Unit 3: Learning from other people

5. The structure in language

11/19/2020

The structure in language

1. You can learn a lot form the co-occurrence structure of words in language

2. Latent semantic analysis and Topics models both use this structure to learn about the world

3. But some information is not (straightforwardly) in the co-occurrence structure of language

How do you know so much without being told about it?

Plato's Problem:
Even uneducated people seem to know a lot

Plato's Solution:
Knowledge is innate

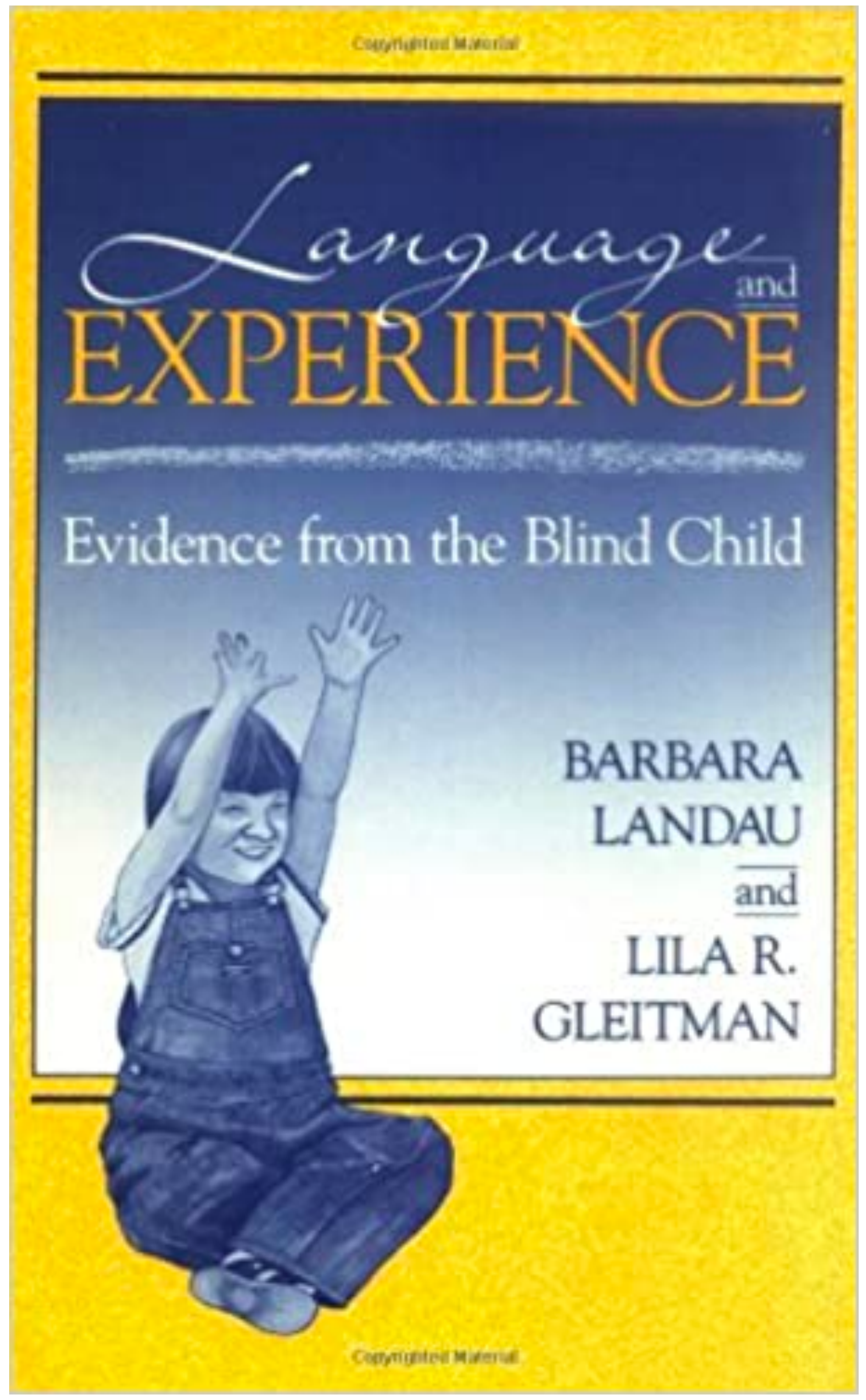
Plato (380 BC)

Chomsky's Problem:
Children seem to learn language from insufficient input

Chomsky's Solution:
Universal grammar is innate

Chomsky (1986)

Blind children know the meanings of sight words!



Look up!

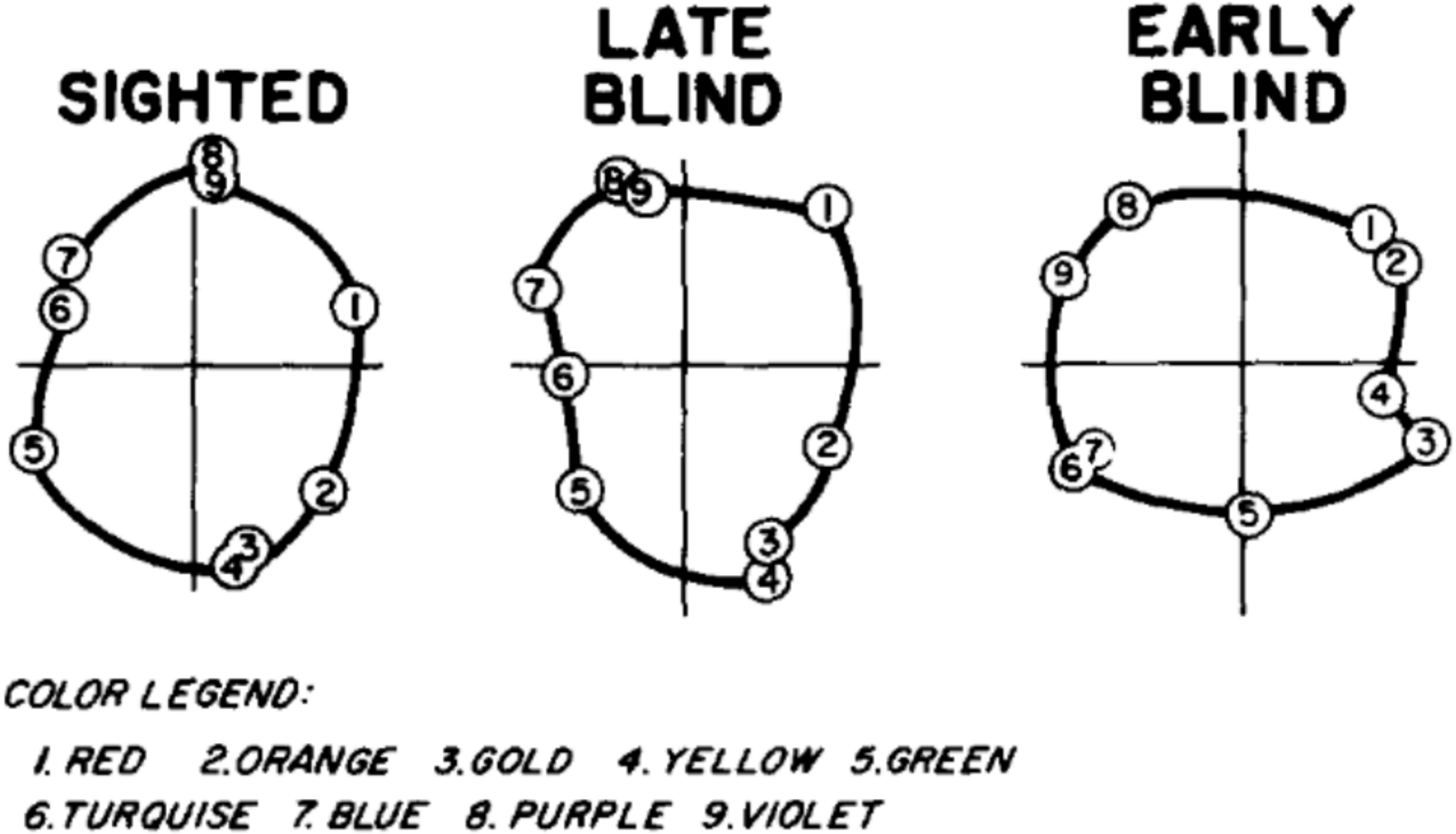
Let me see the back of your pants

Make it so mommy can't see the car

Let mommy *see* the car

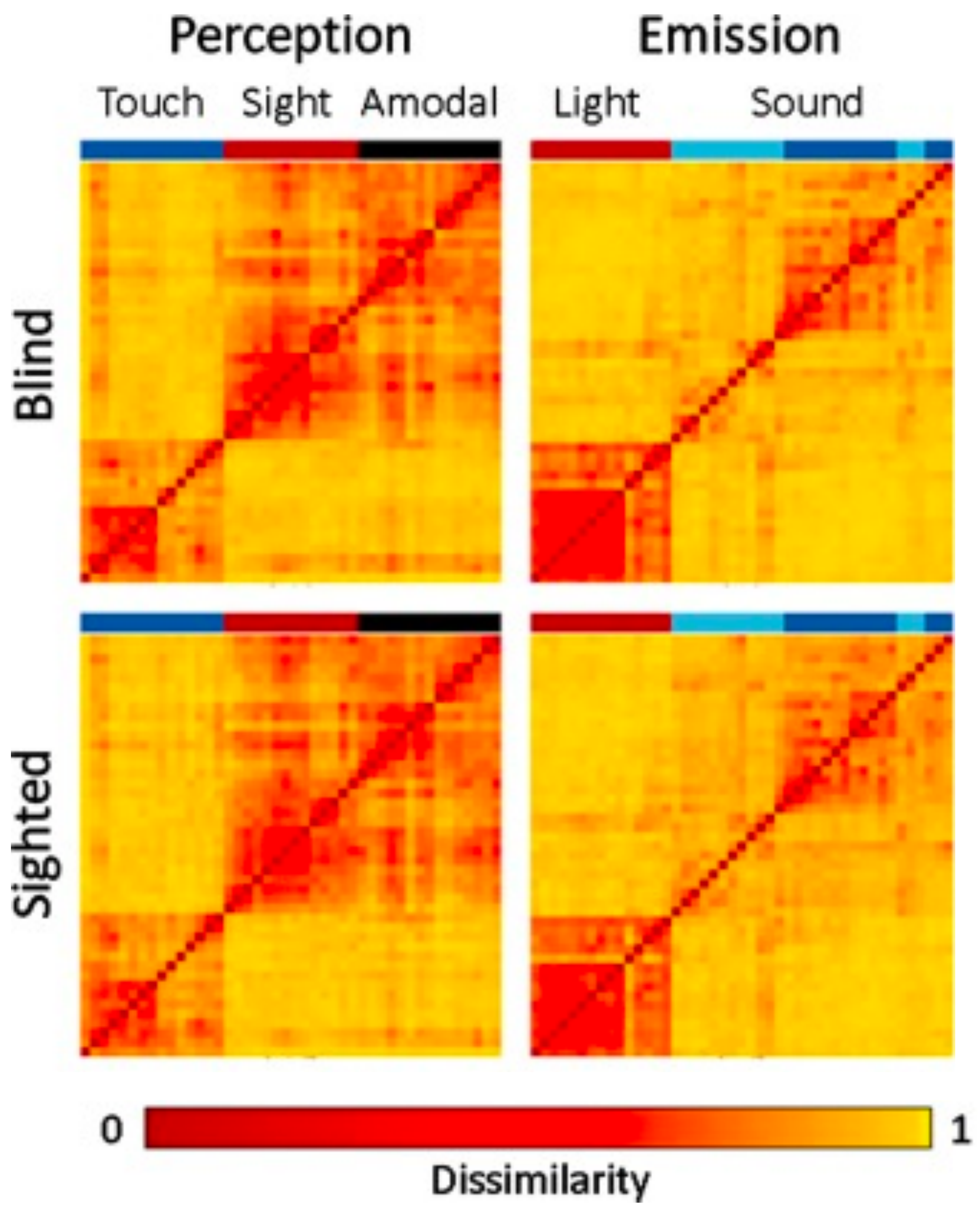
Let mommy *touch* the car

Blind adults color similarities look a lot like sighted adults



Marmor (1978)

Blind adults general perceptual verb similarities are like sighted adults’



Visual	Touch	Amodal
gawk	caress	characterize
gaze	dab	classify
glance	feel	discover
glimpse	grip	examine
leer	nudge	identify
look	pat	investigate
peek	pet	learn
peer	pinch	note
scan	prod	notice
see	pub	perceive
spot	scrape	question
stare	stroke	recognize
view	tap	scrutinize
watch	tickle	search
*ogle**	touch	study

Emission			Manner of Motion
Light	**Animate Sound**	**Inanimate Sound**	
blaze	bark	beep	bounce
blink	bellow	boom	float
flare	groan	buzz	glide
flash	growl	chime	hobble
flicker	grumble	clang	roll
gleam	grunt	clank	saunter
glimmer	howl	click	scurry
glint	moan	crackle	skip
glisten	mutter	creak	slither
glitter	shout	crunch	spin
glow	squawk	gurgle	strut
shimmer	wail	hiss	trot
shine	whimper	sizzle	twirl
sparkle	whisper	squeak	twist
twinkle	yelp	twang	waddle

Bedny et al. (2019)

A solution to Plato's problem (Landauer & Dumais, 1997)

Red onions are sweeter than **white** ones

Red hair occurs naturally in one to two percent of the human population

Pittsburgh one of U.S. cities with highest number of **gray** days

Fall tips for a **green** spring lawn

Lake Tahoe stretches 22 miles long and 12 miles wide, with clear **blue** water that's more than 99 percent pure

Direct information:
There is a relationship between e.g. red and hair

Indirect information:
Red, white, gray, green, and blue are used in *similar contexts*.

