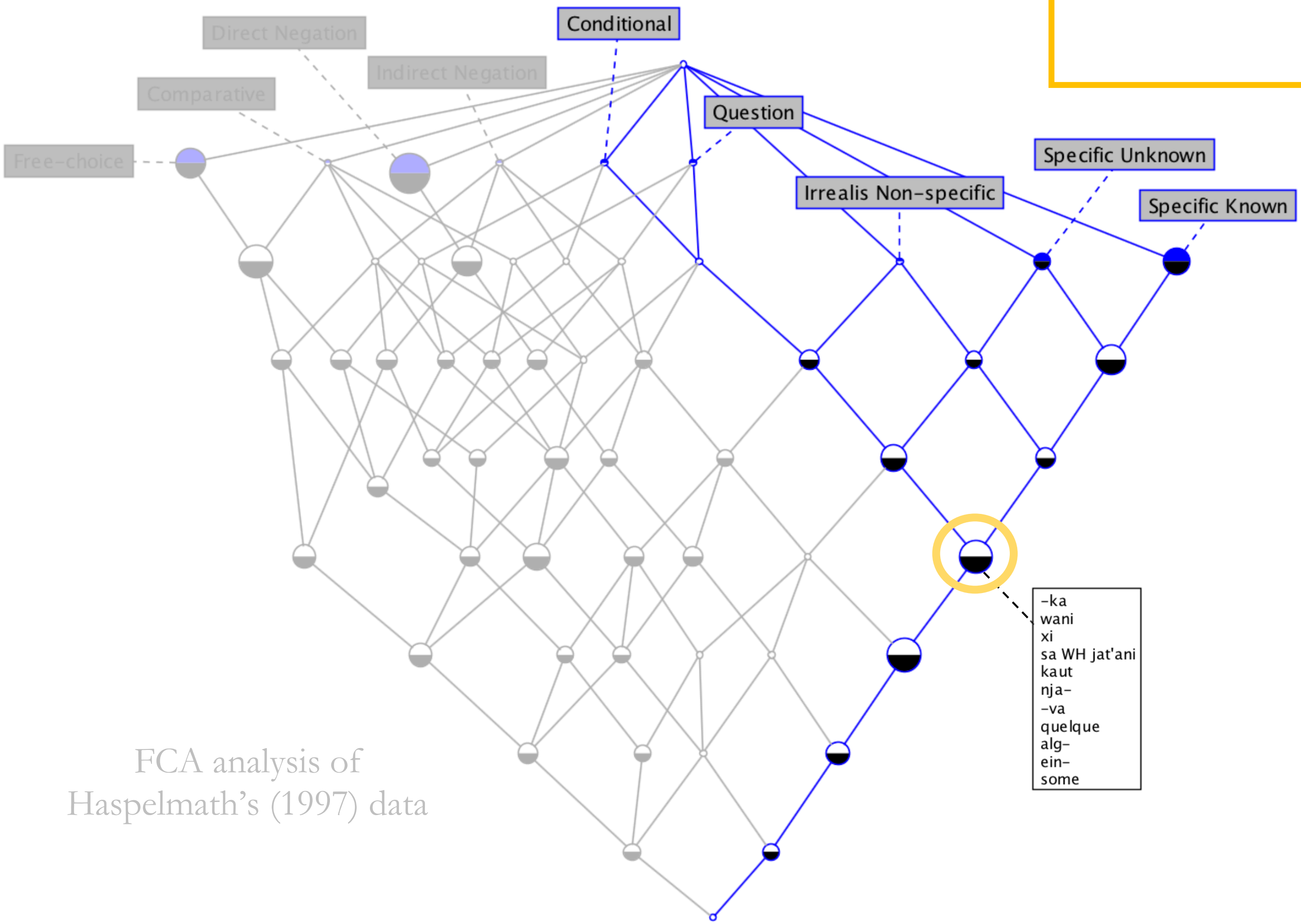

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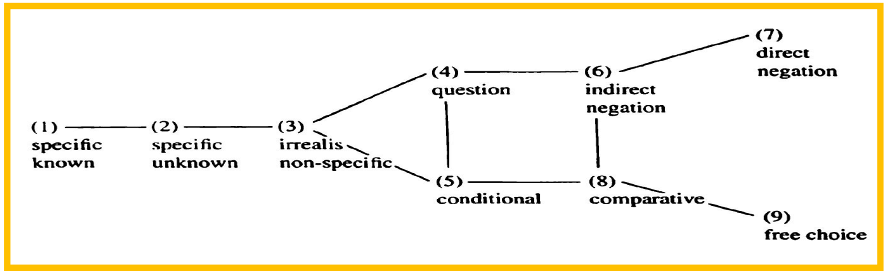

