the title of this talk (yes, it sounds like a journal name)

TOPICS AND TRENDS IN COGNITIVE SCIENCE

Anselm Rothe Alexander Rich Zhi-Wei Li







equal contribution by all authors



New York University

		La Jolla Conference on		Monday August 13 1979
		Cognitive Science	12:00 PM-1:00 PM	Time for lunch
		Jerence		Session Chair DONALD A. NORMAN
		Sunday August 12 1979	1:00 PM-2:00 PM	Phillip Johnson-Laird University of Sussex
University of California San Diego La Jolla, California	4:00 PM-9:00 PM	Registration		The Role of Mental Models in Cognition
	4.00 FIVE-5.00 FIVE	Tenaya Hall, Muir College	2:30 PM-3:30 PM	George Lakoff University of California, Berkeley
	6:00 PM-11:00 PM	Gathering—refreshments Muir Main Dining Room		An Experientalist Perspective on Cognitive Science
August 13-16, 1979		Monday August 13	3:30 PM	Coffee Break
		1979	4:00 PM-5:00 PM	Marvin Minsky Massachusetts Institute of Technolo
	8:00 AM-5:00 PM	Registration Mandeville Auditorium		K-Lines: A Theory of Memory
	8:55 AM-9:00 AM	Welcome Mandeville Auditorium	6:00 PM	Mexican Buffet Muir Main Dining Room
La Jolla		DONALD A. NORMAN	8:30 PM	Business meeting: Cognitive Science Society
Conference on		Session Chair GEORGE MANDLER		Room 1110 Psychology/Linguistics Building
Cognitive	9:00 AM-10:00 AM	Herbert Simon Carnegie-Mellon University	8:30 PM	Gathering Muir Main Dining Room
Coionaca		Cognitive Science: The Newest Science of Artificial Phenomena		
ocience	10:00 AM	Coffee Break		
	10:30 AM-11:30 AM	Norman Geschwind Harvard Medical School, Boston		
		Neurological Knowledge and Complex Behavior	2	

← Program of the first conference

• CogSci 1979

- 1 track
- 5 categories
- 42 talks

• CogSci 2018

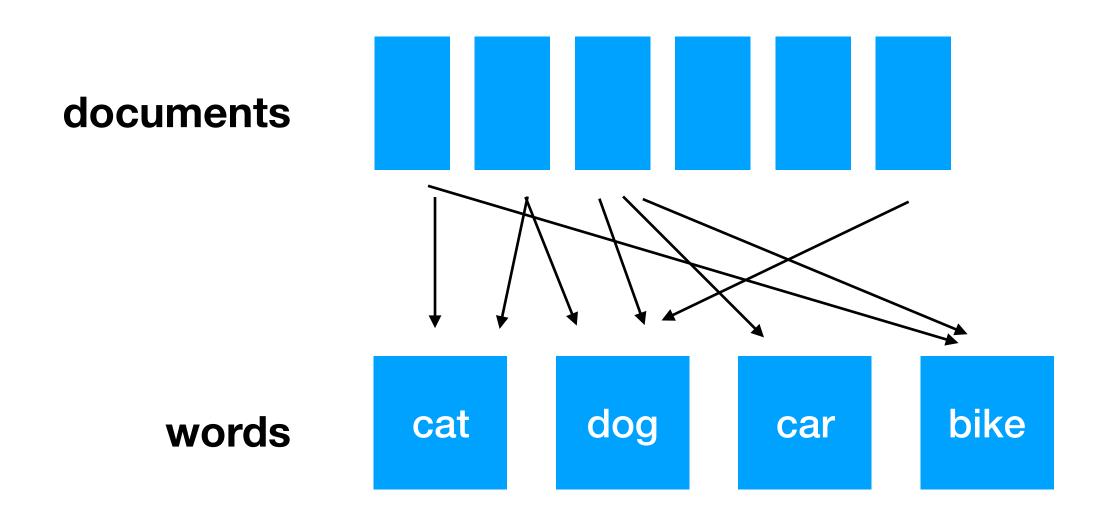
- 10 parallel tracks
- 57 categories
- 213 talks

Overview

- Problem: Deal with complexity of the field, discover topics and trends
- Tool: Dynamic Topic Modeling
- Results: CogSci topics, topic space, global trends, comparison of labs, paper recommendation system

Topic Modeling

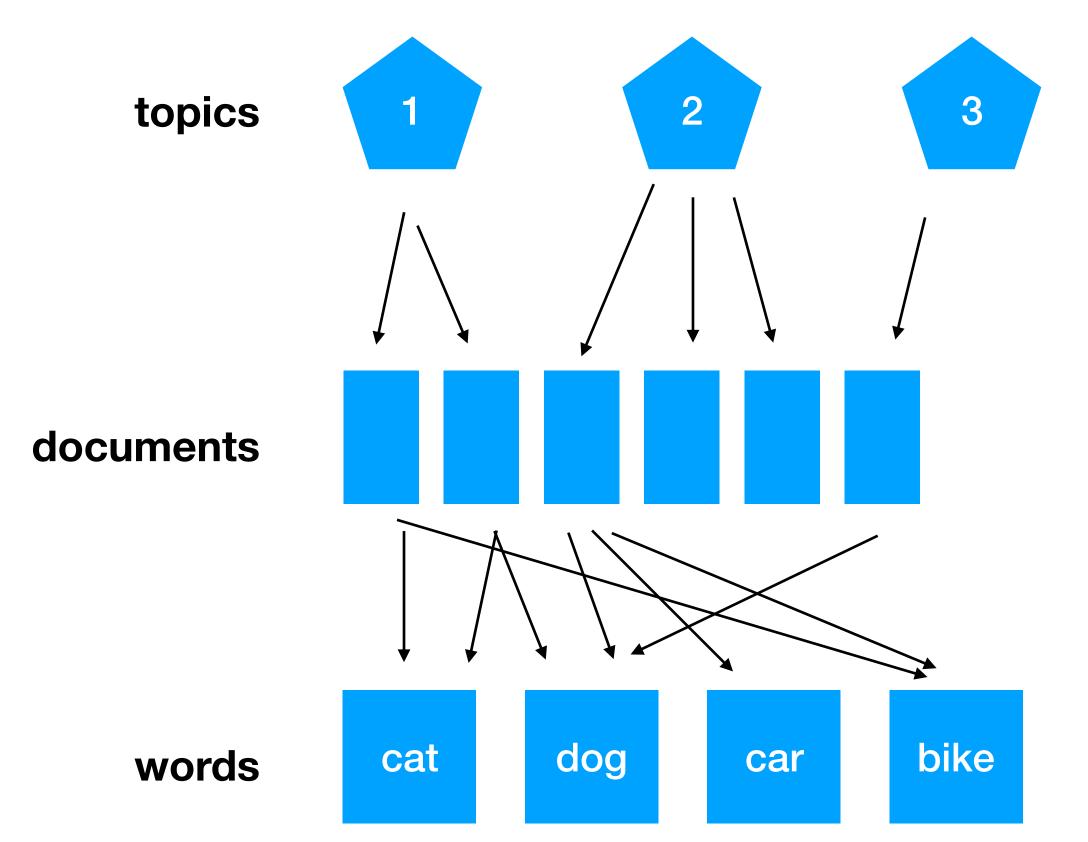
• Capture structure in large text corpora and make them more human-understandable (Blei, Ng, & Jordan 2003, Cohen Priva & Austerweil 2015)



(papers, news articles, customer reviews, etc.)