Contexts for e.g. blue and green are more similar than blue and red

Start with a term x document matrix

Document

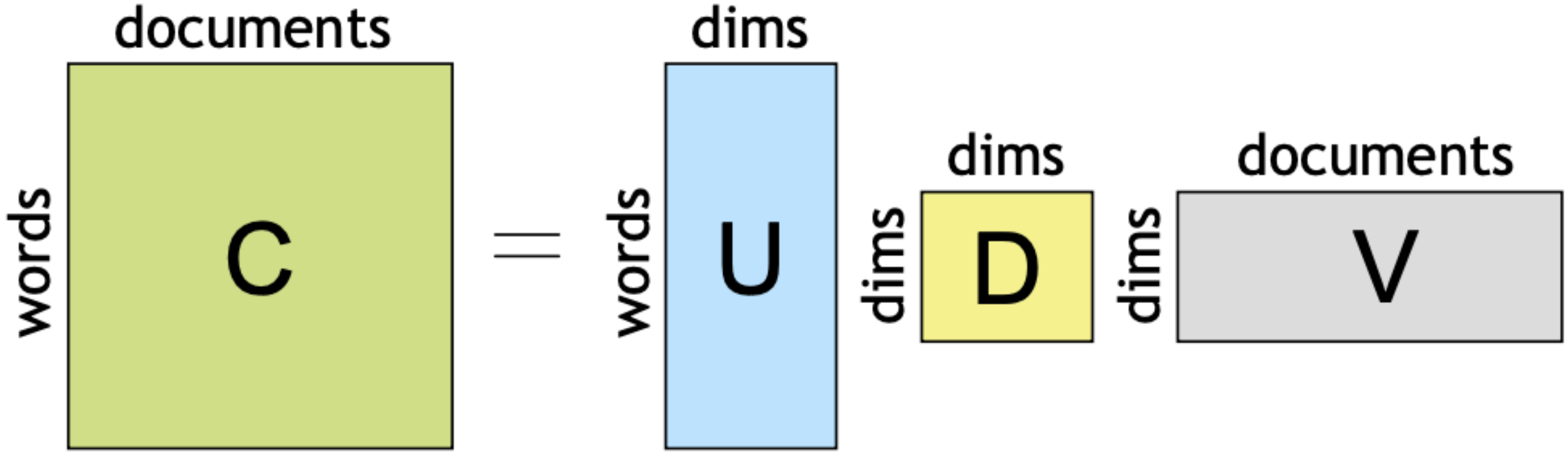
Term

	d1	d2	d3	d4	d5	d6
rock	2	1	0	2	0	1
granite	1	0	1	0	0	0
marble	1	2	0	0	0	0
music	0	0	0	1	2	0
song	0	0	0	1	0	2
band	0	0	0	0	1	0

Words that occur in similar documents are probably similar

Adapted from Ho Tu Bao

Latent semantic analysis: Finding the hidden structure in documents



Instead of representing words by co-occurrence in documents,
we want to represent their co-occurrence in semantic dimensions

Semantics are a low-dimensional compression of documents

Adapted from Ho Tu Bao

An example of LSA (Landauer, Foltz, & Laham, 1998)

Technical Memo Titles

c1: *Human* machine *interface* for ABC *computer* applications
c2: A *survey* of *user* opinion of *computer system response time*
c3: The *EPS user interface* management *system*
c4: *System* and *human system* engineering testing of *EPS*
c5: Relation of *user* perceived *response time* to error measurement

m1: The generation of random, binary, ordered *trees*
m2: The intersection *graph* of paths in *trees*
m3: *Graph minors* IV: Widths of *trees* and well-quasi-ordering
m4: *Graph minors*: A *survey*

An example of LSA (Landauer, Foltz, & Laham, 1998)

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

r(human, user) = -.38

r(human, minors) = -.29

Decomposing the matrix

C

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

U

0.22	-0.11	0.29	-0.41	-0.11	-0.34	0.52	-0.06	-0.41
0.20	-0.07	0.14	-0.55	0.28	0.50	-0.07	-0.01	-0.11
0.24	0.04	-0.16	-0.59	-0.11	-0.25	-0.30	0.06	0.49
0.40	0.06	-0.34	0.10	0.33	0.38	0.00	0.00	0.01
0.64	-0.17	0.36	0.33	-0.16	-0.21	-0.17	0.03	0.27
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.30	-0.14	0.33	0.19	0.11	0.27	0.03	-0.02	-0.17
0.21	0.27	-0.18	-0.03	-0.54	0.08	-0.47	-0.04	-0.58
0.01	0.49	0.23	0.03	0.59	-0.39	-0.29	0.25	-0.23
0.04	0.62	0.22	0.00	-0.07	0.11	0.16	-0.68	0.23
0.03	0.45	0.14	-0.01	-0.30	0.28	0.34	0.68	0.18

D

3.34								
	2.54							
		2.35						
			1.64					
				1.50				
					1.31			
						0.85		
							0.56	
								0.36

V

0.20	0.61	0.46	0.54	0.28	0.00	0.01	0.02	0.08
-0.06	0.17	-0.13	-0.23	0.11	0.19	0.44	0.62	0.53
0.11	-0.50	0.21	0.57	-0.51	0.10	0.19	0.25	0.08
-0.95	-0.03	0.04	0.27	0.15	0.02	0.02	0.01	-0.03
0.05	-0.21	0.38	-0.21	0.33	0.39	0.35	0.15	-0.60
-0.08	-0.26	0.72	-0.37	0.03	-0.30	-0.21	0.00	0.36
0.18	-0.43	-0.24	0.26	0.67	-0.34	-0.15	0.25	0.04
-0.01	0.05	0.01	-0.02	-0.06	0.45	-0.76	0.45	-0.07
-0.06	0.24	0.02	-0.08	-0.26	-0.62	0.02	0.52	-0.45

A low-dimensional reconstruction using the first 2 dimensions

C

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

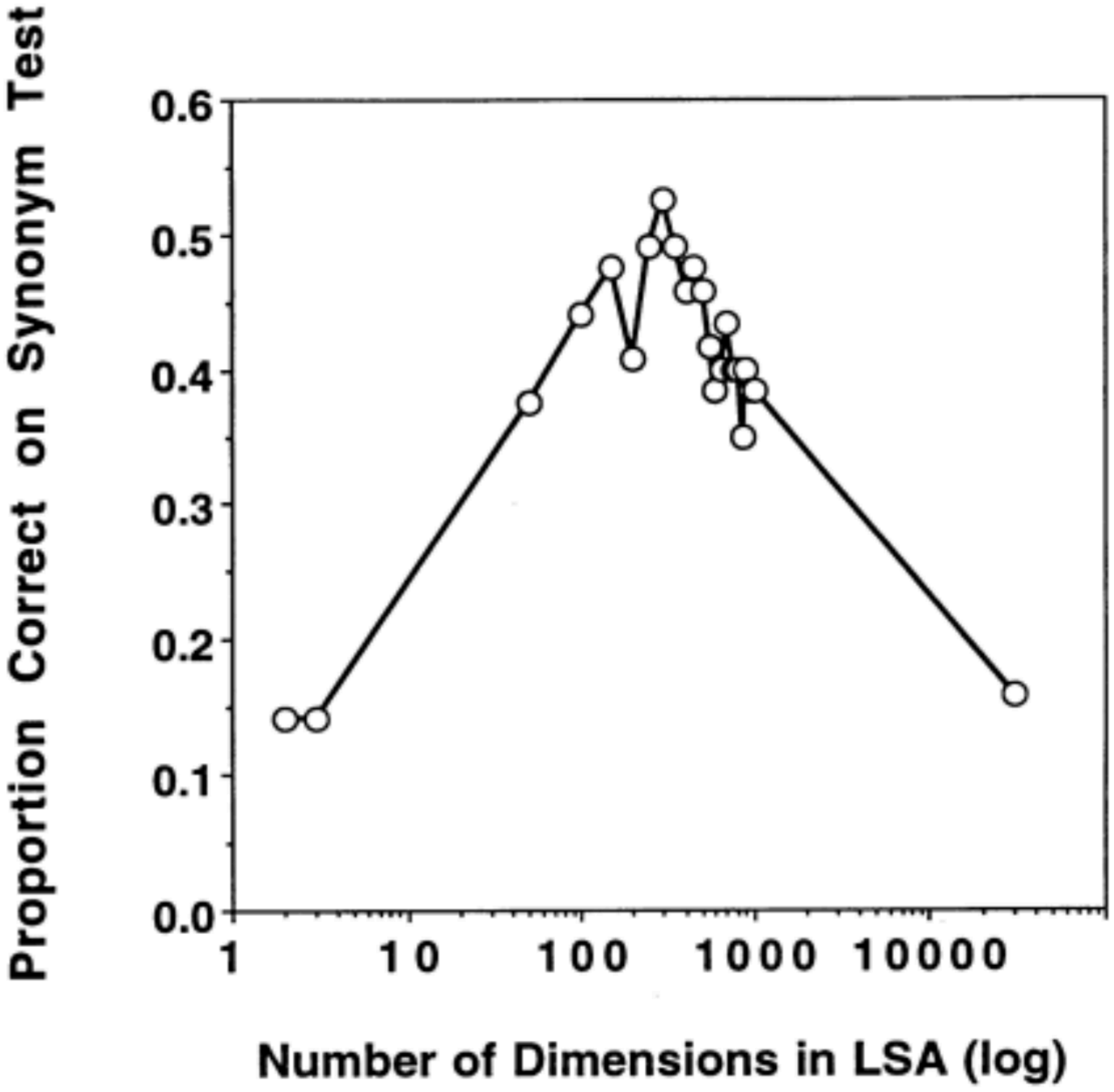
r(human, user) = .94

r(human, minors) = -.83

C’

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	0.16	0.40	0.38	0.47	0.18	-0.05	-0.12	-0.16	-0.09
interface	0.14	0.37	0.33	0.40	0.16	-0.03	-0.07	-0.10	-0.04
computer	0.15	0.51	0.36	0.41	0.24	0.02	0.06	0.09	0.12
user	0.26	0.84	0.61	0.70	0.39	0.03	0.08	0.12	0.19
system	0.45	1.23	1.05	1.27	0.56	-0.07	-0.15	-0.21	-0.05
response	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
time	0.16	0.58	0.38	0.42	0.28	0.06	0.13	0.19	0.22
EPS	0.22	0.55	0.51	0.63	0.24	-0.07	-0.14	-0.20	-0.11
survey	0.10	0.53	0.23	0.21	0.27	0.14	0.31	0.44	0.42
trees	-0.06	0.23	-0.14	-0.27	0.14	0.24	0.55	0.77	0.66
graph	-0.06	0.34	-0.15	-0.30	0.20	0.31	0.69	0.98	0.85
minors	-0.04	0.25	-0.10	-0.21	0.15	0.22	0.50	0.71	0.62