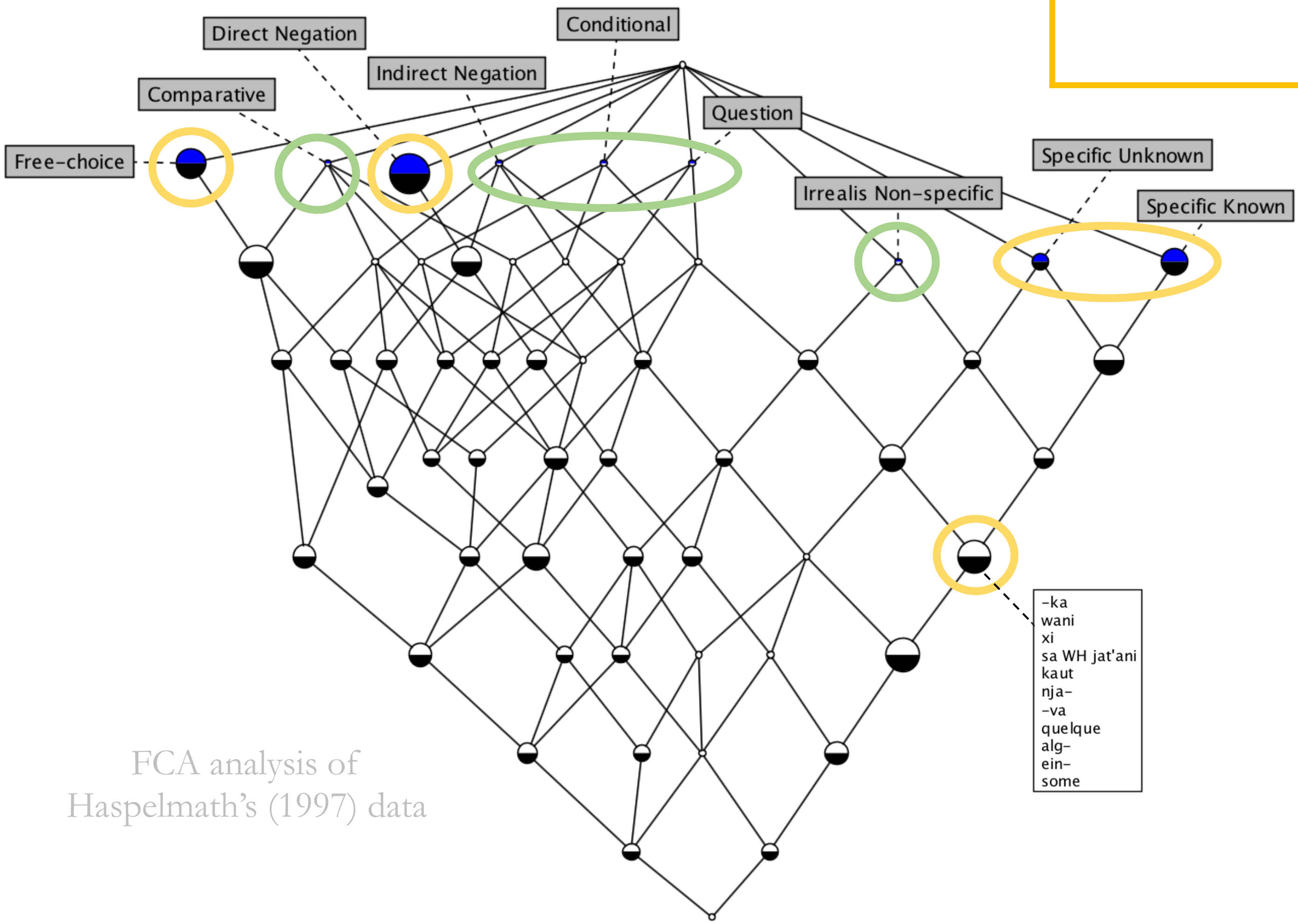

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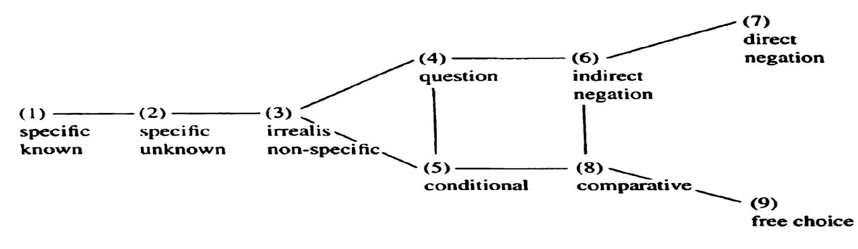