Topic Modeling

 Capture structure in large text corpora and make them more human-understandable (Blei, Ng, & Jordan 2003, Cohen Priva & Austerweil 2015)

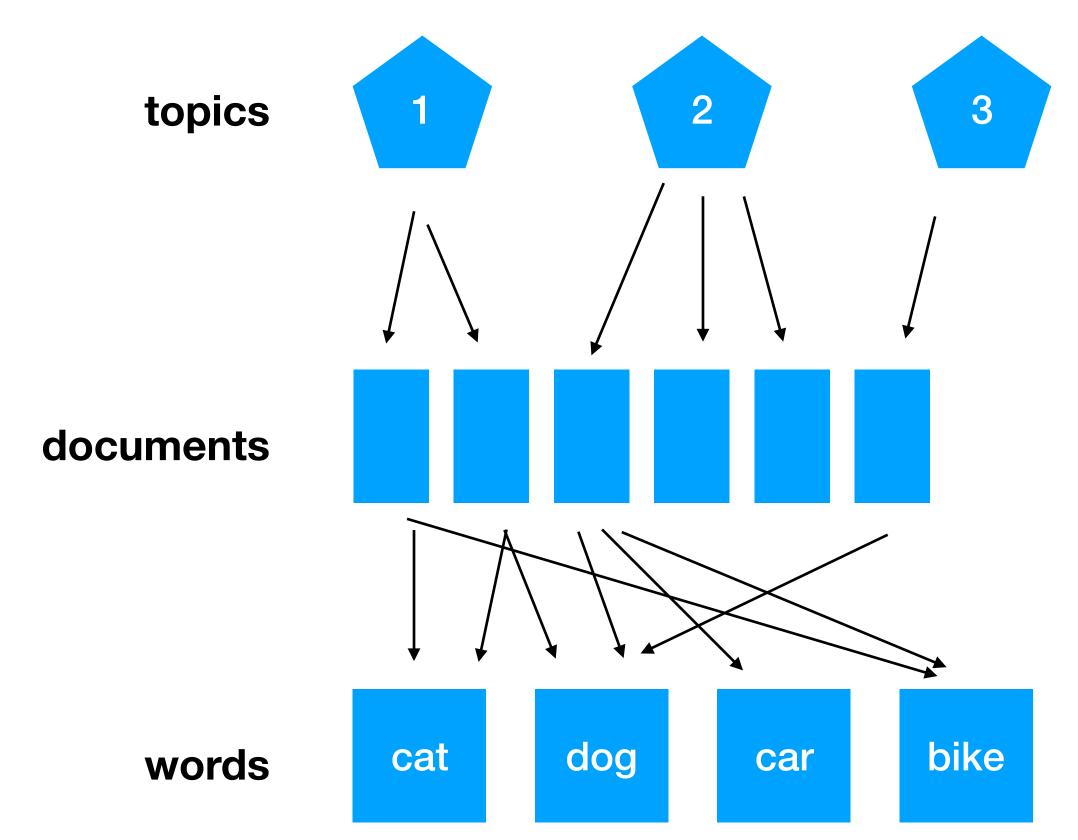


Assumed generative model

- a document is sampled from a topic
- a word in a document is generated given this topic
- based on sample probabilities (arrow weights)

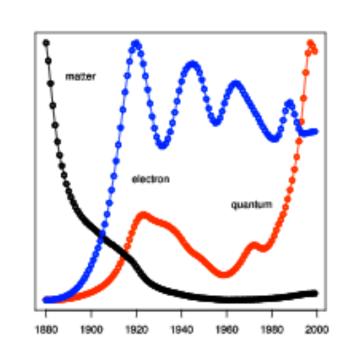
Topic Modeling

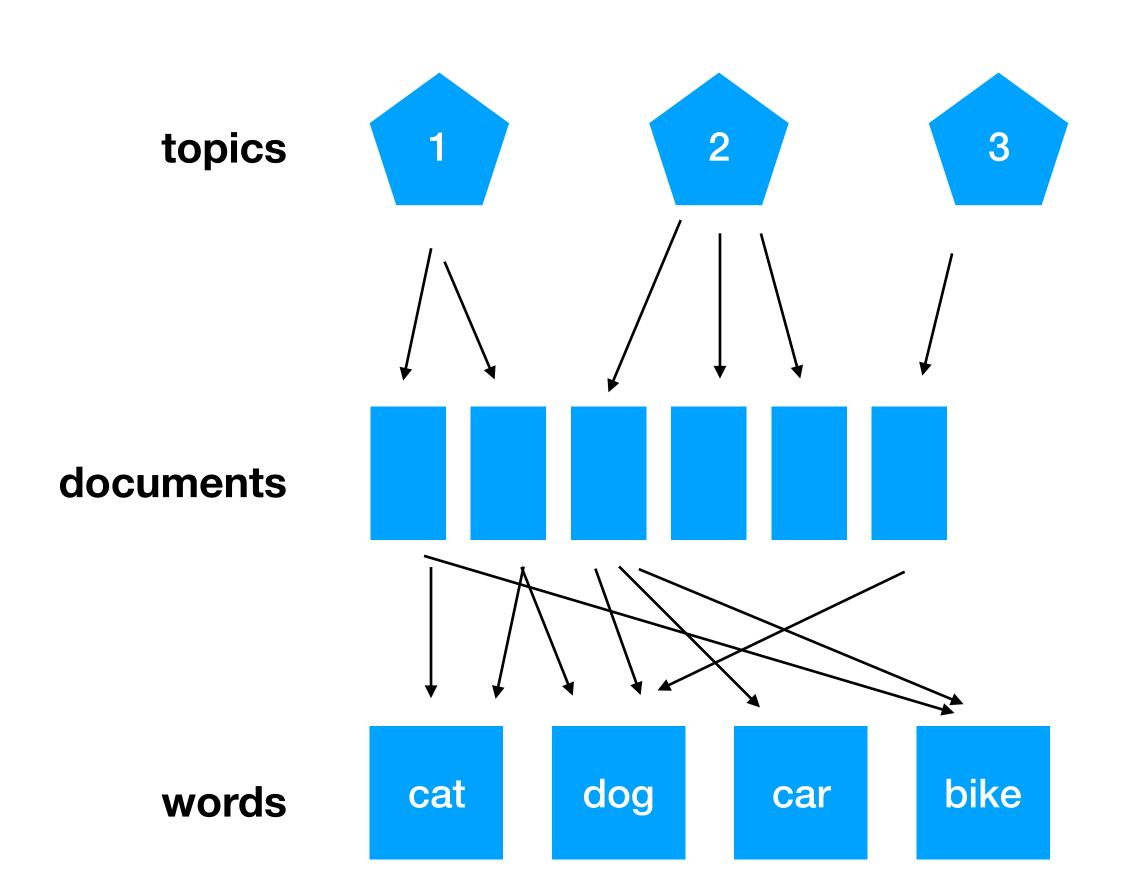
 Capture structure in large text corpora and make them more human-understandable (Blei, Ng, & Jordan 2003, Cohen Priva & Austerweil 2015)



- Topic Model makes reverse inference over the generative model
 - given document x (with the words w), how likely was topic y₁ its generating topic
 - simultaneously: which documenttopic assignment works best across all documents
 - indirectly: which words go with which topic

Dynamic Topic Modeling





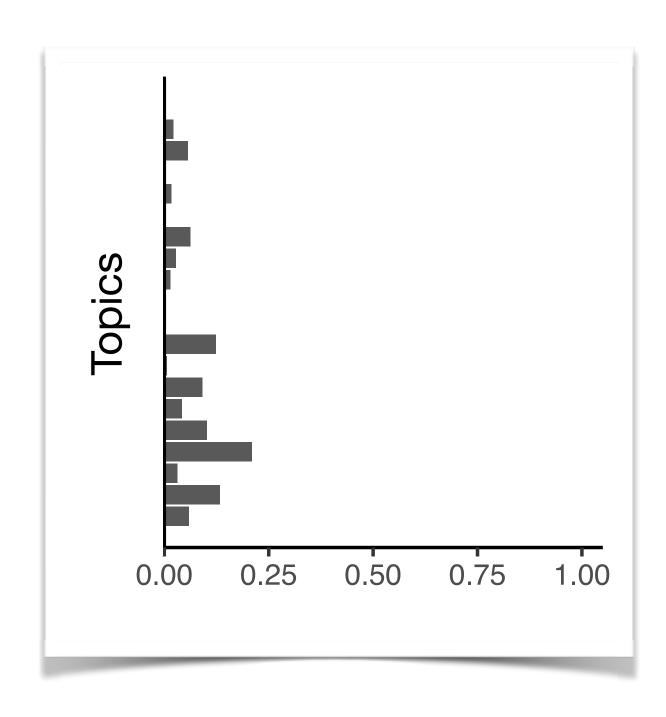
- Dynamic Topic Models are capturing change over time (Blei & Lafferty 2006)
- Example: The topic "Communication" might have a high likelihood for "fax machine" in news articles from 1990 but for today instead a high likelihood for "internet"
- => Which words go with which topic is allowed to change over time