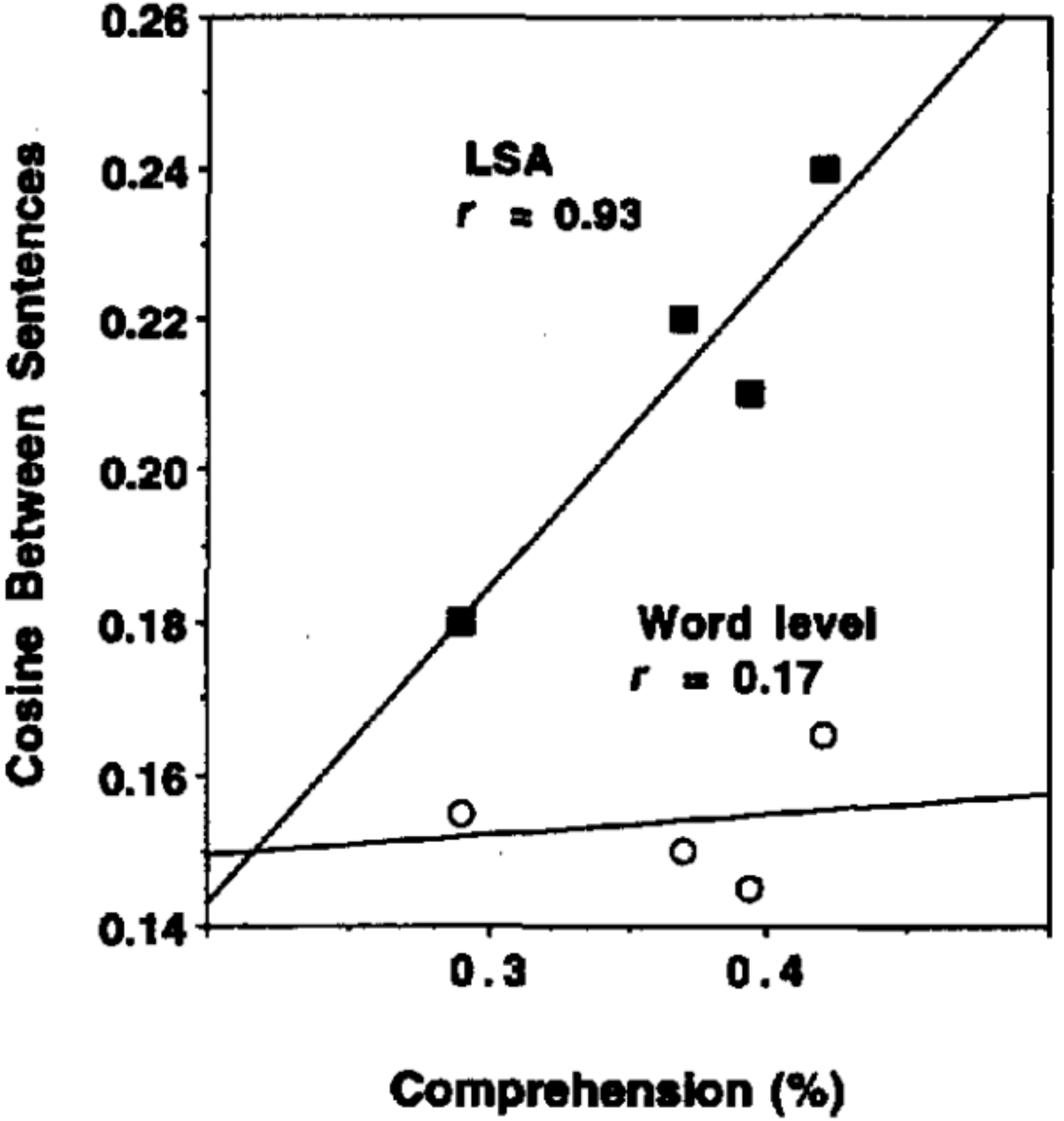
Latent semantic analysis predicts human similarity judgments



LSA can pass the synonym part of the TOEFL!

Chance is 25%
Applicants to US Universities on average get 52.7%

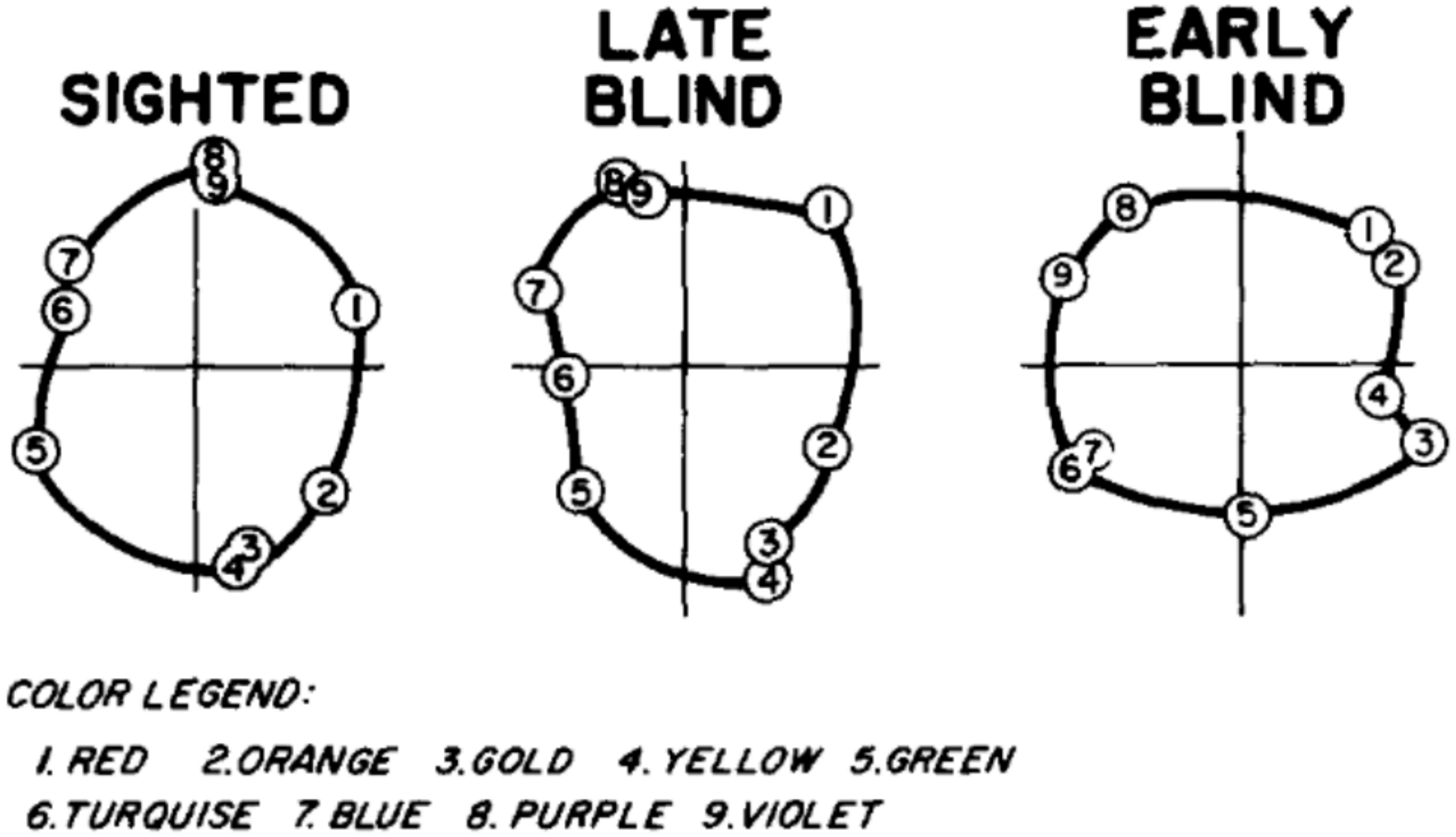
Latent semantic analysis predicts sentence comprehensibility



Mammals have very specialized teeth. There are four types of teeth in mammals: incisors, canines, premolars, and molars. The number and shape of each of these types of teeth are related to the kind of food the mammal eats.

Another physical trait of mammals is that they can eat many different kinds of food because they have very specialized teeth. This trait also helps them to live in different kinds of environments

Can LSA recover perceptual similarities?



Visual	Touch	Amodal
gawk	caress	characterize
gaze	dab	classify
glance	feel	discover
glimpse	grip	examine
leer	nudge	identify
look	pat	investigate
peek	pet	learn
peer	pinch	note
scan	prod	notice
see	pub	perceive
spot	scrape	question
stare	stroke	recognize
view	tap	scrutinize
watch	tickle	search
ogle[*]	touch	study

Emission			Manner of Motion
Light	**Animate Sound**	**Inanimate Sound**	
blaze	bark	beep	bounce
blink	bellow	boom	float
flare	groan	buzz	glide
flash	growl	chime	hobble
flicker	grumble	clang	roll
gleam	grunt	clank	saunter
glimmer	howl	click	scurry
glint	moan	crackle	skip
glisten	mutter	creak	slither
glitter	shout	crunch	spin
glow	squawk	gurgle	strut
shimmer	wail	hiss	trot
shine	whimper	sizzle	twirl
sparkle	whisper	squeak	twist
twinkle	yelp	twang	waddle

https://bit.ly/test-lsa

But what are these underlying dimensions?

C

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1

U

0.22	-0.11	0.29	-0.41	-0.11	-0.34	0.52	-0.06	-0.41
0.20	-0.07	0.14	-0.55	0.28	0.50	-0.07	-0.01	-0.11
0.24	0.04	-0.16	-0.59	-0.11	-0.25	-0.30	0.06	0.49
0.40	0.06	-0.34	0.10	0.33	0.38	0.00	0.00	0.01
0.64	-0.17	0.36	0.33	-0.16	-0.21	-0.17	0.03	0.27
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.27	0.11	-0.43	0.07	0.08	-0.17	0.28	-0.02	-0.05
0.30	-0.14	0.33	0.19	0.11	0.27	0.03	-0.02	-0.17
0.21	0.27	-0.18	-0.03	-0.54	0.08	-0.47	-0.04	-0.58
0.01	0.49	0.23	0.03	0.59	-0.39	-0.29	0.25	-0.23
0.04	0.62	0.22	0.00	-0.07	0.11	0.16	-0.68	0.23
0.03	0.45	0.14	-0.01	-0.30	0.28	0.34	0.68	0.18

D

3.34								
	2.54							
		2.35						
			1.64					
				1.50				
					1.31			
						0.85		
							0.56	
								0.36

V

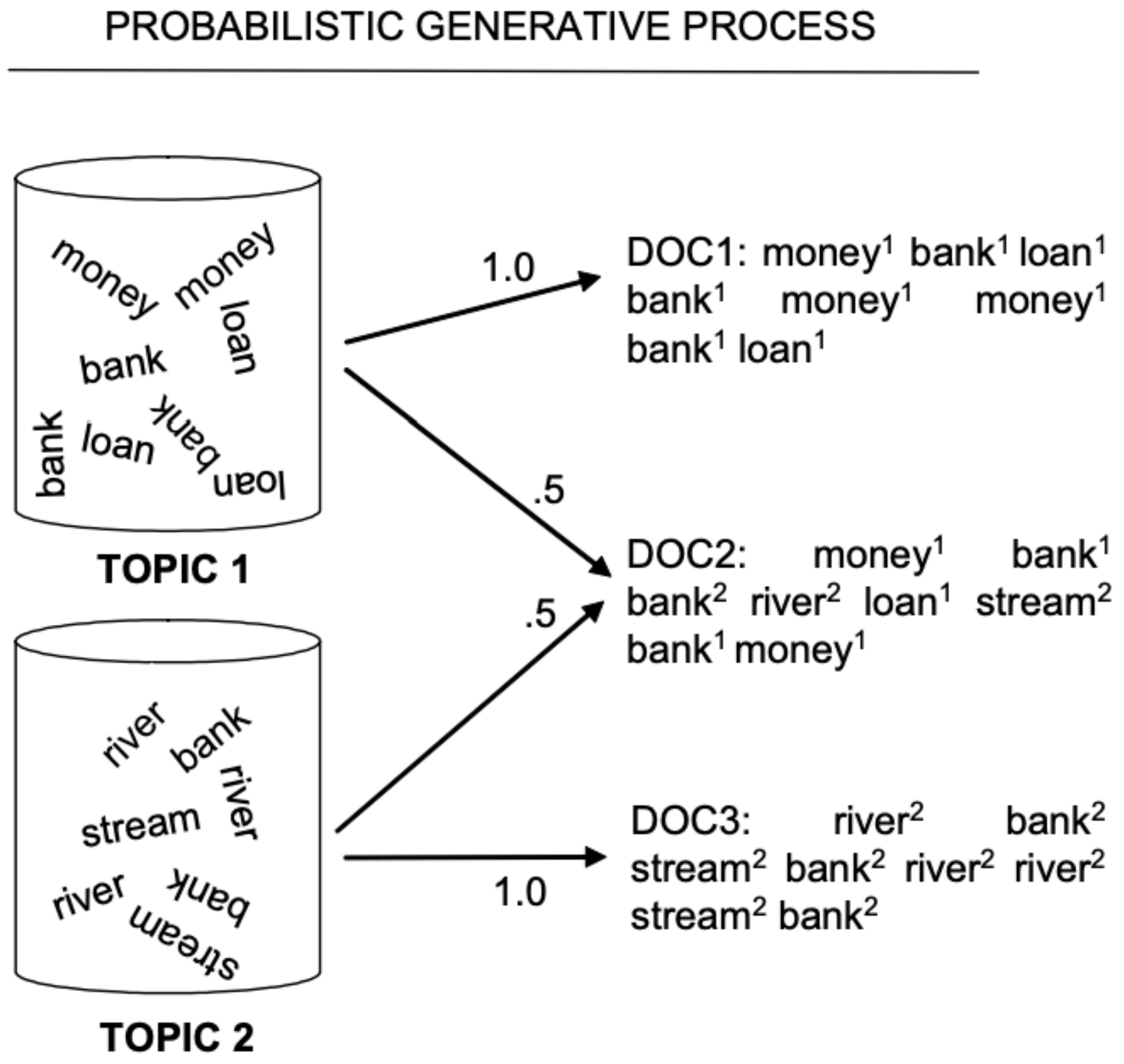
0.20	0.61	0.46	0.54	0.28	0.00	0.01	0.02	0.08
-0.06	0.17	-0.13	-0.23	0.11	0.19	0.44	0.62	0.53
0.11	-0.50	0.21	0.57	-0.51	0.10	0.19	0.25	0.08
-0.95	-0.03	0.04	0.27	0.15	0.02	0.02	0.01	-0.03
0.05	-0.21	0.38	-0.21	0.33	0.39	0.35	0.15	-0.60
-0.08	-0.26	0.72	-0.37	0.03	-0.30	-0.21	0.00	0.36
0.18	-0.43	-0.24	0.26	0.67	-0.34	-0.15	0.25	0.04
-0.01	0.05	0.01	-0.02	-0.06	0.45	-0.76	0.45	-0.07
-0.06	0.24	0.02	-0.08	-0.26	-0.62	0.02	0.52	-0.45

Topic Models (Latent Dirichlet Allocation) - Steyvers & Griffiths (2007)

Idea: A generative model for how words appear in documents

Each document is created by picking a set of topics, each with some weight.