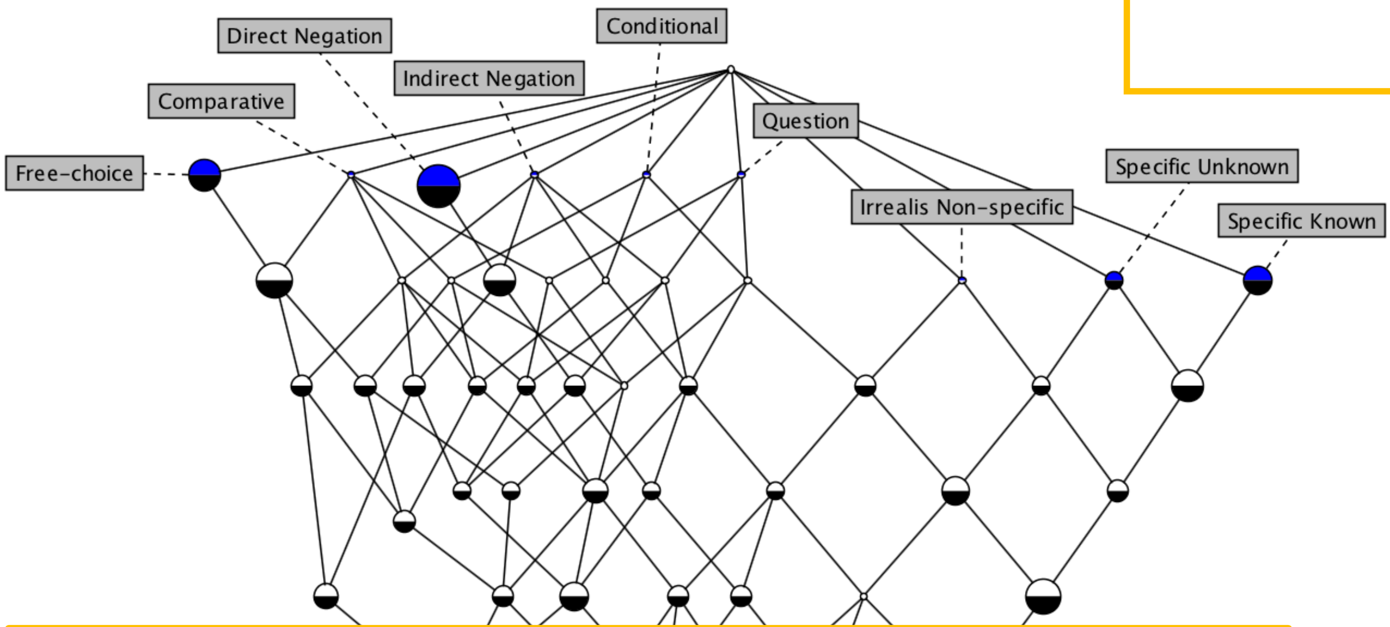

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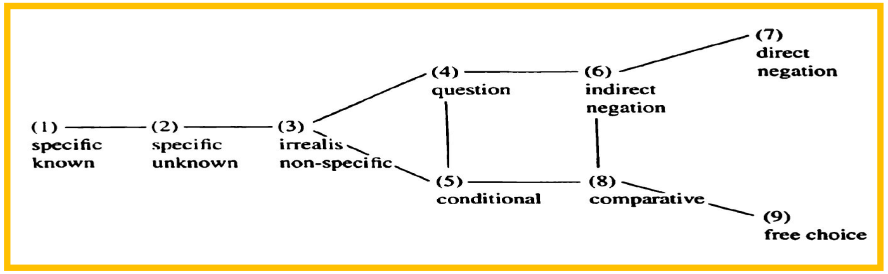

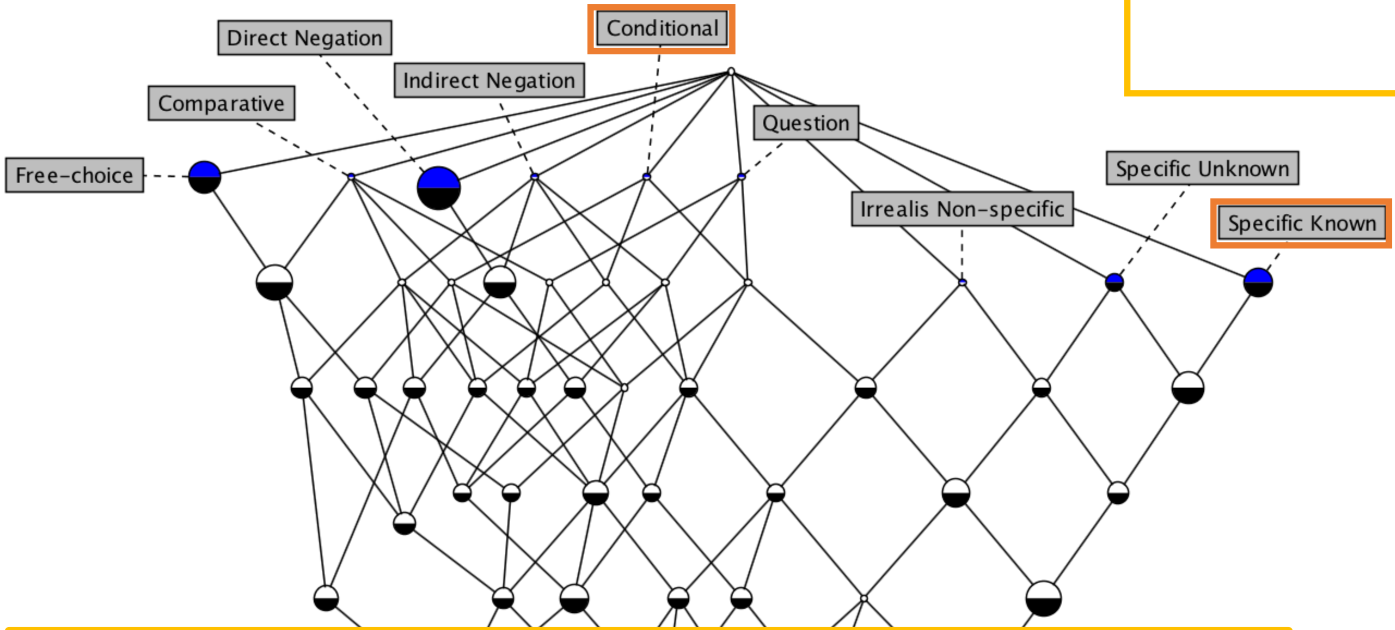

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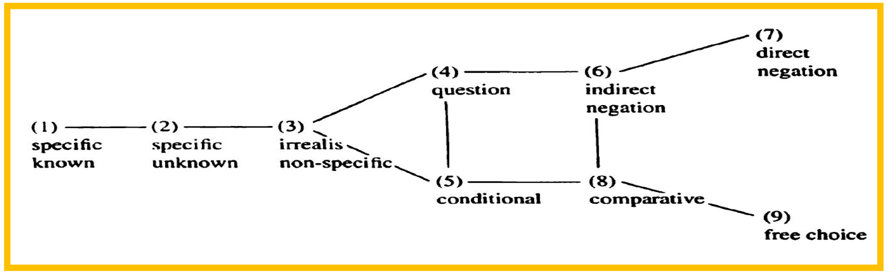