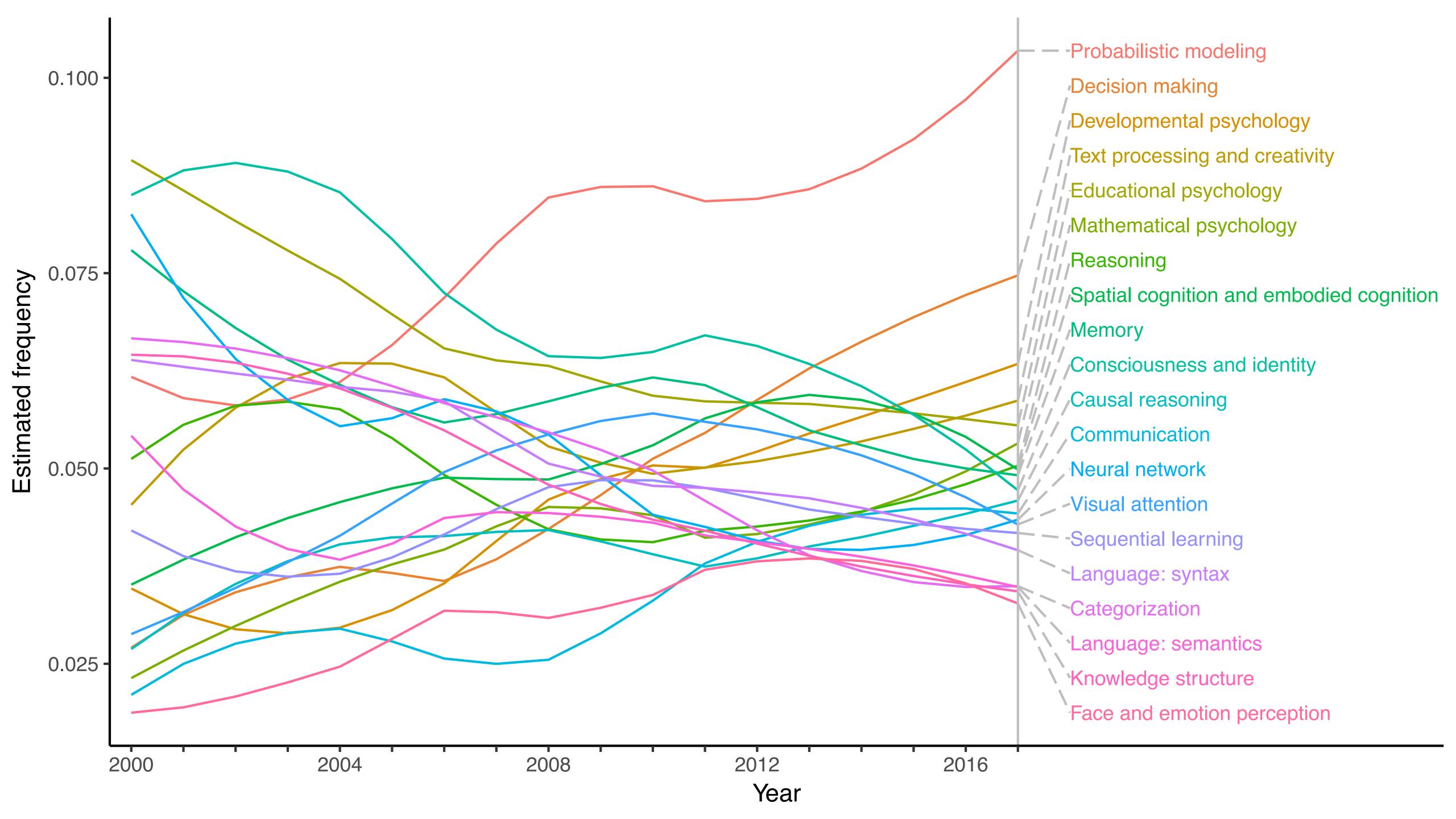
Data set: 18 years of CogSci

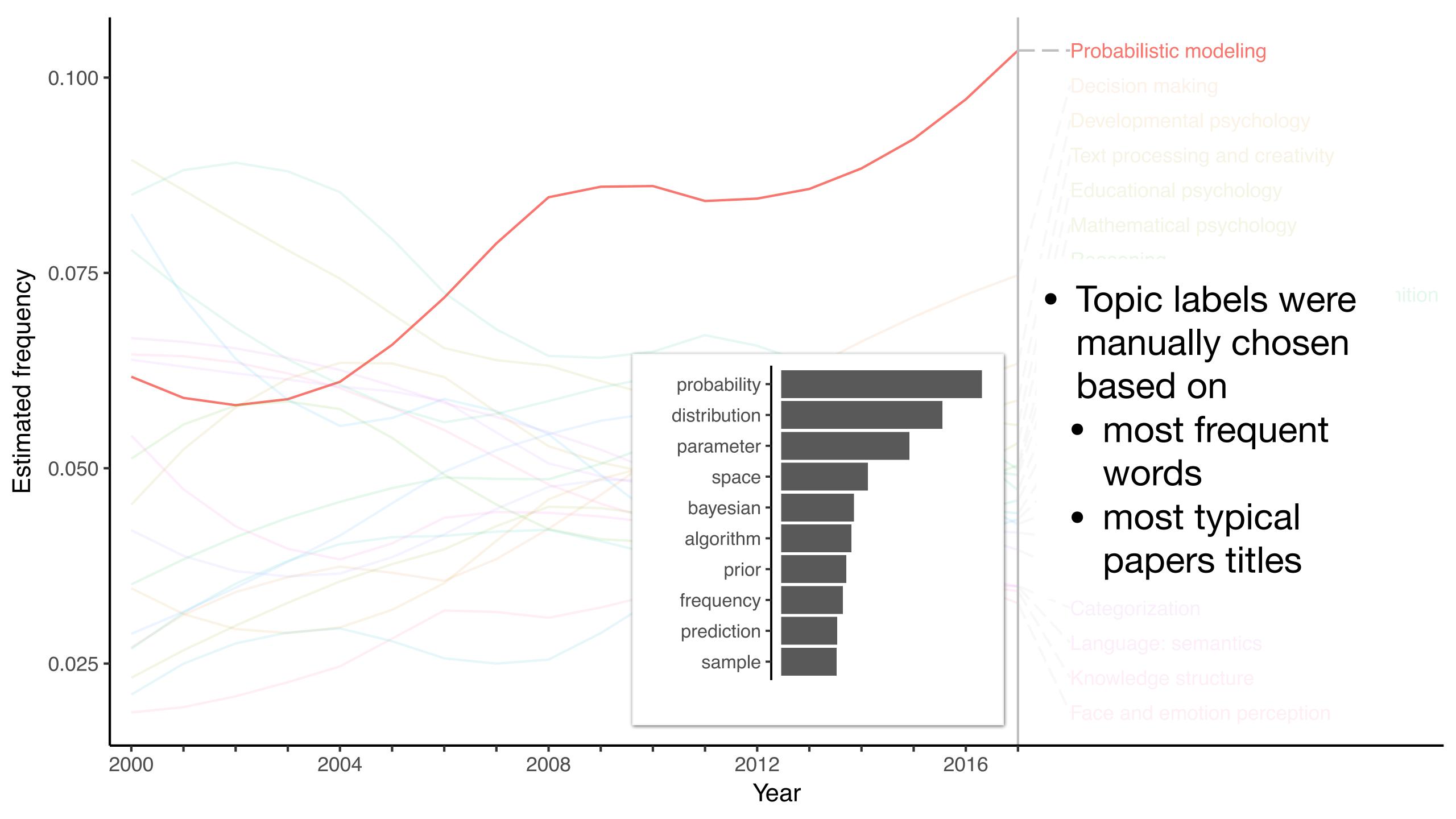
- Conference proceedings are particularly useful because there are many fresh ideas rapidly published
- 6920 PDFs from the CogSci archives
- Years 2000-2017 (usable PDFs)
- Preprocessing
 - PDFtoText
 - tokenizing (splitting text into words)
 - lemmatizing (e.g., walked → walk)
 - removing very rare and very frequent words
 - etc.
- Final vocabulary: 9710 words