For every word in the document, it is chosen from one of the topics according to their weight



Model from Blei, Ng, & Jordan (2003)

Topic Models (Latent Dirichlet Allocation) - Steyvers & Griffiths (2007)

For each **topic** $1 \ldots t$:

Draw a **multinomial over words** $\phi_t \sim Dirichlet(\boldsymbol{\beta})$

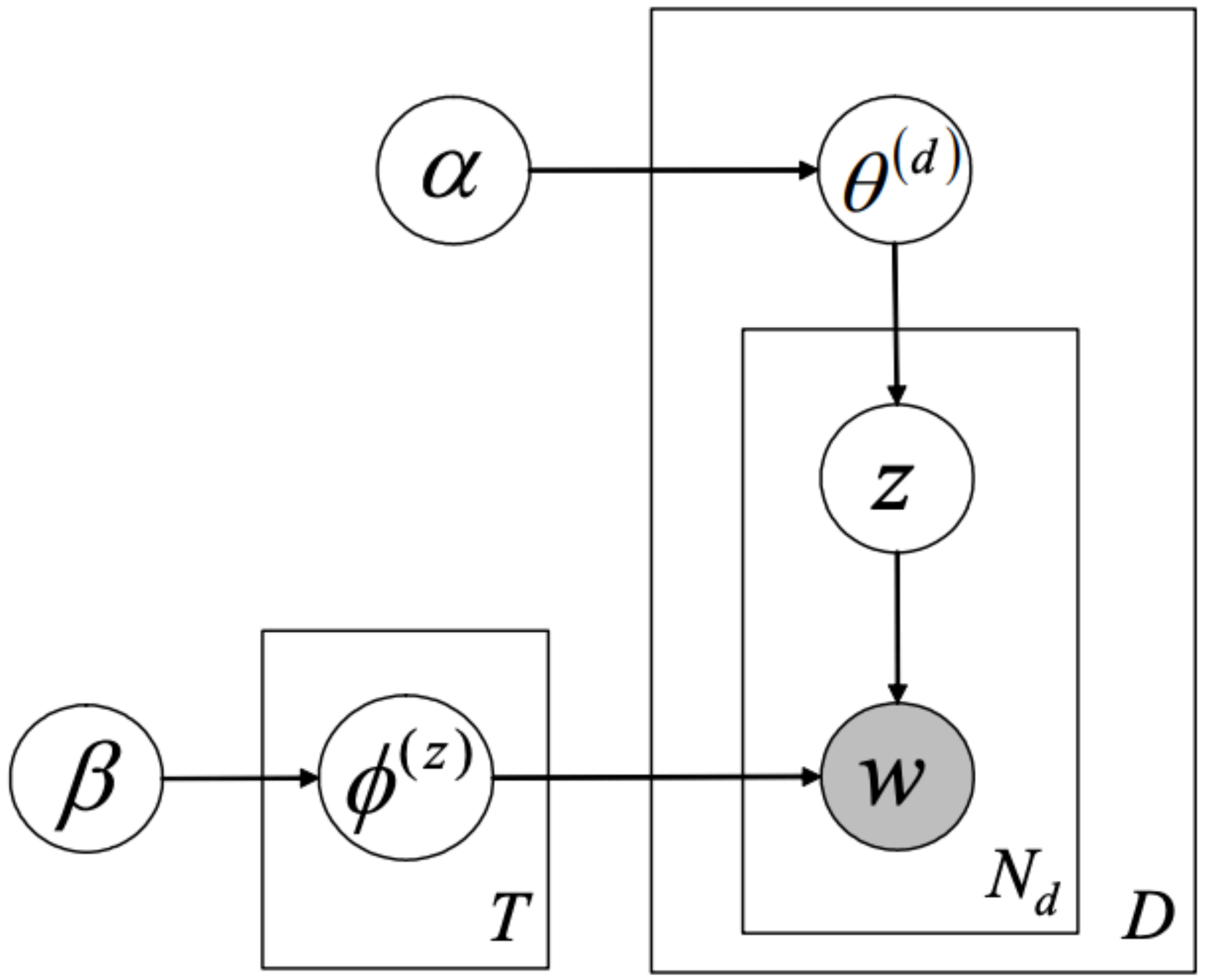
For each **document** $1 \ldots d$:

Draw a **multinomial over topics** $\theta_d \sim Dirichlet(\boldsymbol{\alpha})$

For each word $w_{d,n}$:

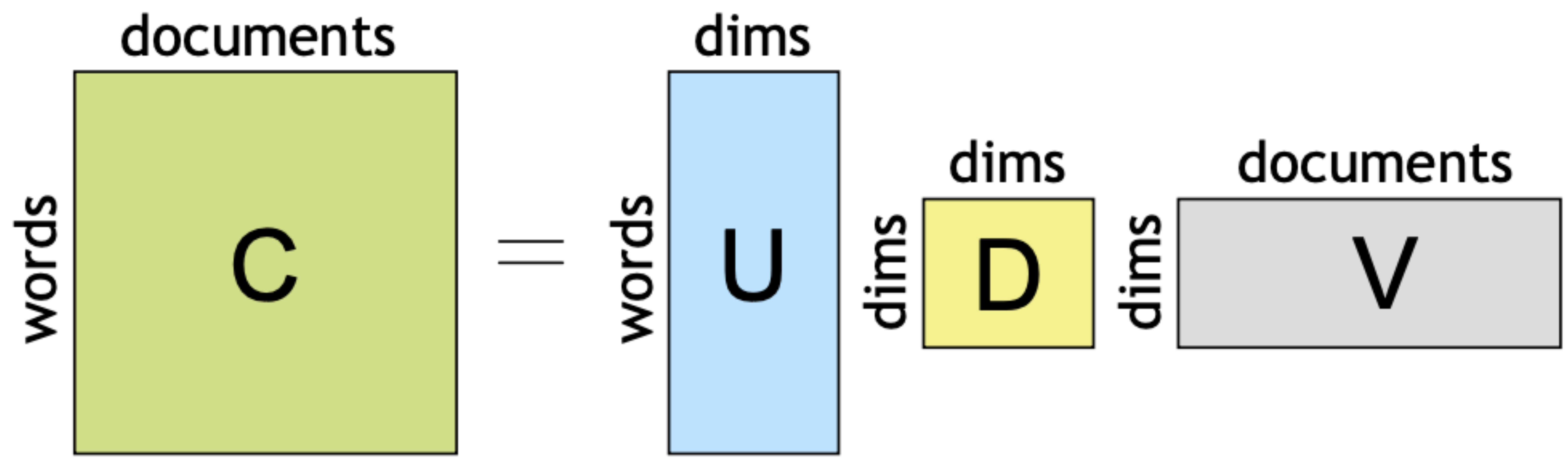
Draw a topic $Z_{d,n} \sim$ Multinomial (θ_d) with $Z_{d,n} \in [1 \ldots t]$