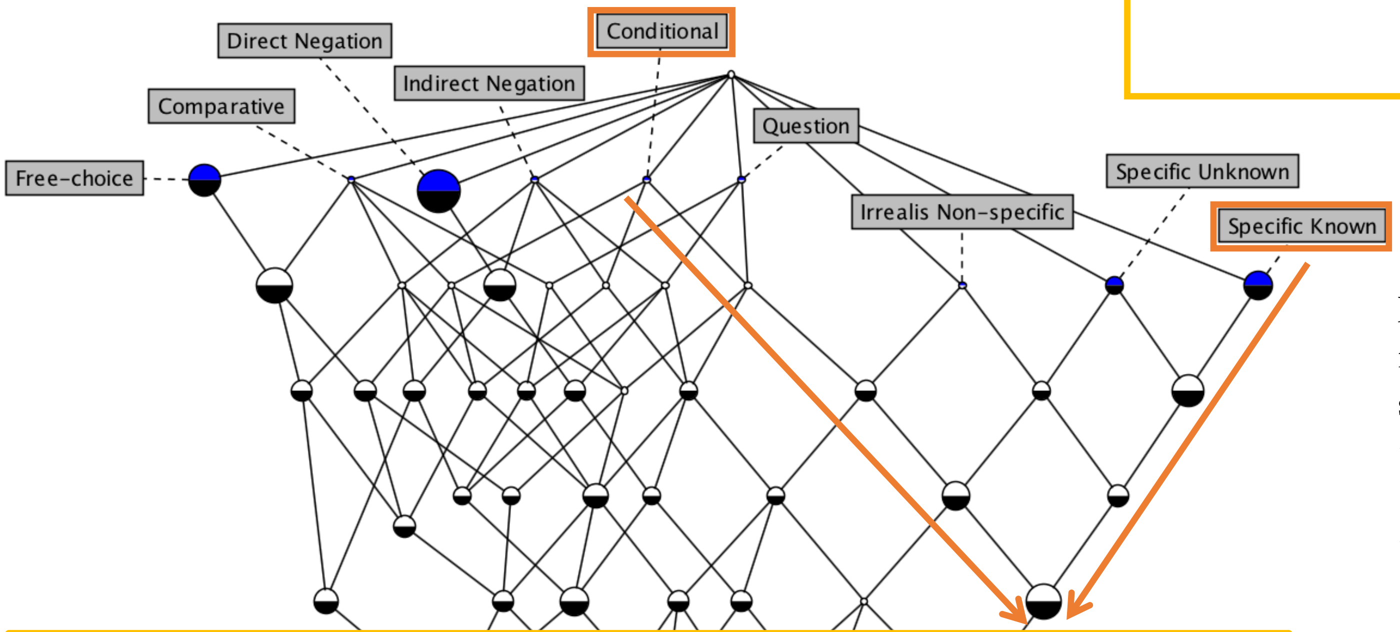

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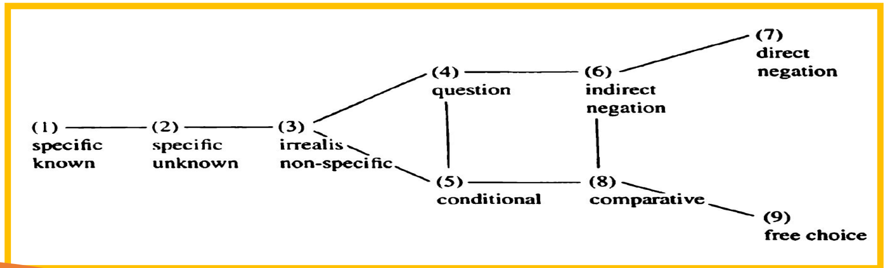