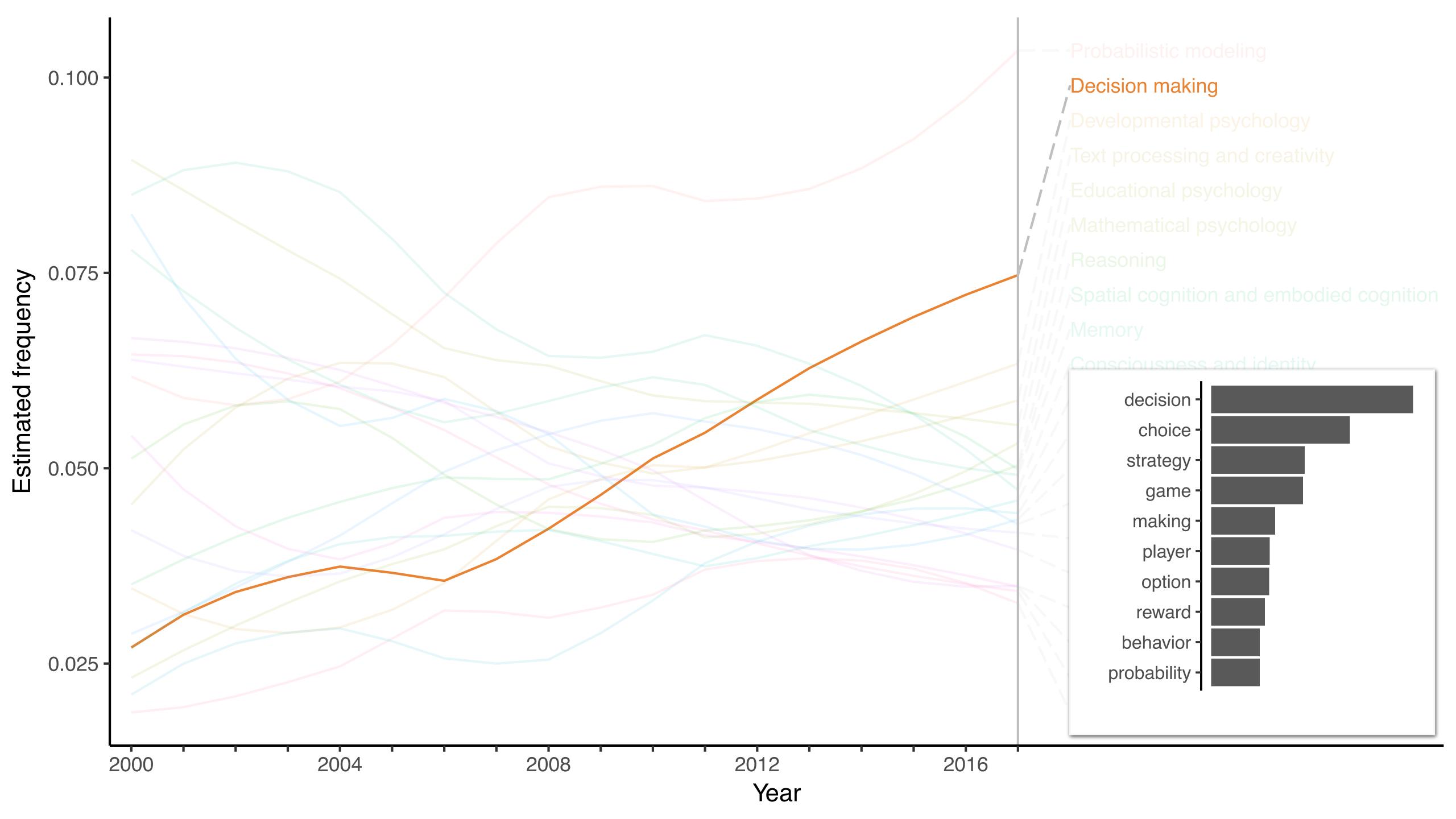
Output

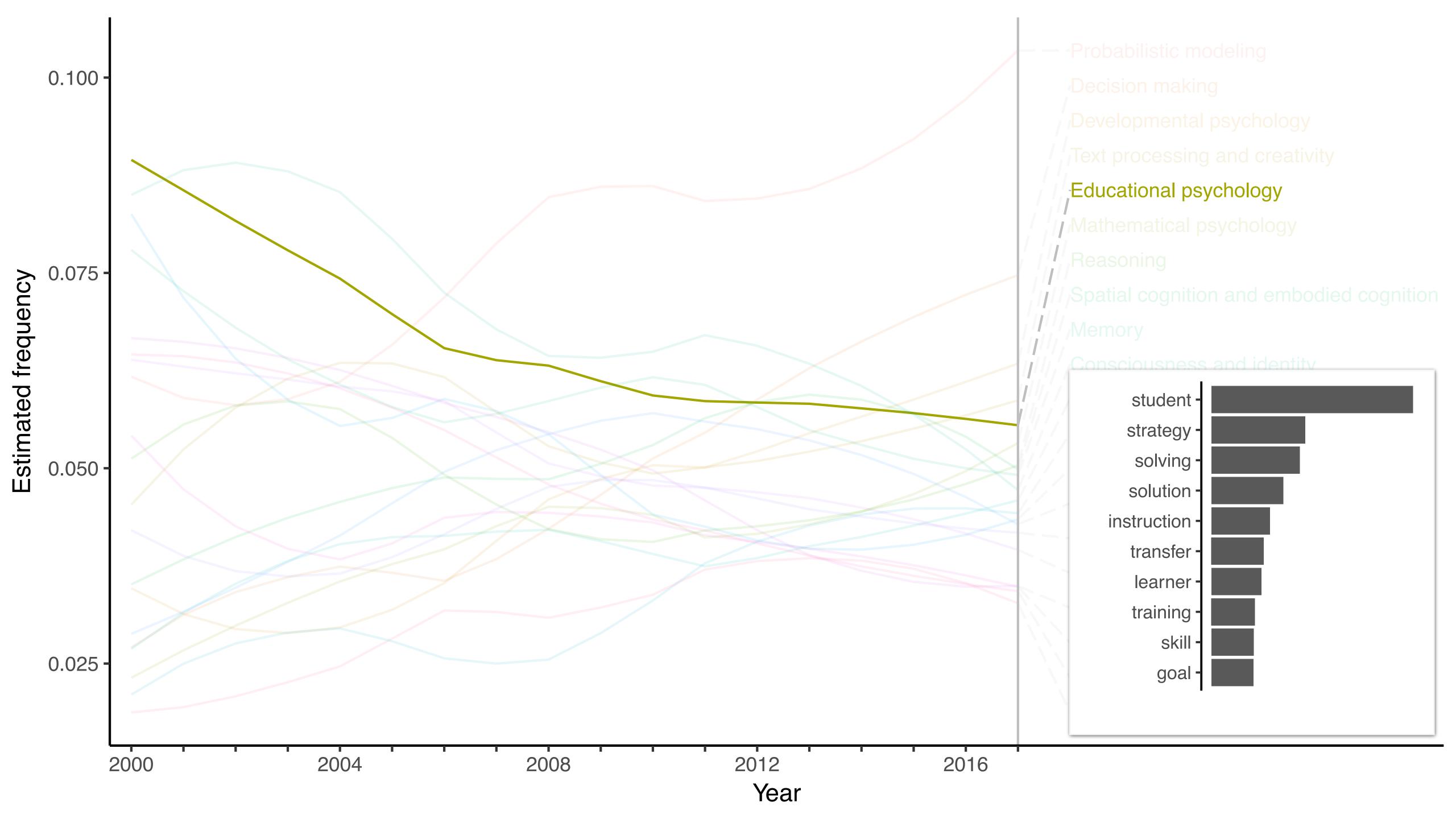
- For each document (CogSci paper) we have
 - a score of each topic for this document (all the score make a "topic vector")
 - the words of the document
 - the year of the document
 - from that we can extract a bunch of visualizations and insights