Draw a word $w_{d,n} \sim$ Multinomial $\left(\beta_{Z_{d,n}}\right)$

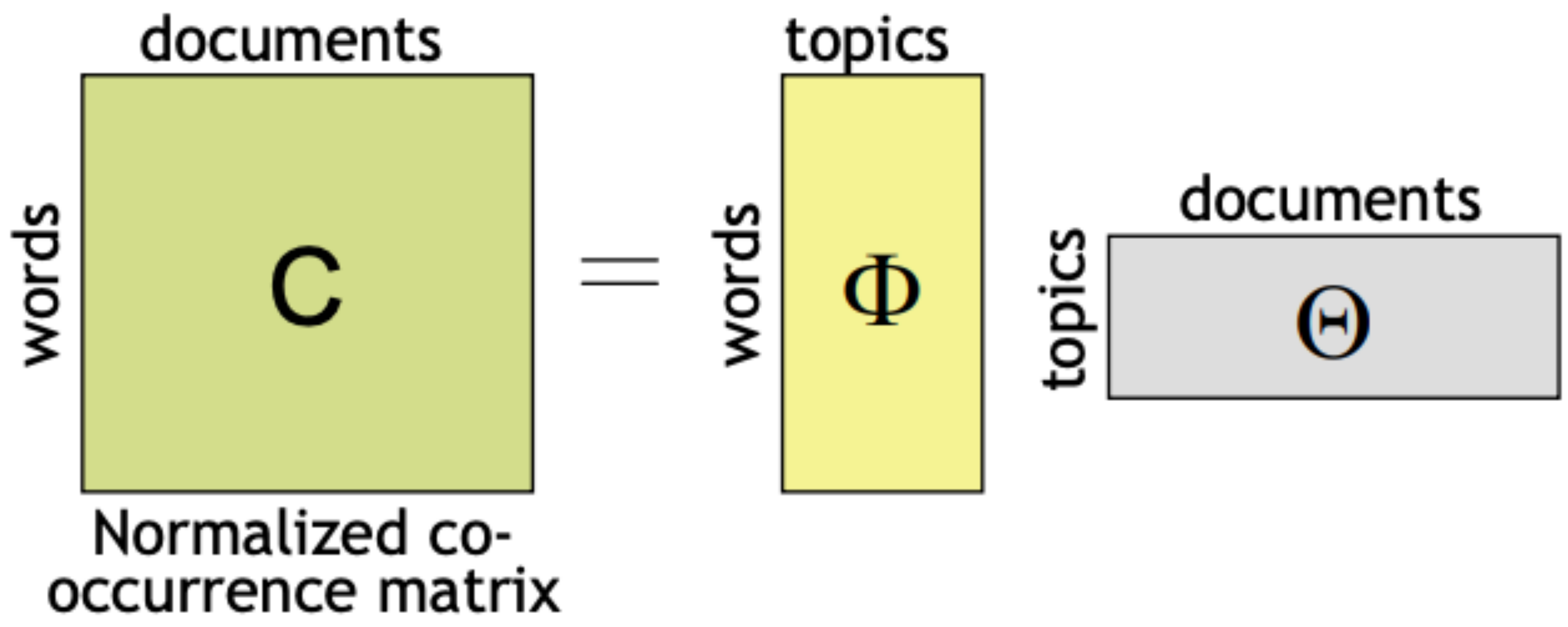


Comparing LSA and Topic Models

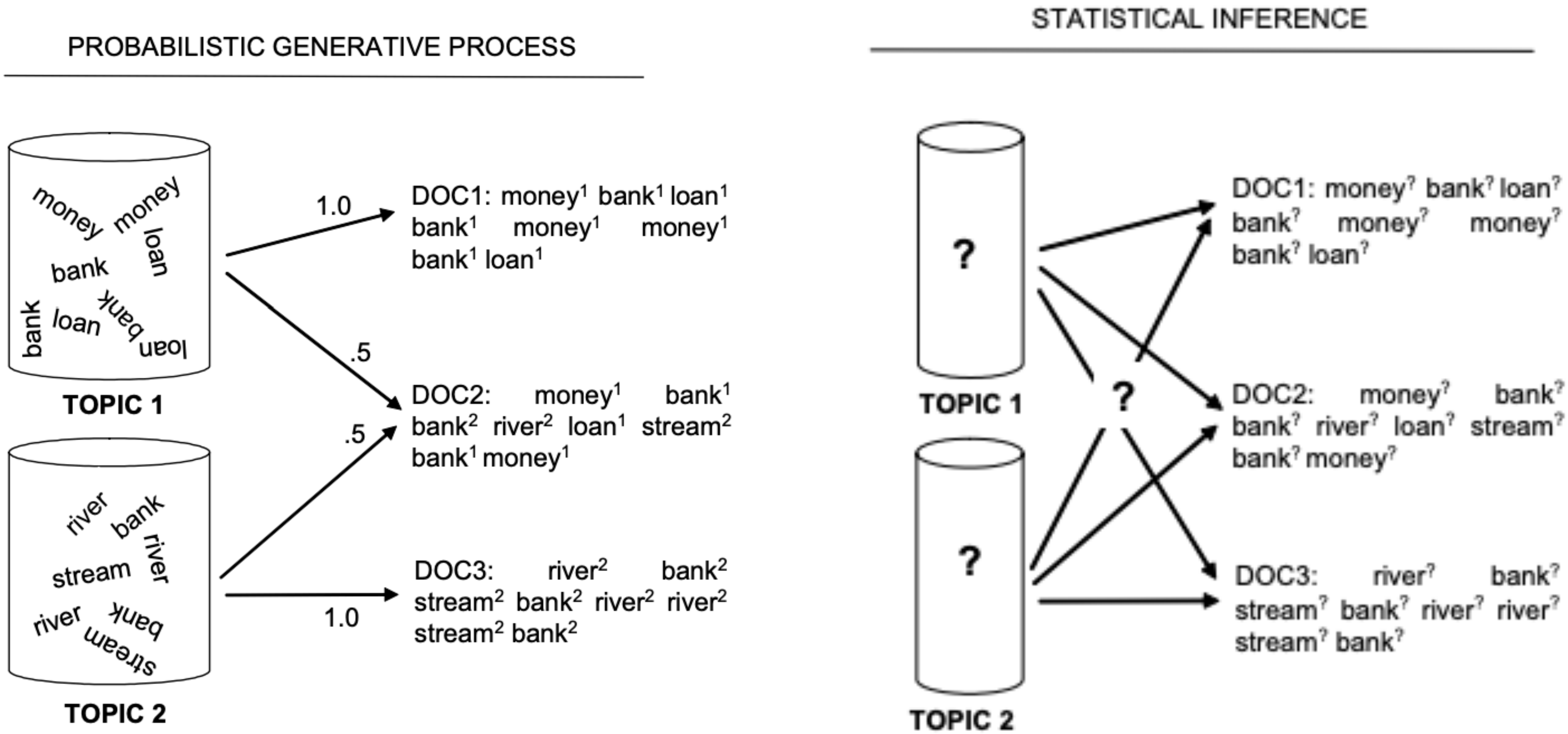
LSA



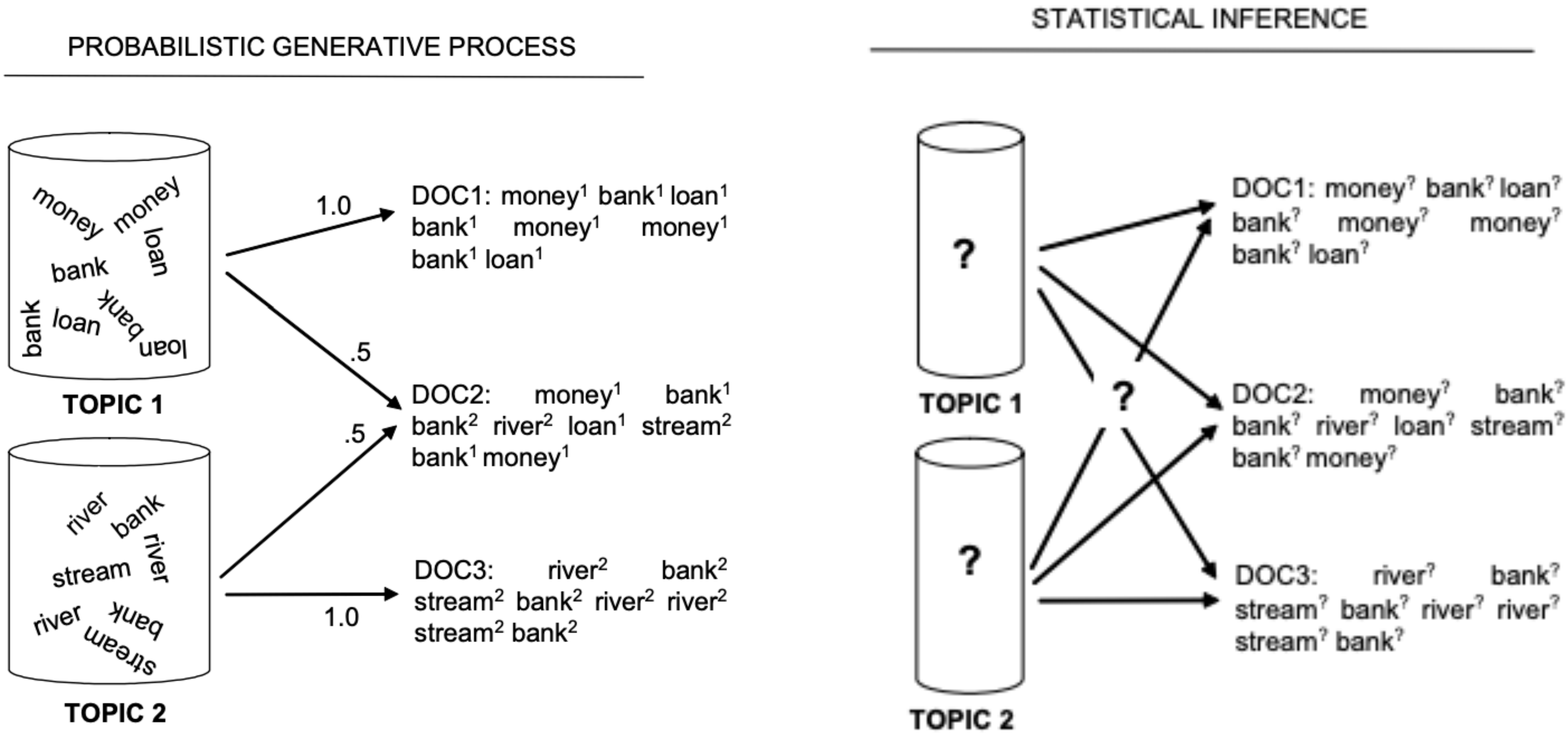
Topic Model



Inferring topics by Bayesian inference using sampling



Inferring topics by Bayesian inference using sampling



Example topics form the Touchstone Applied Sciences Association (TASA) corpus

Topic 247

word	prob.
DRUGS	.069
DRUG	.060
MEDICINE	.027
EFFECTS	.026
BODY	.023
MEDICINES	.019
PAIN	.016
PERSON	.016
MARIJUANA	.014
LABEL	.012
ALCOHOL	.012
DANGEROUS	.011
ABUSE	.009
EFFECT	.009
KNOWN	.008
PILLS	.008

Topic 5

word	prob.
RED	.202
BLUE	.099
GREEN	.096
YELLOW	.073
WHITE	.048
COLOR	.048
BRIGHT	.030
COLORS	.029
ORANGE	.027
BROWN	.027
PINK	.017
LOOK	.017
BLACK	.016
PURPLE	.015
CROSS	.011
COLORED	.009

Topic 43

word	prob.
MIND	.081
THOUGHT	.066
REMEMBER	.064
MEMORY	.037
THINKING	.030
PROFESSOR	.028
FELT	.025
REMEMBERED	.022
THOUGHTS	.020
FORGOTTEN	.020
MOMENT	.020
THINK	.019
THING	.016
WONDER	.014
FORGET	.012
RECALL	.012

Topic 56

word	prob.
DOCTOR	.074
DR.	.063
PATIENT	.061
HOSPITAL	.049
CARE	.046
MEDICAL	.042
NURSE	.031
PATIENTS	.029
DOCTORS	.028
HEALTH	.025
MEDICINE	.017
NURSING	.017
DENTAL	.015
NURSES	.013
PHYSICIAN	.012
HOSPITALS	.011

Topics models can resolve polysemy

Bix beiderbecke, at age^{060} fifteen^{207}, sat^{174} on the slope^{071} of a bluff^{055} overlooking^{027} the mississippi^{137} river^{137}. He was listening^{077} to music^{077} coming^{009} from a passing^{043} riverboat. The music^{077} had already captured^{006} his heart^{157} as well as his ear^{119}. It was jazz^{077}. Bix beiderbecke had already had music^{077} lessons^{077}. He showed^{002} promise^{134} on the piano^{077}, and his parents^{035} hoped^{268} he might consider^{118} becoming a concert^{077} pianist^{077}. But bix was interested^{268} in another kind^{050} of music^{077}. He wanted^{268} to $\boxed{\text{play}^{077}}$ the cornet. And he wanted^{268} to $\boxed{\text{play}^{077}}$ jazz^{077}...

Topic 77

word	prob.
MUSIC	.090
DANCE	.034
SONG	.033
PLAY	.030
SING	.026
SINGING	.026
BAND	.026
PLAYED	.023
SANG	.022
SONGS	.021
DANCING	.020
PIANO	.017
PLAYING	.016
RHYTHM	.015
ALBERT	.013
MUSICAL	.013

Topic 82

word	prob.
LITERATURE	.031
POEM	.028
POETRY	.027
POET	.020
PLAYS	.019
POEMS	.019
PLAY	.015
LITERARY	.013
WRITERS	.013
DRAMA	.012
WROTE	.012
POETS	.011
WRITER	.011
SHAKESPEARE	.010
WRITTEN	.009
STAGE	.009

Topic 166

word	prob.
PLAY	.136
BALL	.129
GAME	.065
PLAYING	.042
HIT	.032
PLAYED	.031
BASEBALL	.027
GAMES	.025
BAT	.019
RUN	.019
THROW	.016
BALLS	.015
TENNIS	.011
HOME	.010
CATCH	.010
FIELD	.010

Topics models can resolve polysemy

There is a simple^{050} reason^{106} why there are so few periods^{078} of really great theater^{082} in our whole western^{046} world. Too many things^{300} have to come right at the very same time. The dramatists must have the right actors^{082}, the actors^{082} must have the right playhouses, the playhouses must have the right audiences^{082}. We must remember^{288} that plays^{082} exist^{143} to be performed^{077}, not merely^{050} to be read^{254}. (even when you read^{254} a play^{082} to yourself, try^{288} to perform^{062} it, to put^{174} it on a stage^{078}, as you go along.) as soon^{028} as a play^{082} has to be performed^{082}, then some kind^{126} of theatrical^{082}...

Topic 77

word	prob.
MUSIC	.090
DANCE	.034
SONG	.033
PLAY	.030
SING	.026
SINGING	.026
BAND	.026
PLAYED	.023
SANG	.022
SONGS	.021
DANCING	.020
PIANO	.017
PLAYING	.016
RHYTHM	.015
ALBERT	.013
MUSICAL	.013

Topic 82

word	prob.
LITERATURE	.031
POEM	.028
POETRY	.027
POET	.020
PLAYS	.019
POEMS	.019
PLAY	.015
LITERARY	.013
WRITERS	.013
DRAMA	.012
WROTE	.012
POETS	.011
WRITER	.011
SHAKESPEARE	.010
WRITTEN	.009
STAGE	.009

Topic 166

word	prob.
PLAY	.136
BALL	.129
GAME	.065
PLAYING	.042
HIT	.032
PLAYED	.031
BASEBALL	.027
GAMES	.025
BAT	.019
RUN	.019
THROW	.016
BALLS	.015
TENNIS	.011
HOME	.010
CATCH	.010
FIELD	.010

Topics models can resolve polysemy

Jim^{296} has a game^{166} book^{254}. Jim^{296} reads^{254} the book^{254}. Jim^{296} sees^{081} a game^{166} for one. Jim^{296} plays^{166} the game^{166}. Jim^{296} likes^{081} the game^{166} for one. The game^{166} book^{254} helps^{081} jim^{296}. Don^{180} comes^{040} into the house^{038}. Don^{180} and jim^{296} read^{254} the game^{166} book^{254}. The boys^{020} see a game^{166} for two. The two boys^{020} $\boxed{\text{play}^{166}}$ the game^{166}. The boys^{020} $\boxed{\text{play}^{166}}$ the game^{166} for two. The boys^{020} like the game^{166}. Meg^{282} comes^{040} into the house^{282}. Meg^{282} and don^{180} and jim^{296} read^{254} the book^{254}. They see a game^{166} for three. Meg^{282} and don^{180} and jim^{296} $\boxed{\text{play}^{166}}$ the game^{166}. They $\boxed{\text{play}^{166}}$...