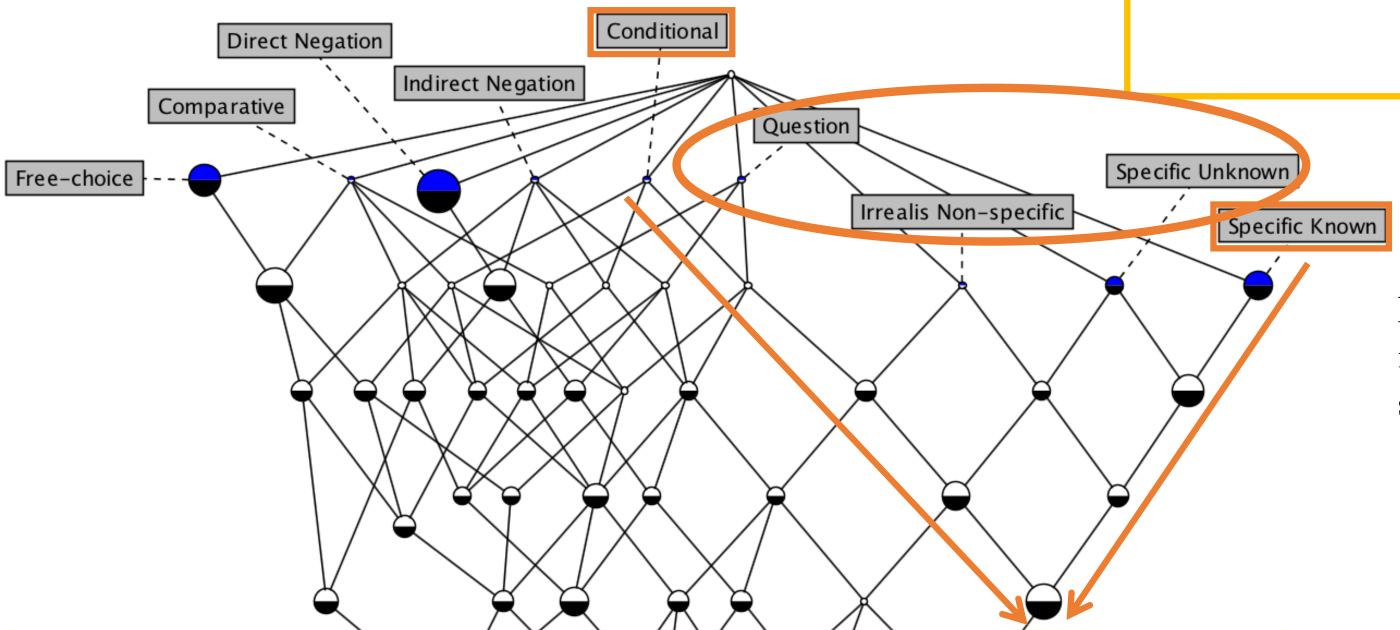

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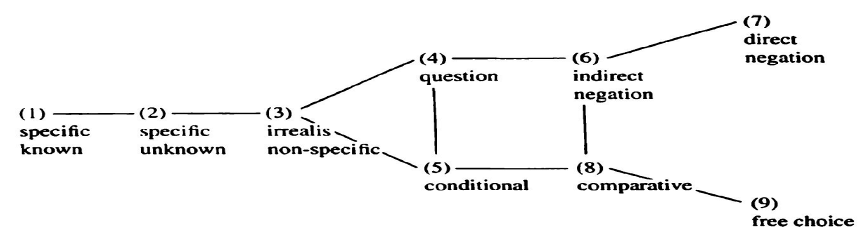