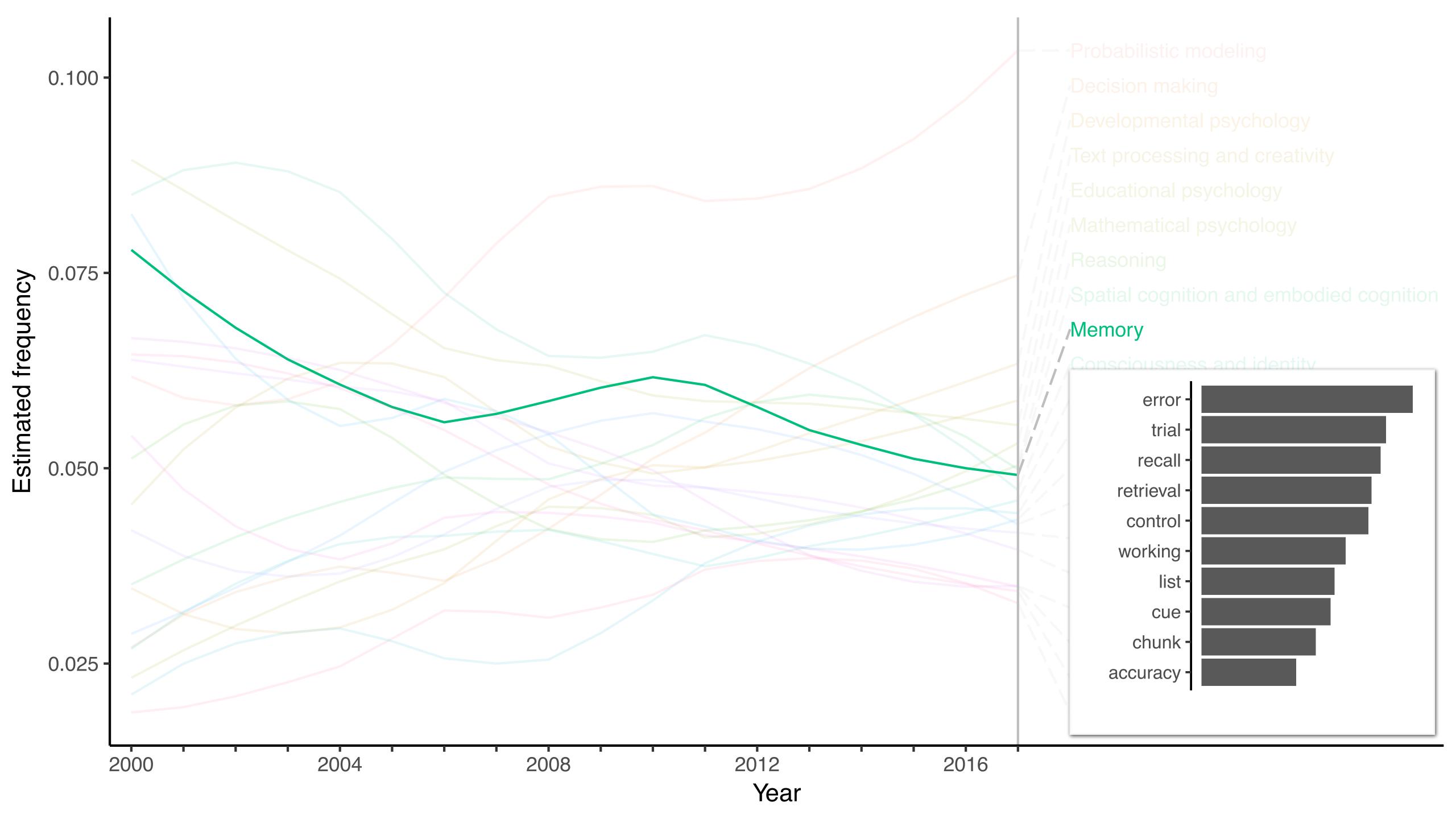


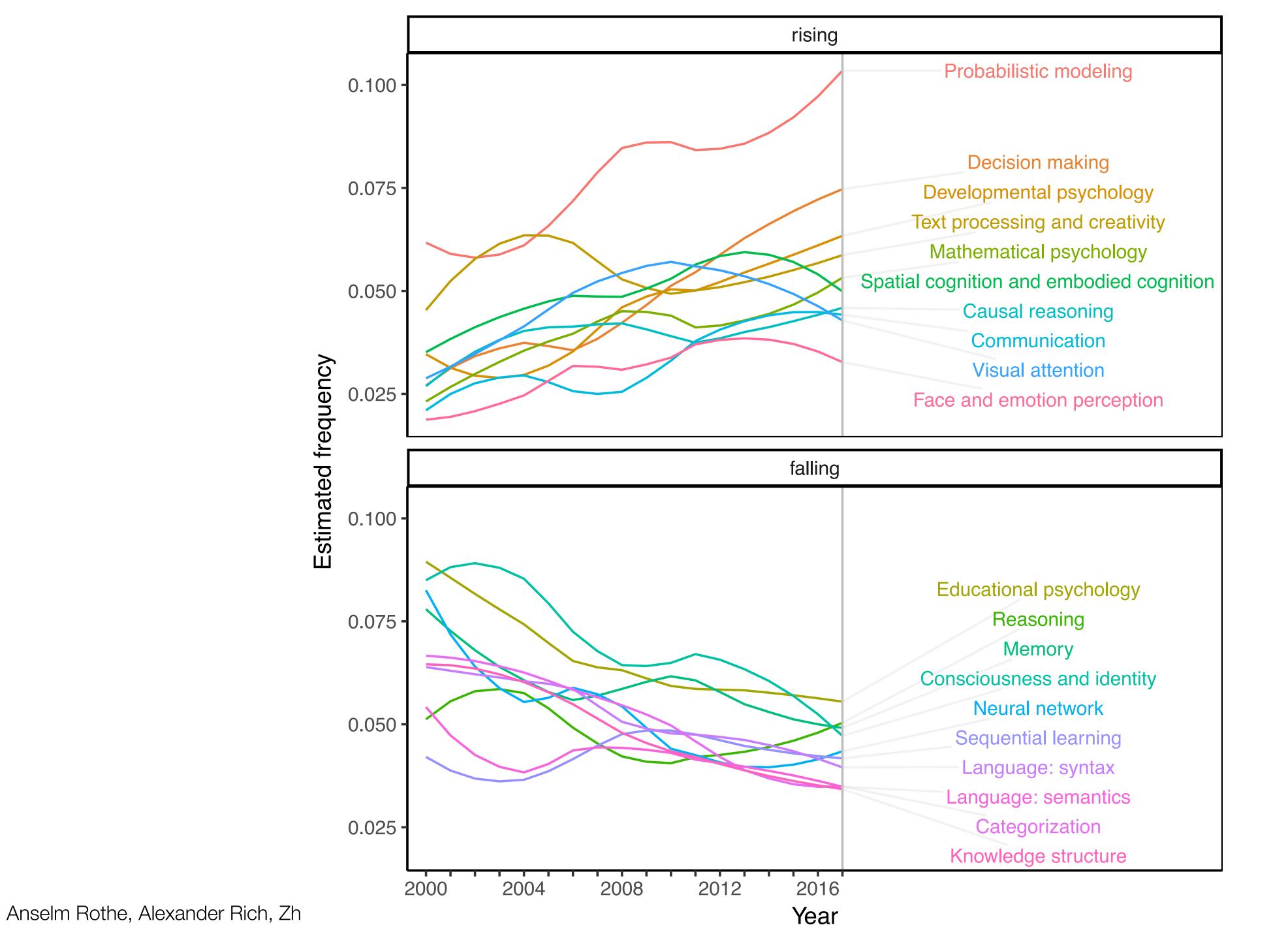


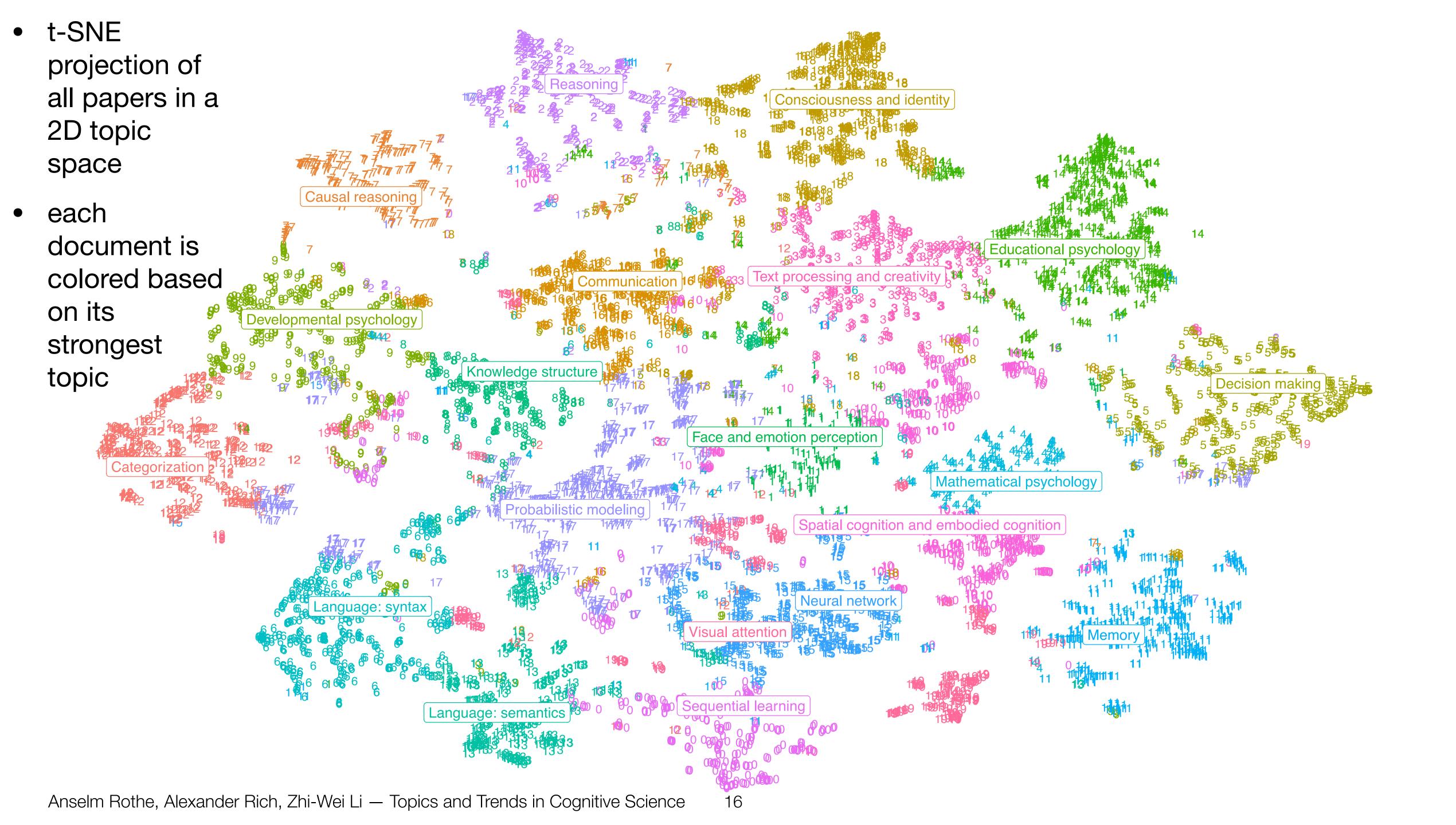


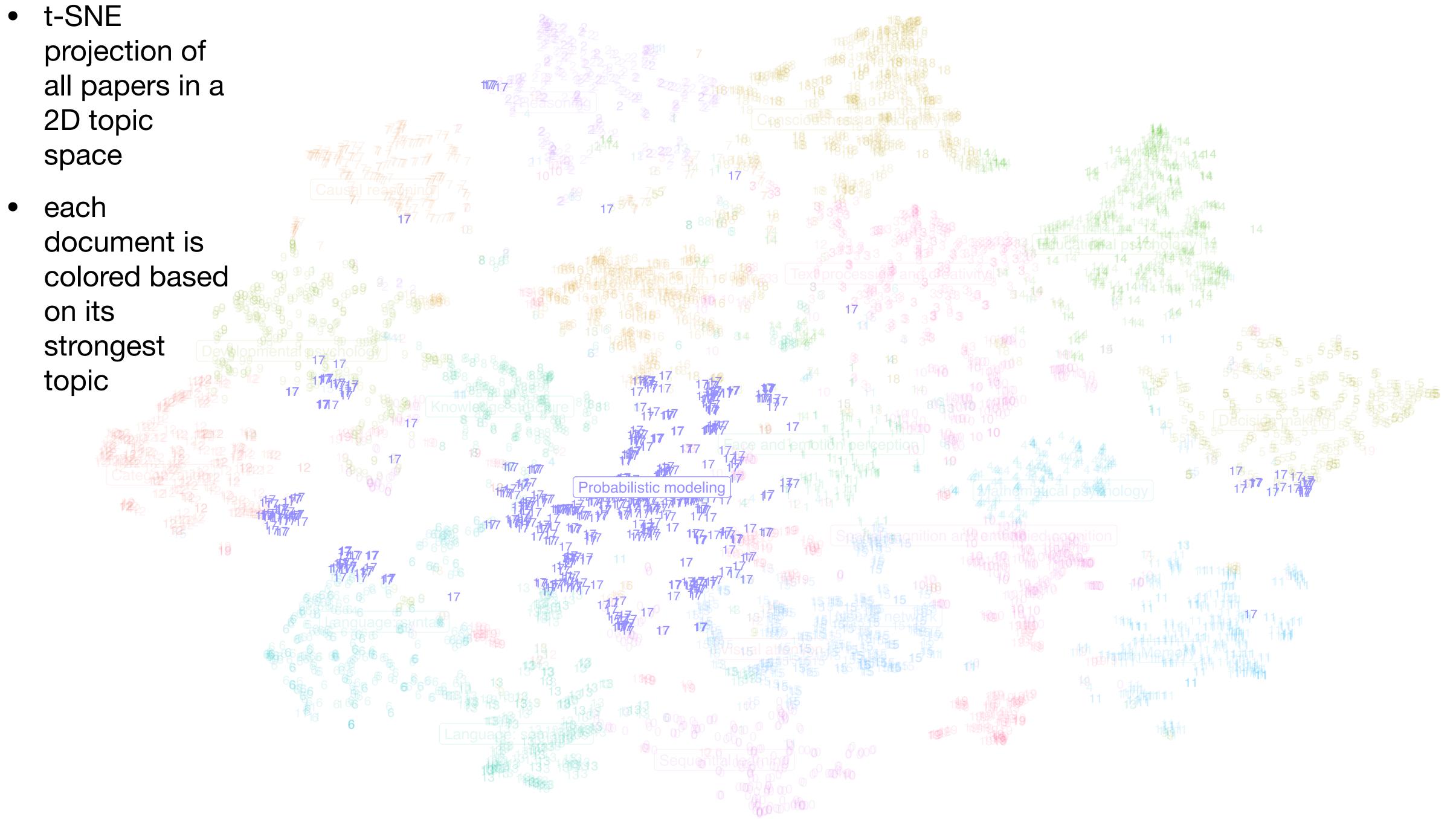












t-SNE
 projection of
 all papers in a
 2D topic
 space

each
document is
colored based
on its
strongest
topic

Convergence Bounds for Language Evolution by Iterated Learning



Anna N. Rafferty (rafferty@cs.berkeley.edu)

Computer Science Division, University of California, Berkeley, CA 94720 USA

Thomas L. Griffiths (tom_griffiths@berkeley.edu)

Department of Psychology, University of California, Berkeley, CA 94720 USA

Dan Klein (klein@cs.berkeley.edu)