Topic 77

word	prob.
MUSIC	.090
DANCE	.034
SONG	.033
PLAY	.030
SING	.026
SINGING	.026
BAND	.026
PLAYED	.023
SANG	.022
SONGS	.021
DANCING	.020
PIANO	.017
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Topic 82

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WRITER	.011
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Topic 166

word	prob.
PLAY	.136
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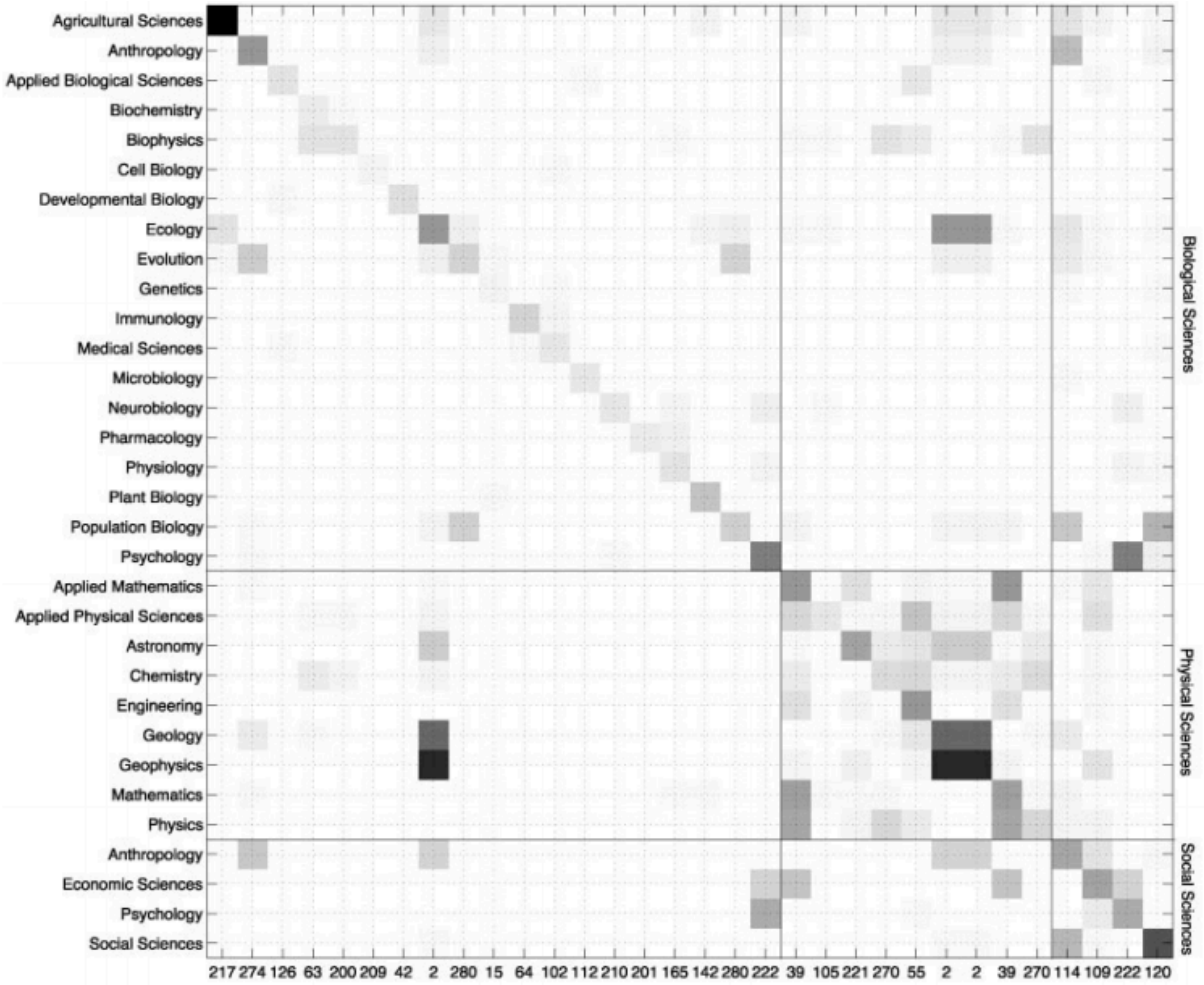
THROW	.016
BALLS	.015
TENNIS	.011
HOME	.010
CATCH	.010
FIELD	.010

Training topic models on twitter

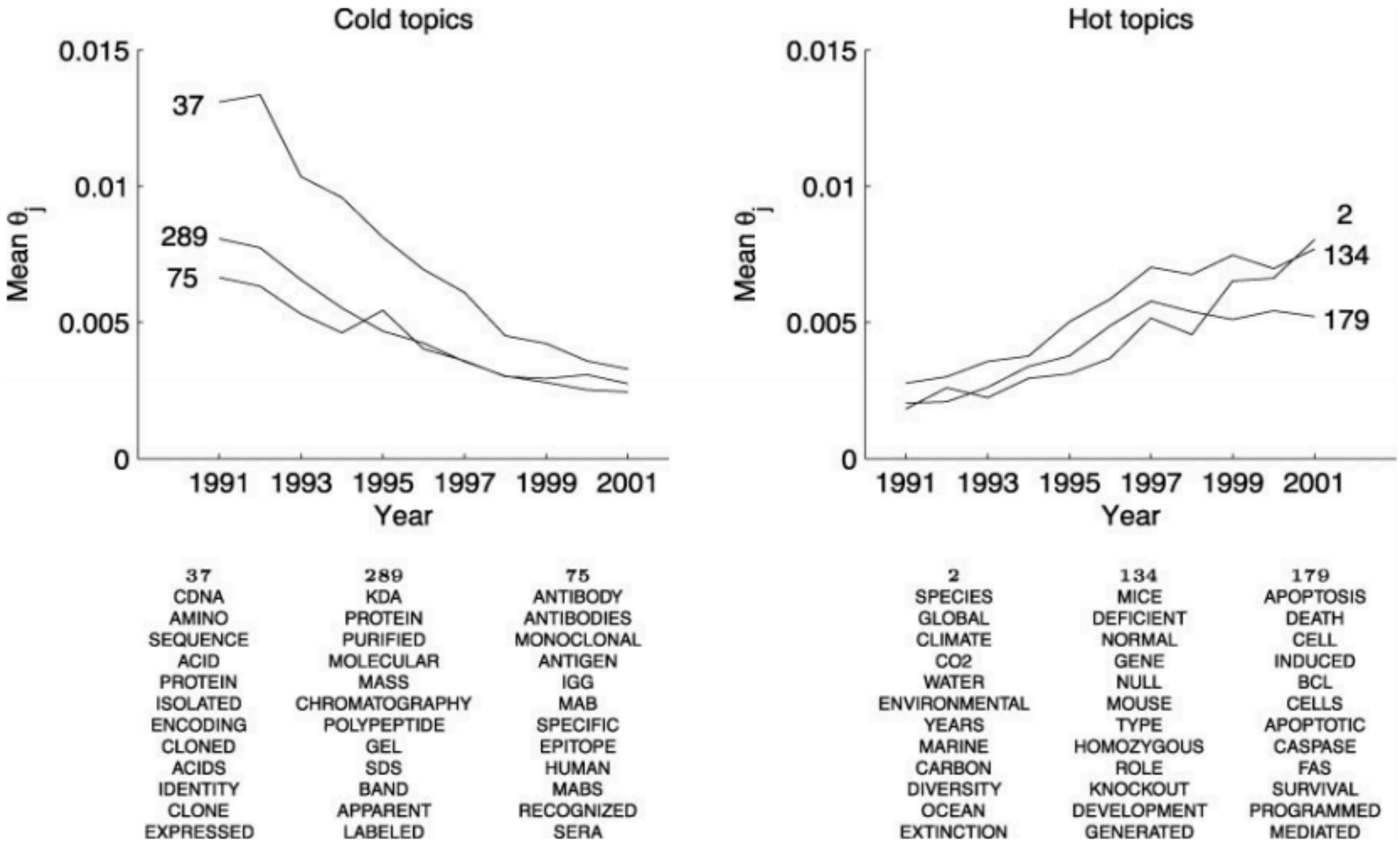
https://ermoore.shinyapps.io/twittr/

Finding scientific topics (Griffiths & Steyvers, 2004)

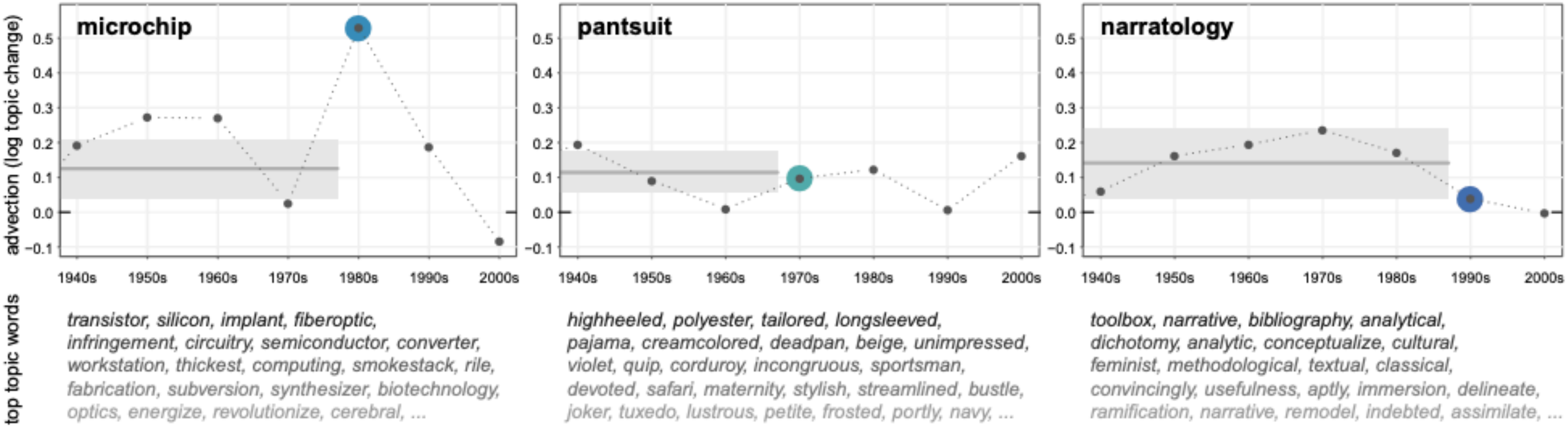


217 INSECT MYB PHEROMONE LENS LARVAE	274 SPECIES PHYLOGENETIC EVOLUTION EVOLUTIONARY SEQUENCES	126 GENE VECTOR VECTORS EXPRESSION TRANSFER	63 STRUCTURE ANGSTROM CRYSTAL RESIDUES STRUCTURES	200 FOLDING NATIVE PROTEIN STATE ENERGY	209 NUCLEAR NUCLEUS LOCALIZATION CYTOPLASM EXPORT
42 NEURAL DEVELOPMENT DORSAL EMBRYOS VENTRAL	2 SPECIES GLOBAL CLIMATE CO2 WATER	280 SPECIES SELECTION EVOLUTION GENETIC POPULATIONS	15 CHROMOSOME REGION CHROMOSOMES KB MAP	64 CELLS CELL ANTIGEN LYMPHOCYTES CD4	102 TUMOR CANCER TUMORS HUMAN CELLS
112 HOST BACTERIAL BACTERIA STRAINS SALMONELLA	210 SYNAPTIC NEURONS POSTSYNAPTIC HIPPOCAMPAL SYNAPSES	201 RESISTANCE RESISTANT DRUG DRUGS SENSITIVE	165 CHANNEL CHANNELS VOLTAGE CURRENT CURRENTS	142 PLANTS PLANT ARABIDOPSIS TOBACCO LEAVES	222 CORTEX BRAIN SUBJECTS TASK AREAS
39 THEORY TIME SPACE GIVEN PROBLEM	105 HAIR MECHANICAL MB SENSORY EAR	221 LARGE SCALE DENSITY OBSERVED OBSERVATIONS	270 TIME SPECTROSCOPY NMR SPECTRA TRANSFER	55 FORCE SURFACE MOLECULES SOLUTION SURFACES	114 POPULATION POPULATIONS GENETIC DIVERSITY ISOLATES
		109 RESEARCH NEW INFORMATION UNDERSTANDING PAPER	120 AGE OLD AGING LIFE YOUNG		

Finding scientific topics (Griffiths & Steyvers, 2004)