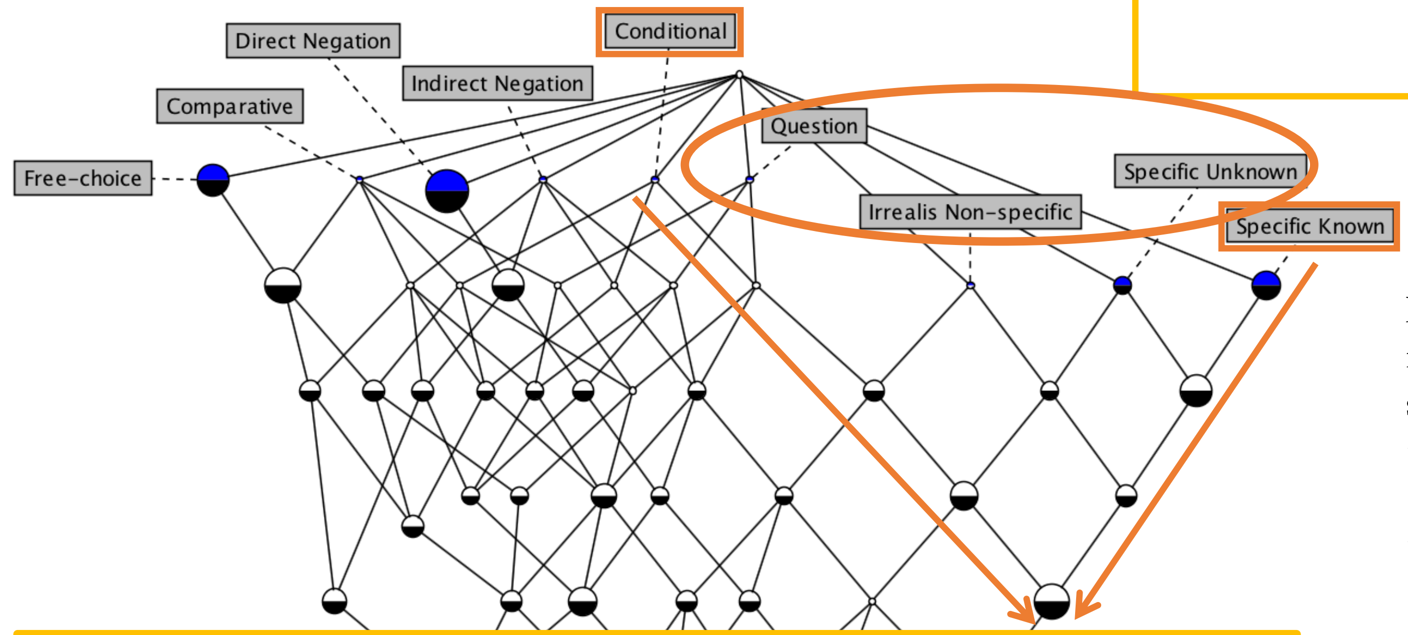

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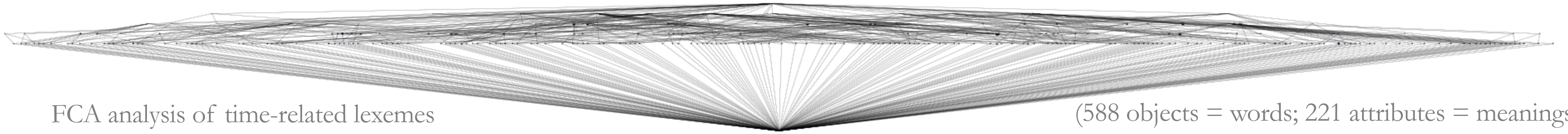
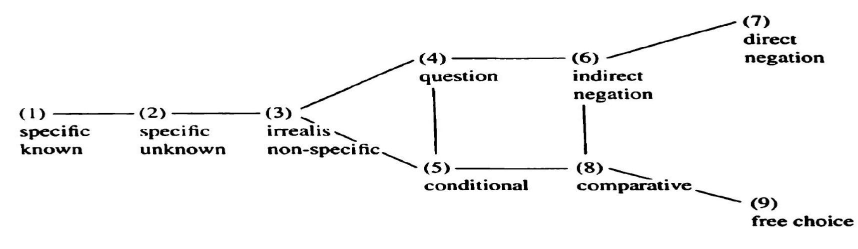
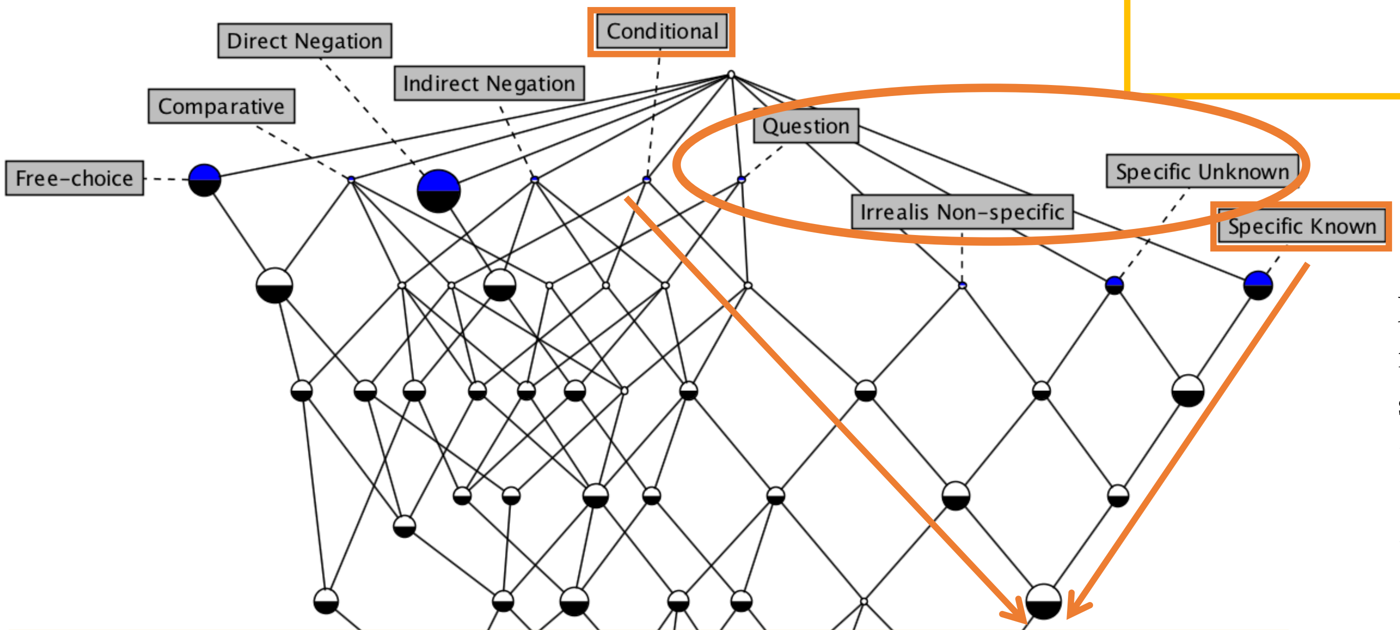


FCA analysis of time-related lexemes (588 objects = words; 221 attributes = meanings)





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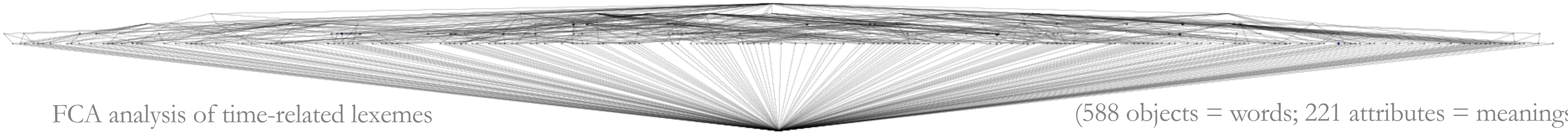

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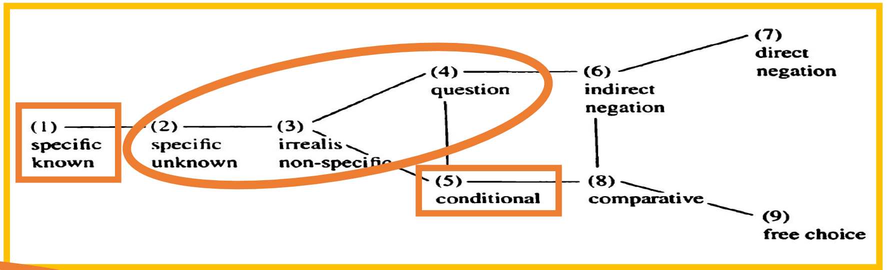