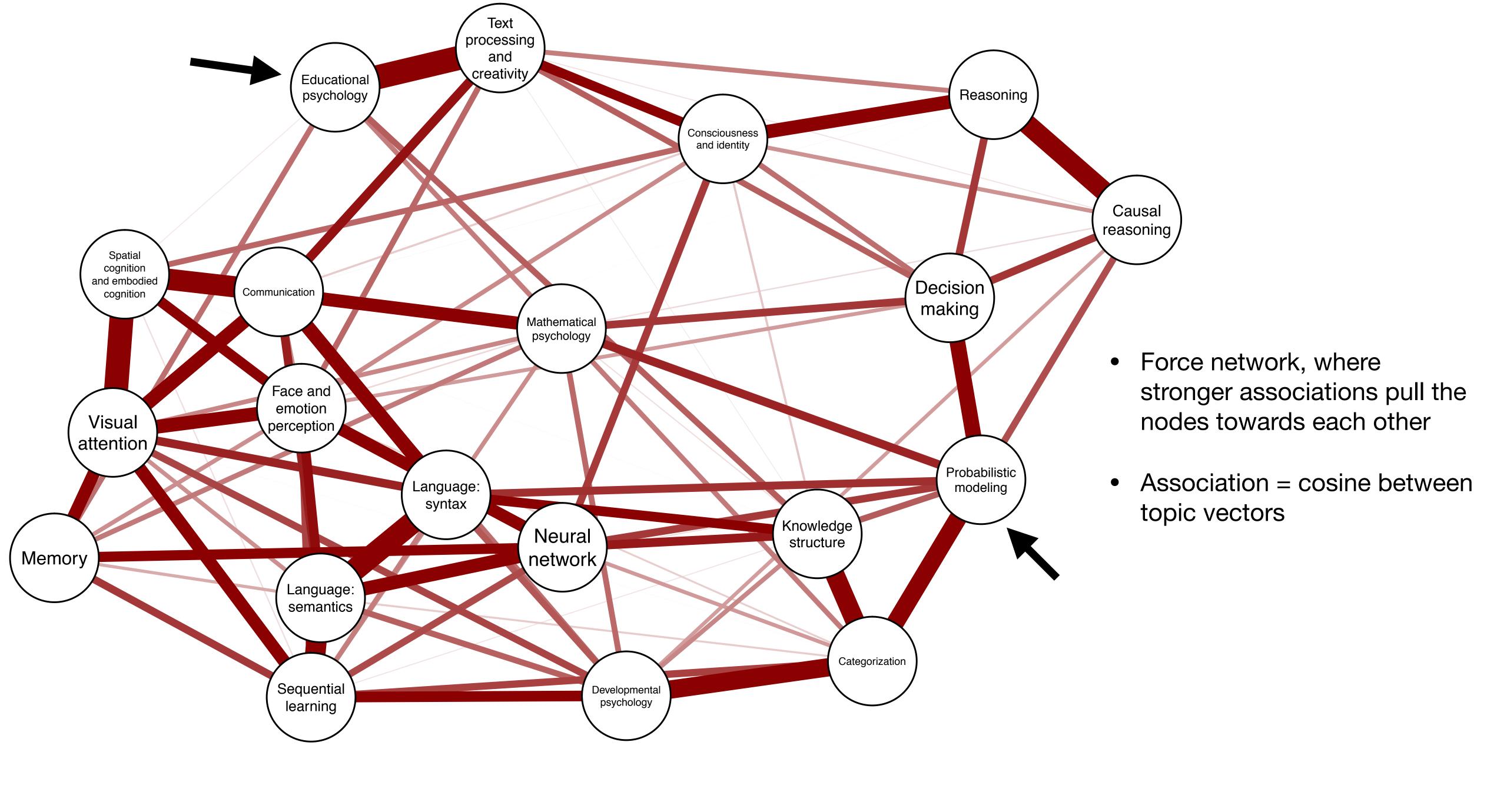
Computer Science Division, University of California, Berkeley, CA 94720 USA