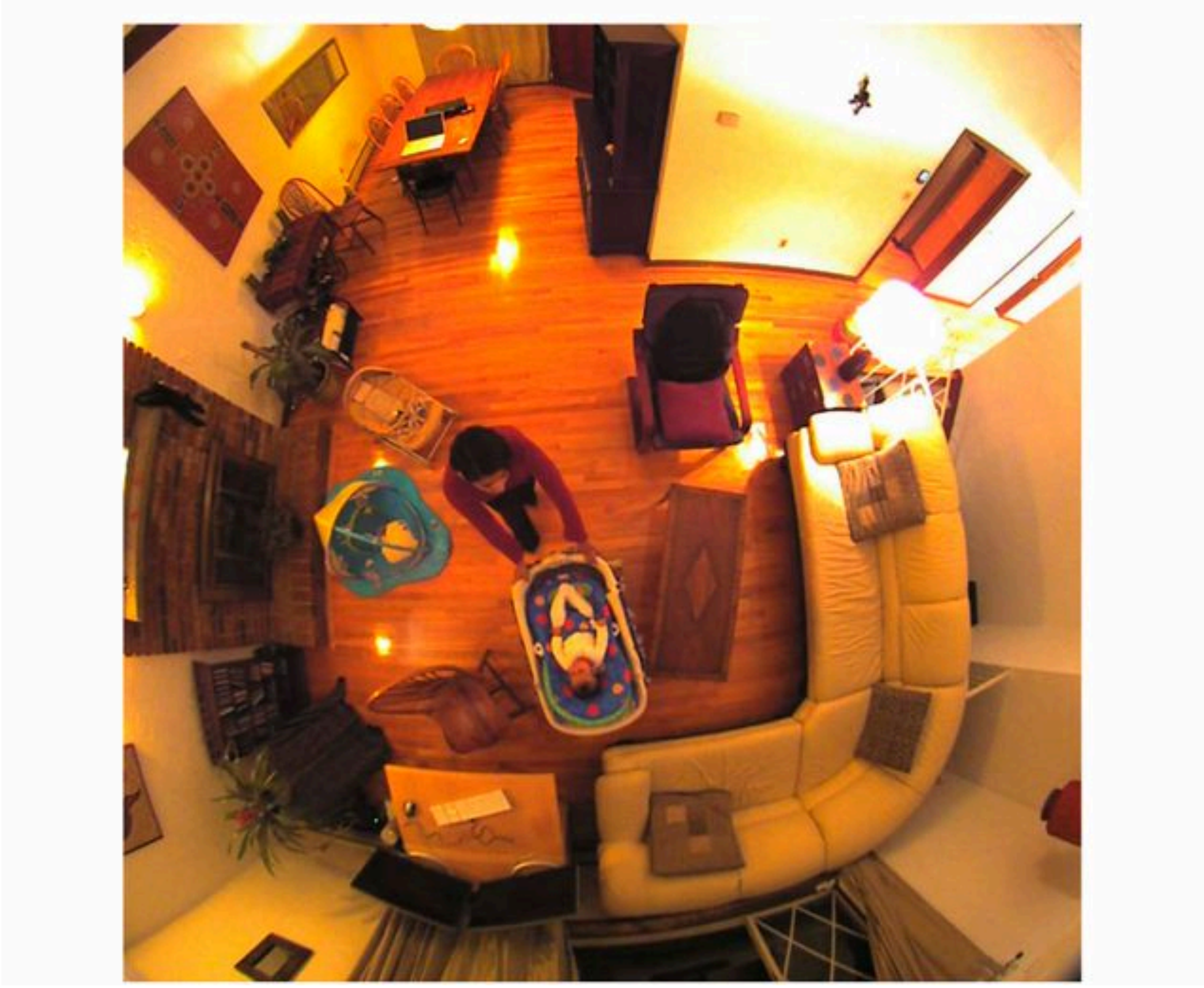


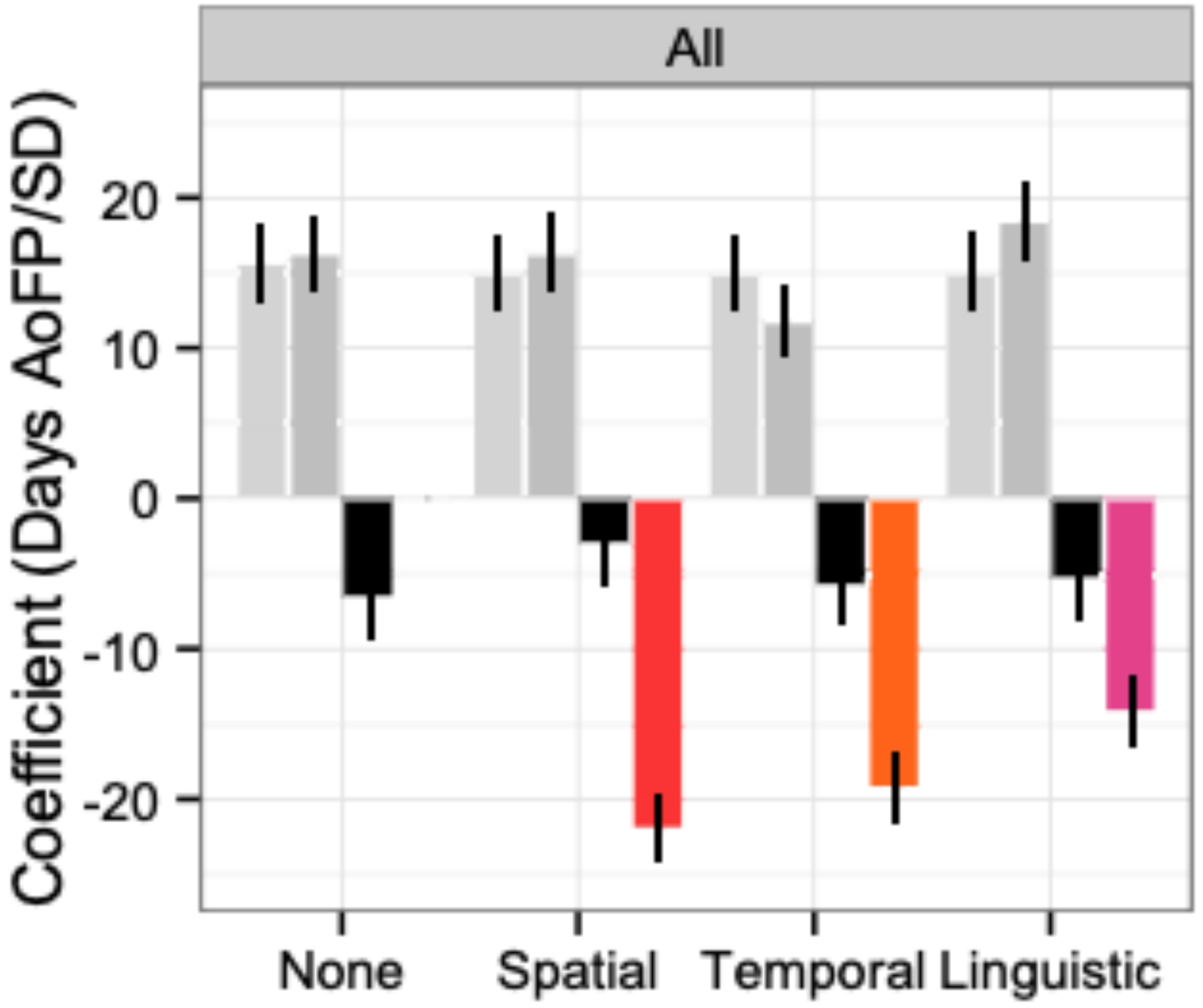
When do words come into language? (Karjus, Blythe, Kirby, Smith, 2020)

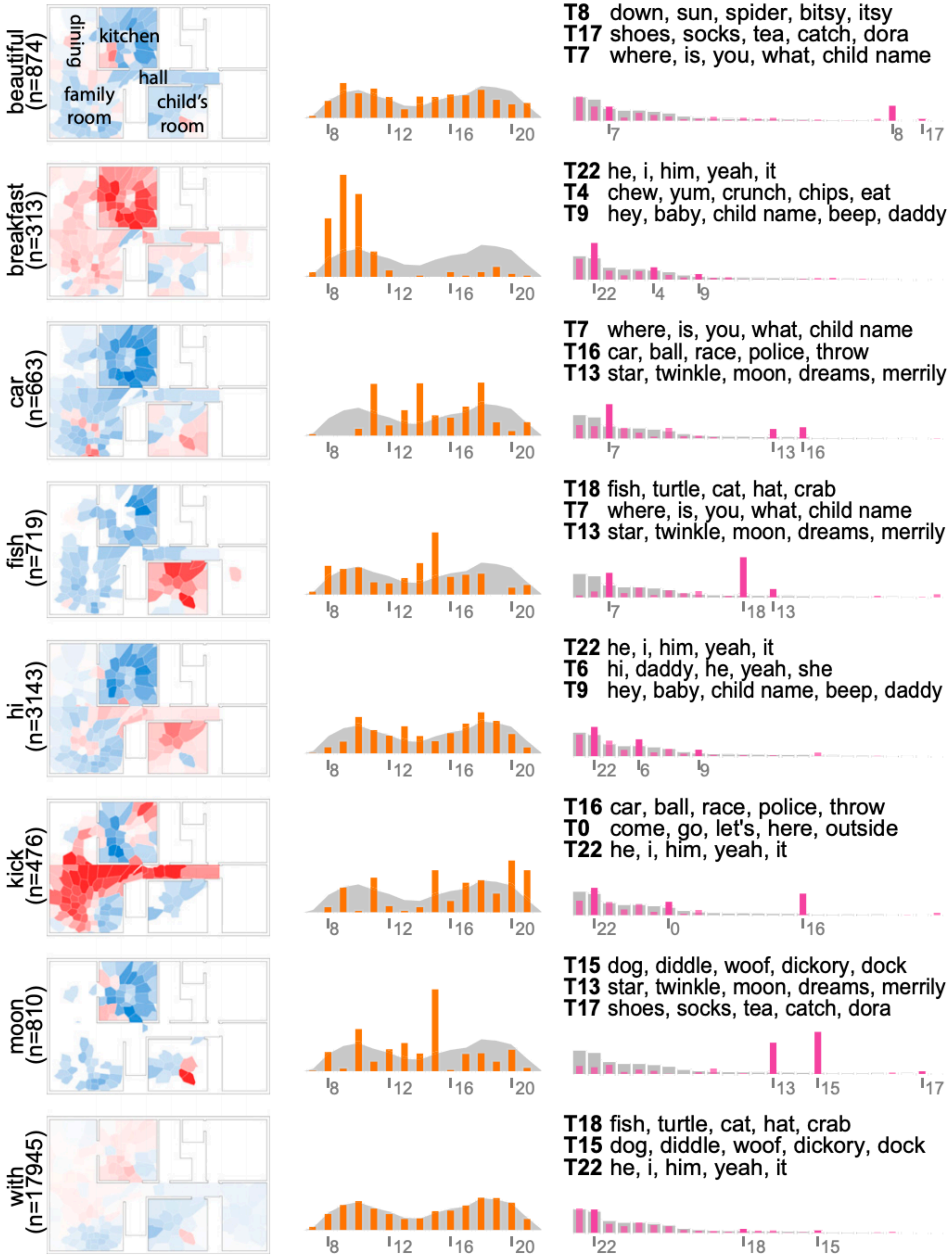


58% of words are coined when their topic is trending

Predicting the birth of words (Roy et al. 2015)



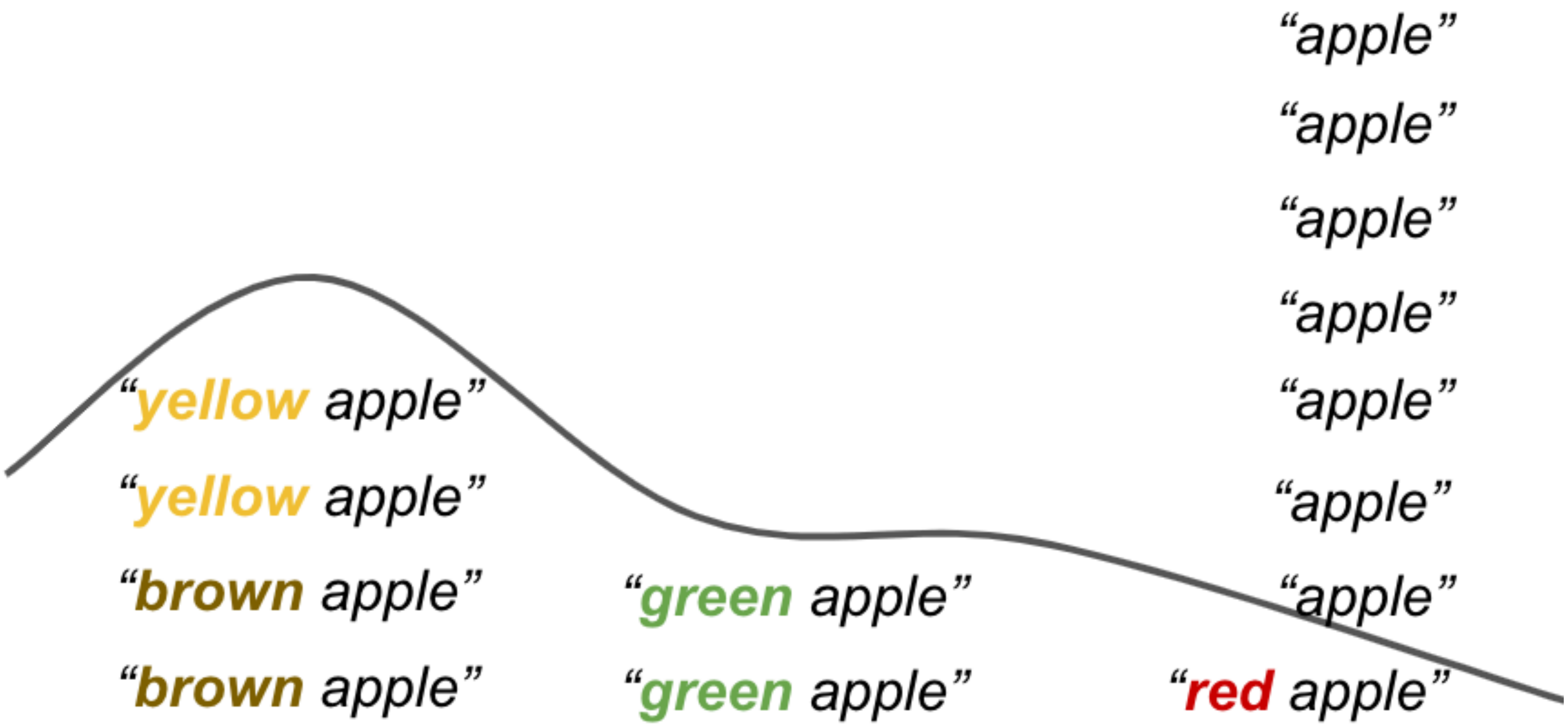




What’s missing from language?