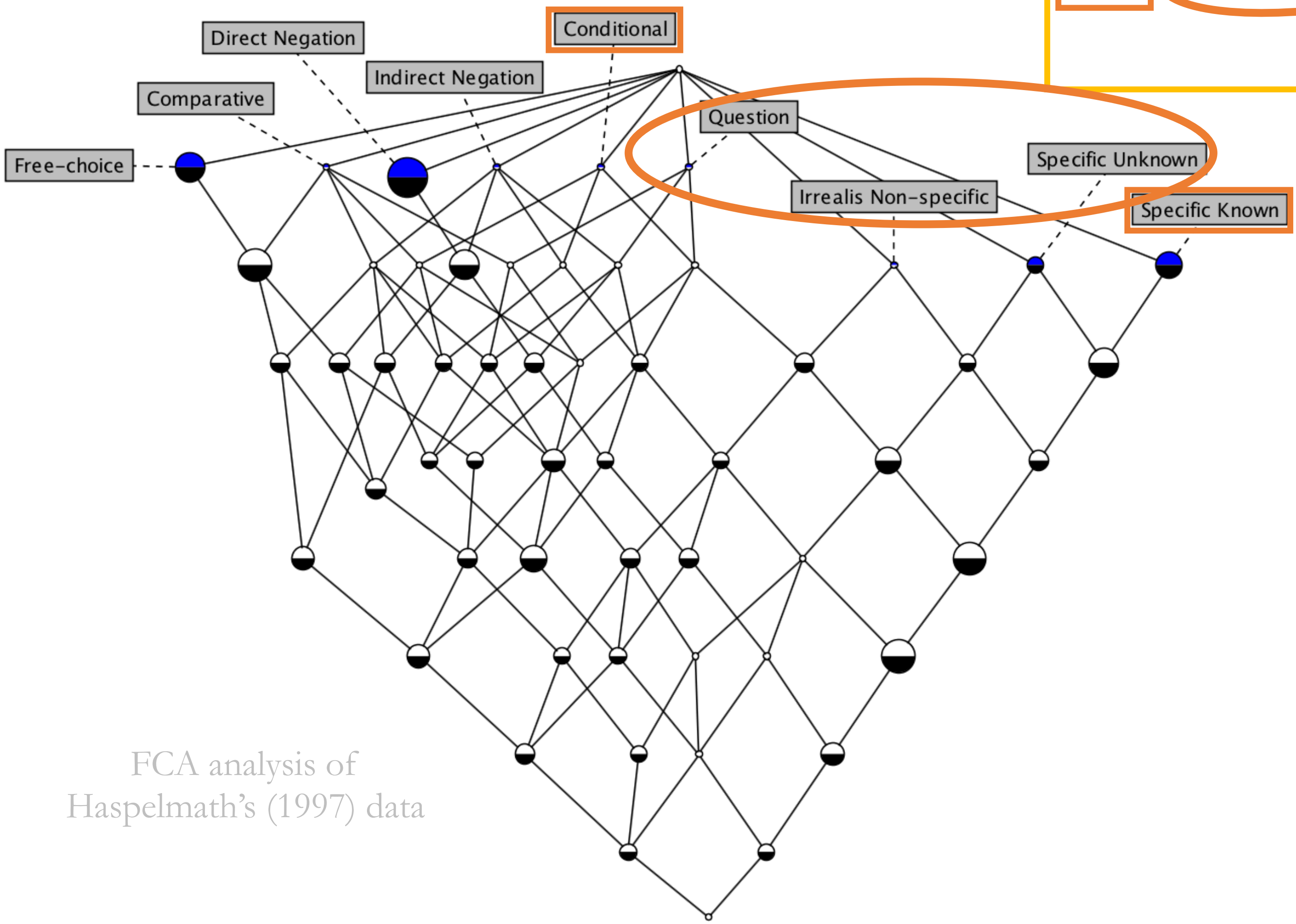

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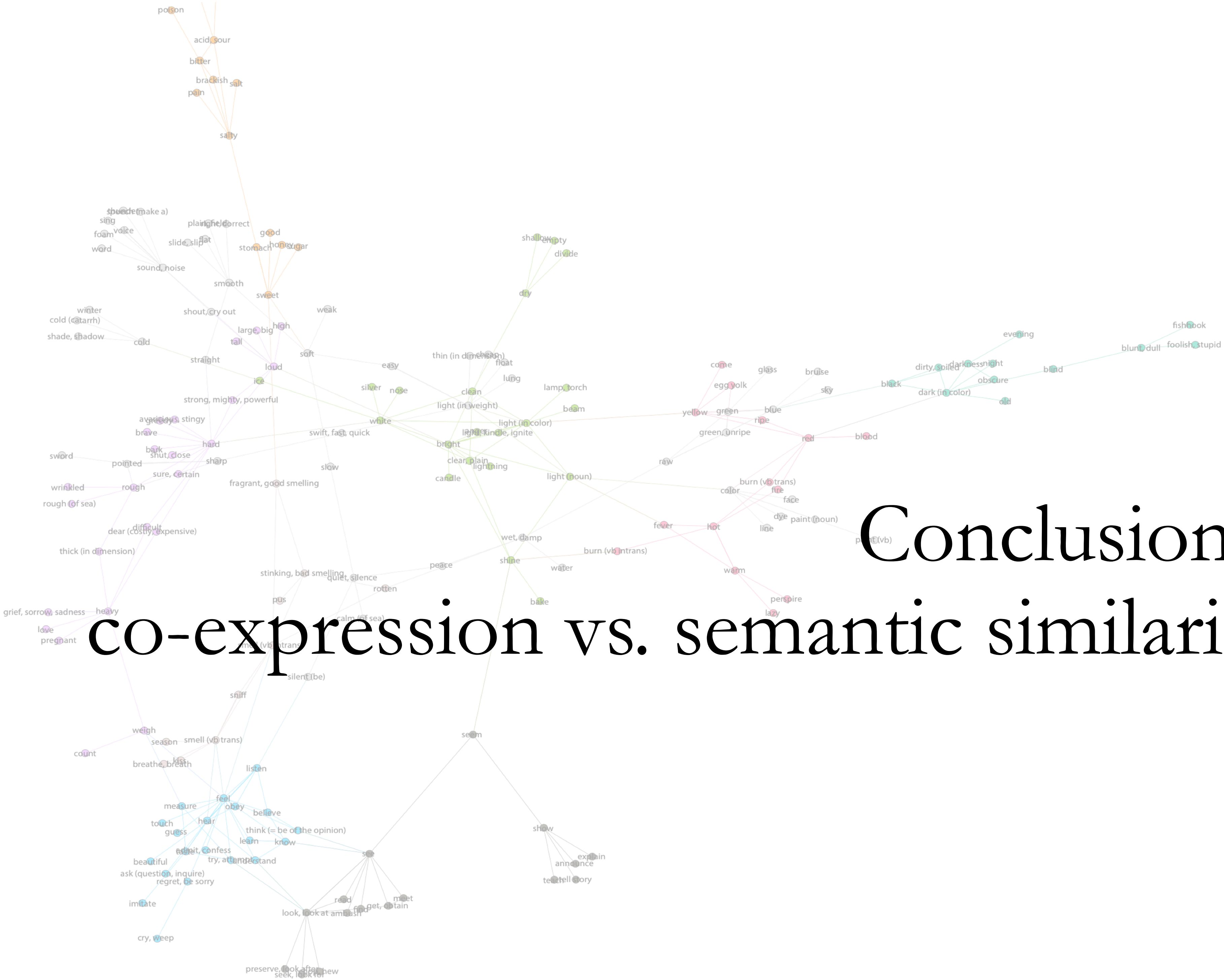
- ◆ Complementarity between the two approaches

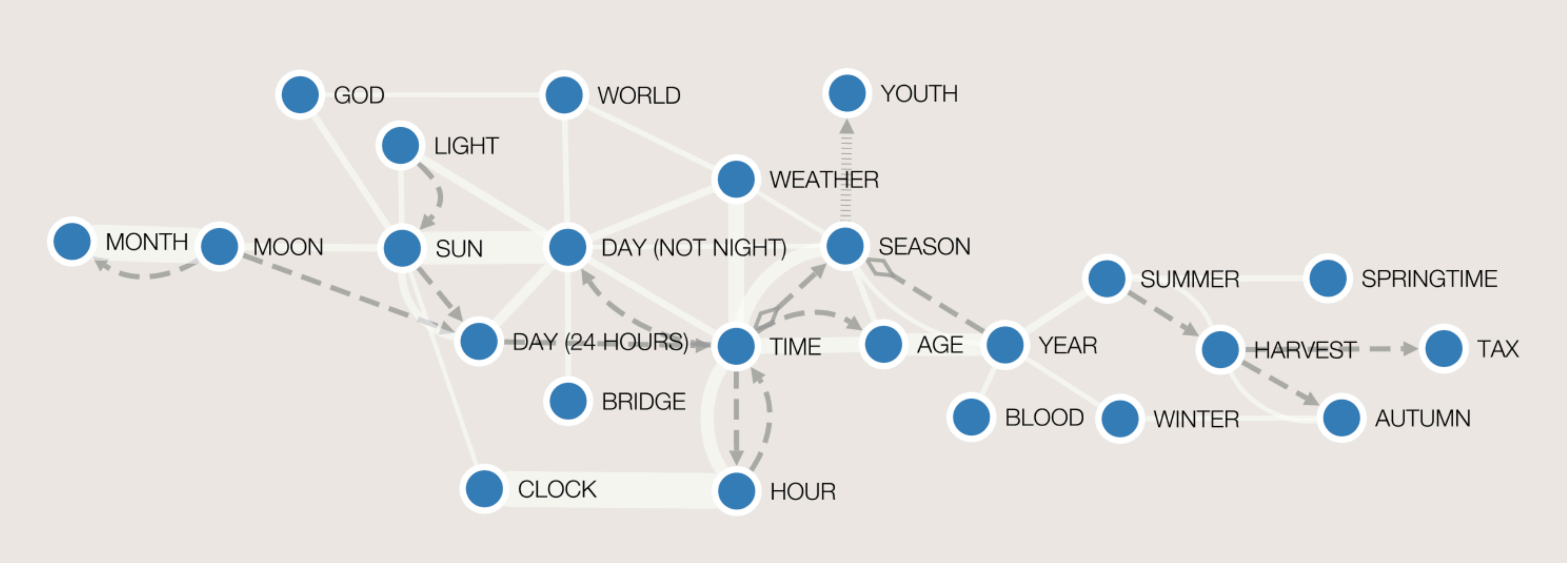


Conclusions: co-expression vs. semantic similarity

Conclusions

- Co-expression $\nLeftrightarrow$ semantic similarity (e.g., Malchukov 2010)
  - No relation
    - Homonyms
  - Symmetrical relations
    - Auto-antonyms (Klégr 2013)
  - Hierarchical relations
    - Auto-hyponyms
    - Auto-meronyms
    - Etc.

Conclusions



Georgakopoulos & Polis (under review), *Dynamic semantic maps of content words. The diachrony of time-related lexemes*, in: *JHL*.

Conclusions

Thanks!

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