What’s missing from language?

We don’t narrate the world! We talk about atypical things.



What does speech to children look like? (Bergey, Morris, & Yurovsky, 2019)

don’t put a **plastic cup** in there.

I like your **scaly skin**.

are **bananas yellow**?

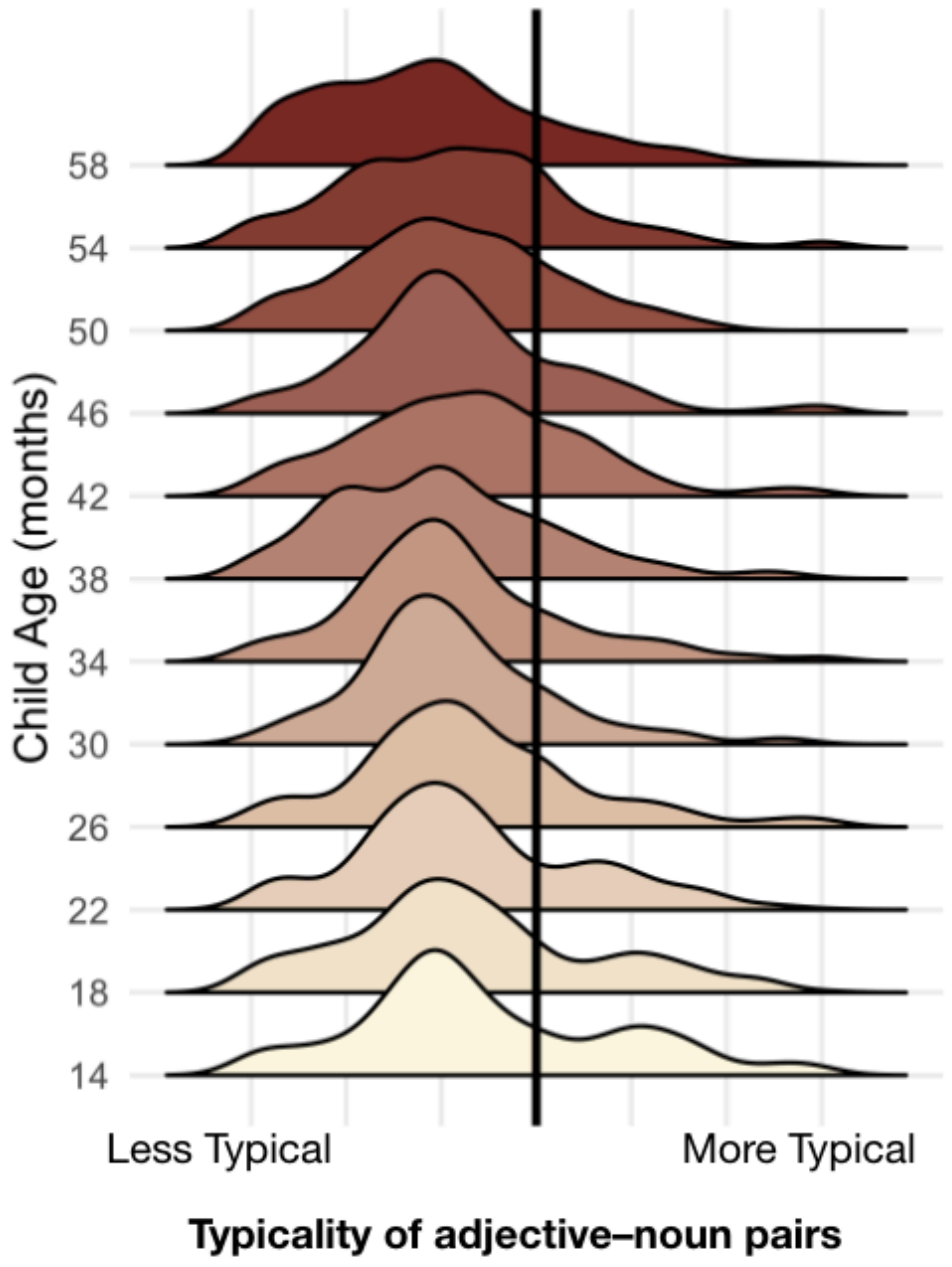
oh, look, are you giving him some nice **curly hair**?

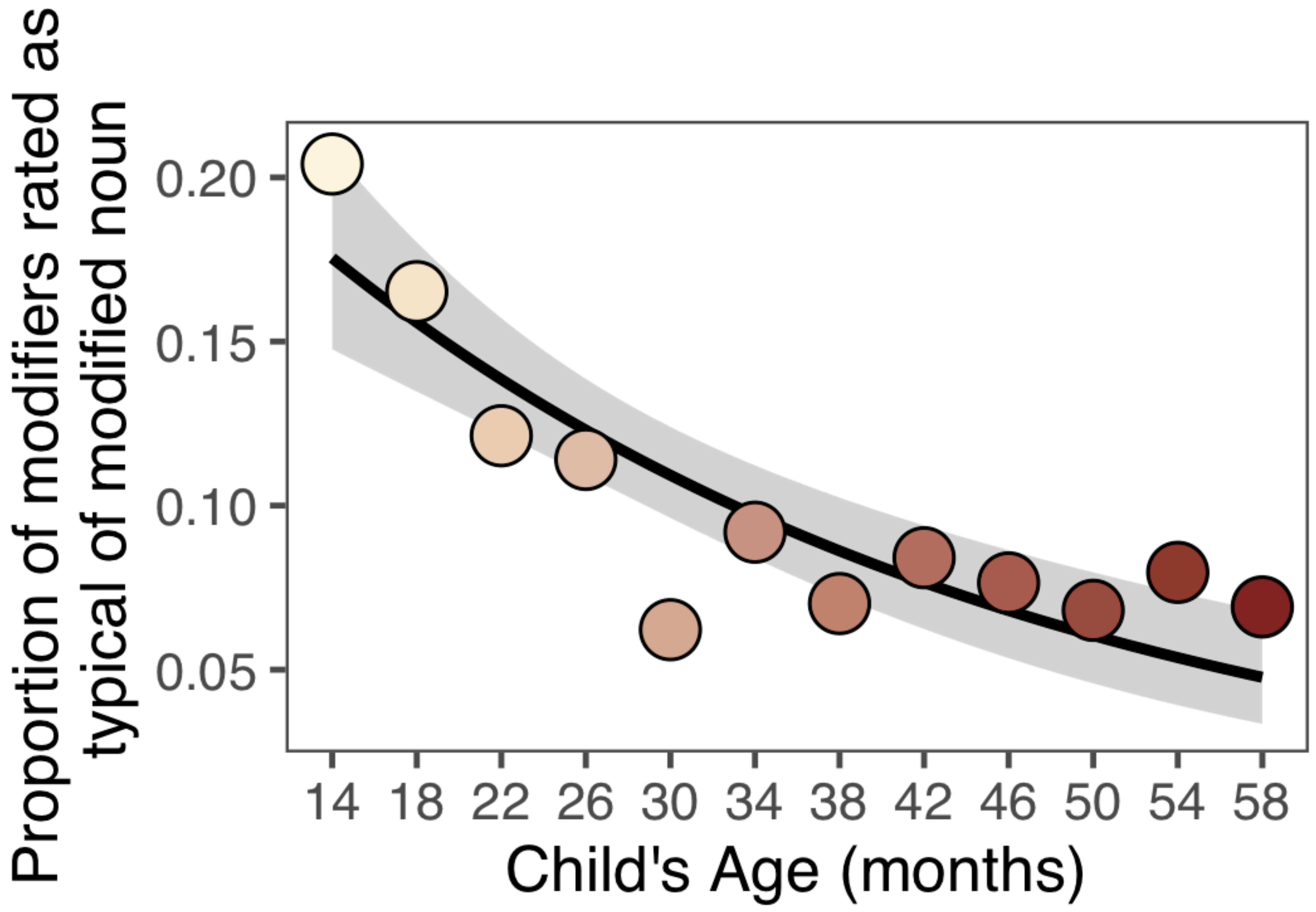
here I’ll put it on because your **hands** are **chalky.**

How common is it for an [apple] to be a [yellow apple]?

never	rarely	sometimes	about half the time	often	almost always	always
(1)	(2)	(3)	(4)	(5)	(6)	(7)

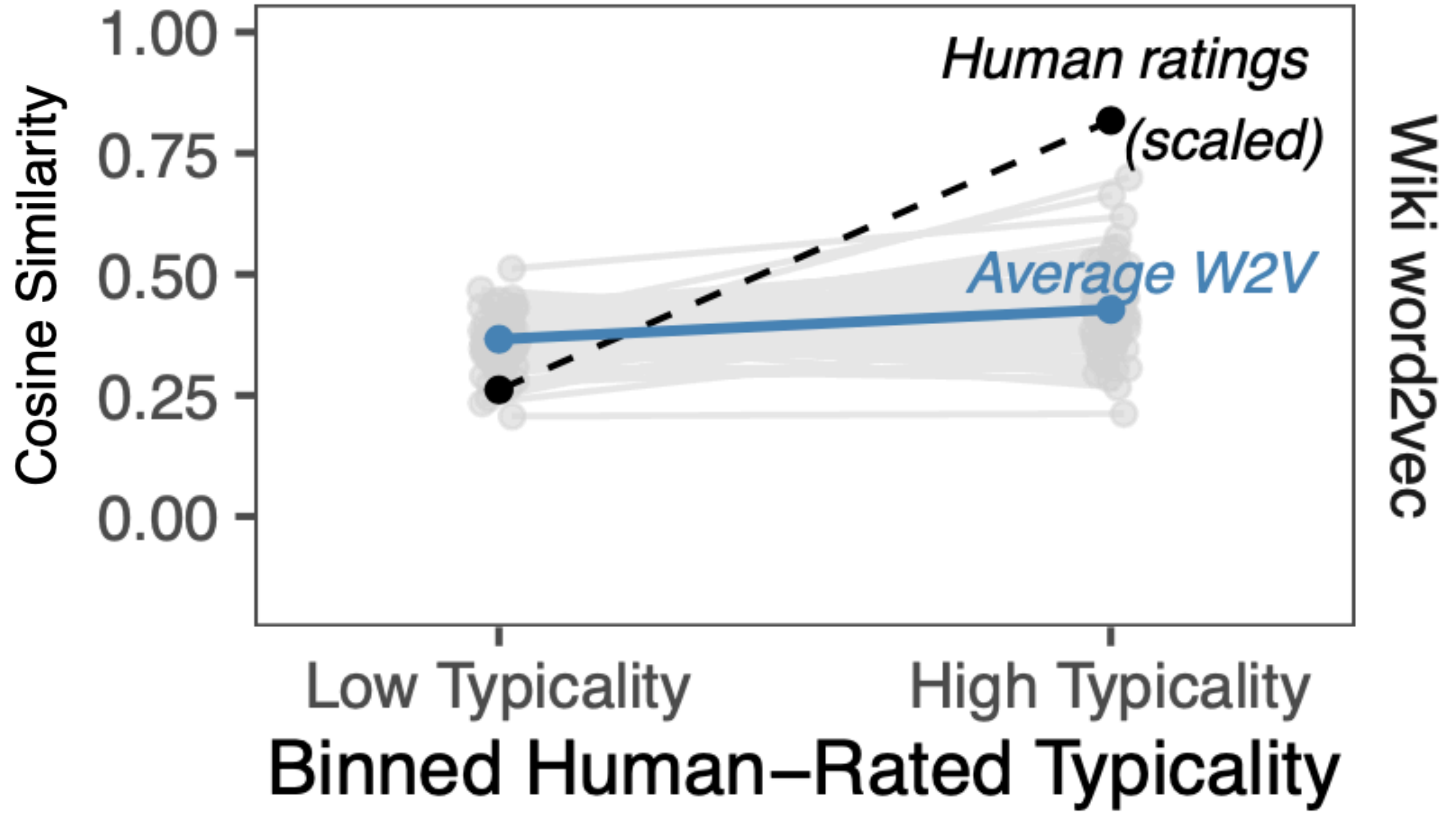
Children hear more about atypical colors





Semantic space models can't recover typical semantics

noun	typical adjective	atypical adjective
puzzle	flat	giant
apple	red	brown
bird	outside	purple
elephant	fat	pink
whale	wet	red
frog	green	purple



The structure in language

1. You can learn a lot form the co-occurrence structure of words in language

2. Latent semantic analysis and Topics models both use this structure to learn about the world

3. But some information is not (straightforwardly) in the co-occurrence structure of language