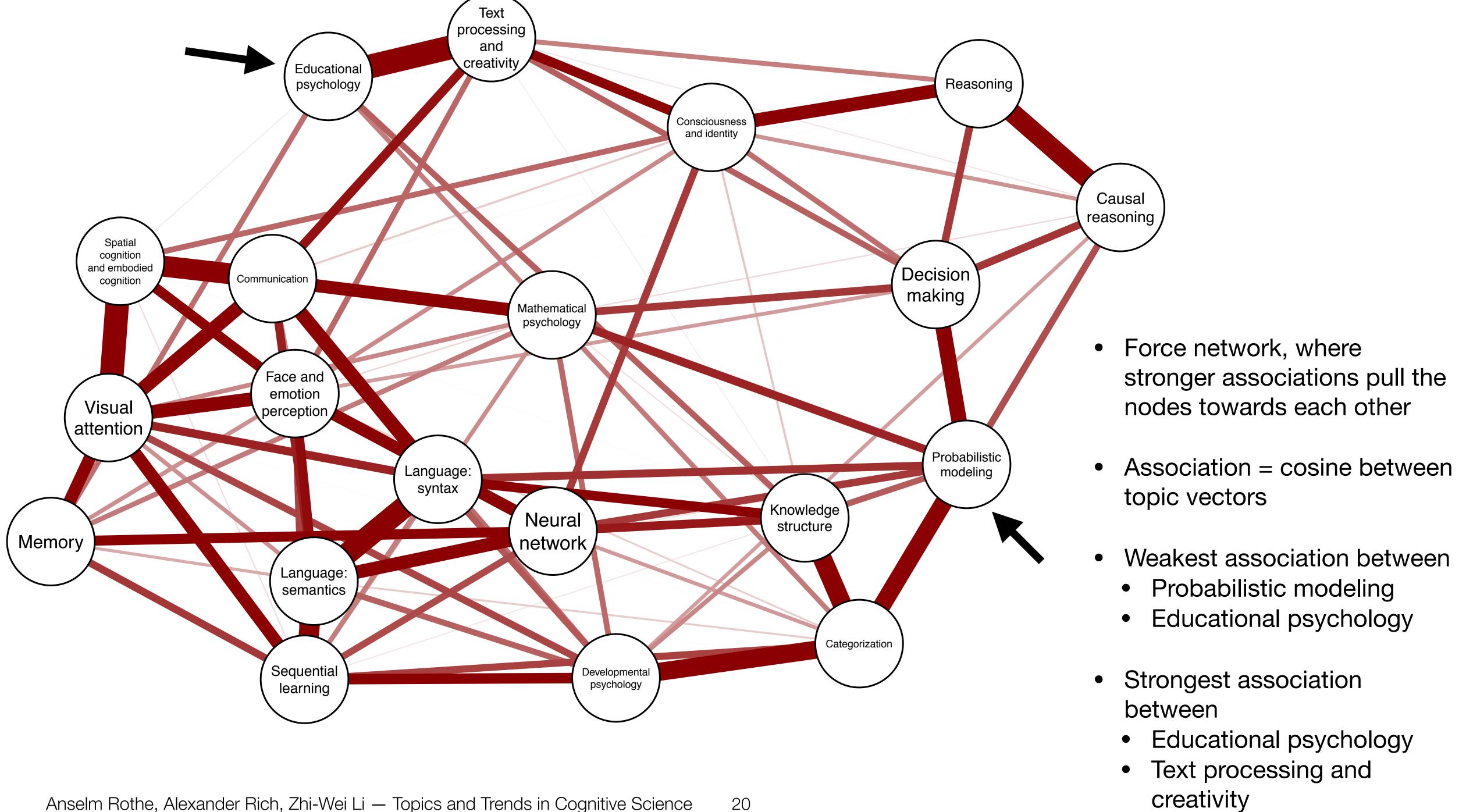
Abstract

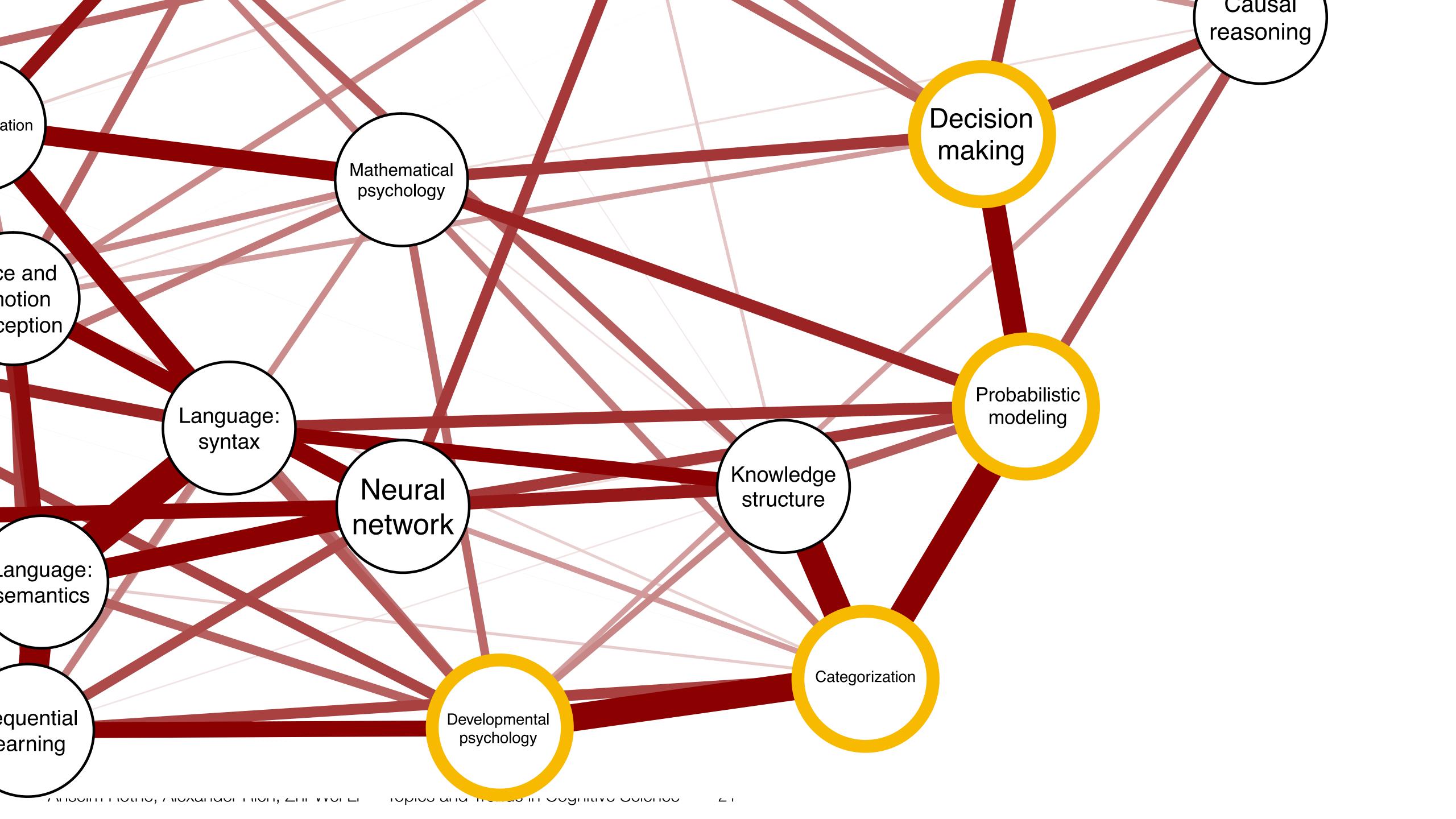
Similarities between human languages are often taken as evidence of constraints on language learning. However, such similarities could also be the result of descent from a common ancestor. In the framework of iterated learning, language evolution converges to an equilibrium that is independent of its starting point, with the effect of shared ancestry decaying over time. Therefore, the central question is the rate of this convergence, which we formally analyze here. We show that convergence occurs in a number of generations that is $O(n \log n)$ for Bayesian learning of the ranking of n constraints or the values of n binary parameters. We also present simulations confirming this result and indicating how convergence is affected by the entropy of the prior distribution over languages.

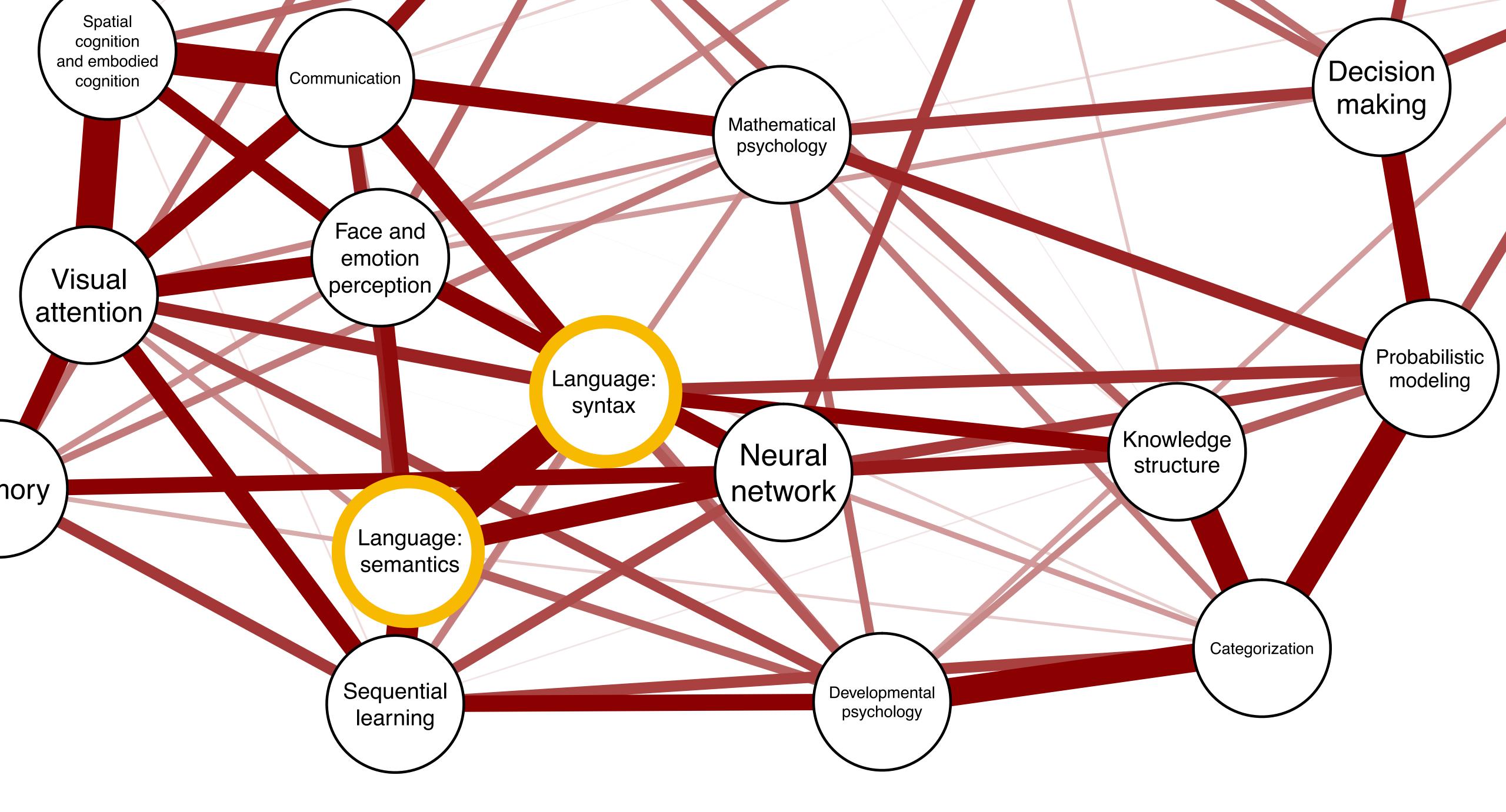
Our key contribution is providing bounds on the number of generations required for convergence, known as the *convergence time*, which we obtain by analyzing Markov chains associated with iterated learning. Bounding the convergence time is a step towards understanding the source of linguistic universals: If convergence occurs in relatively few generations, it suggests constraints on learning are more likely than common descent to be responsible for linguistic universals.

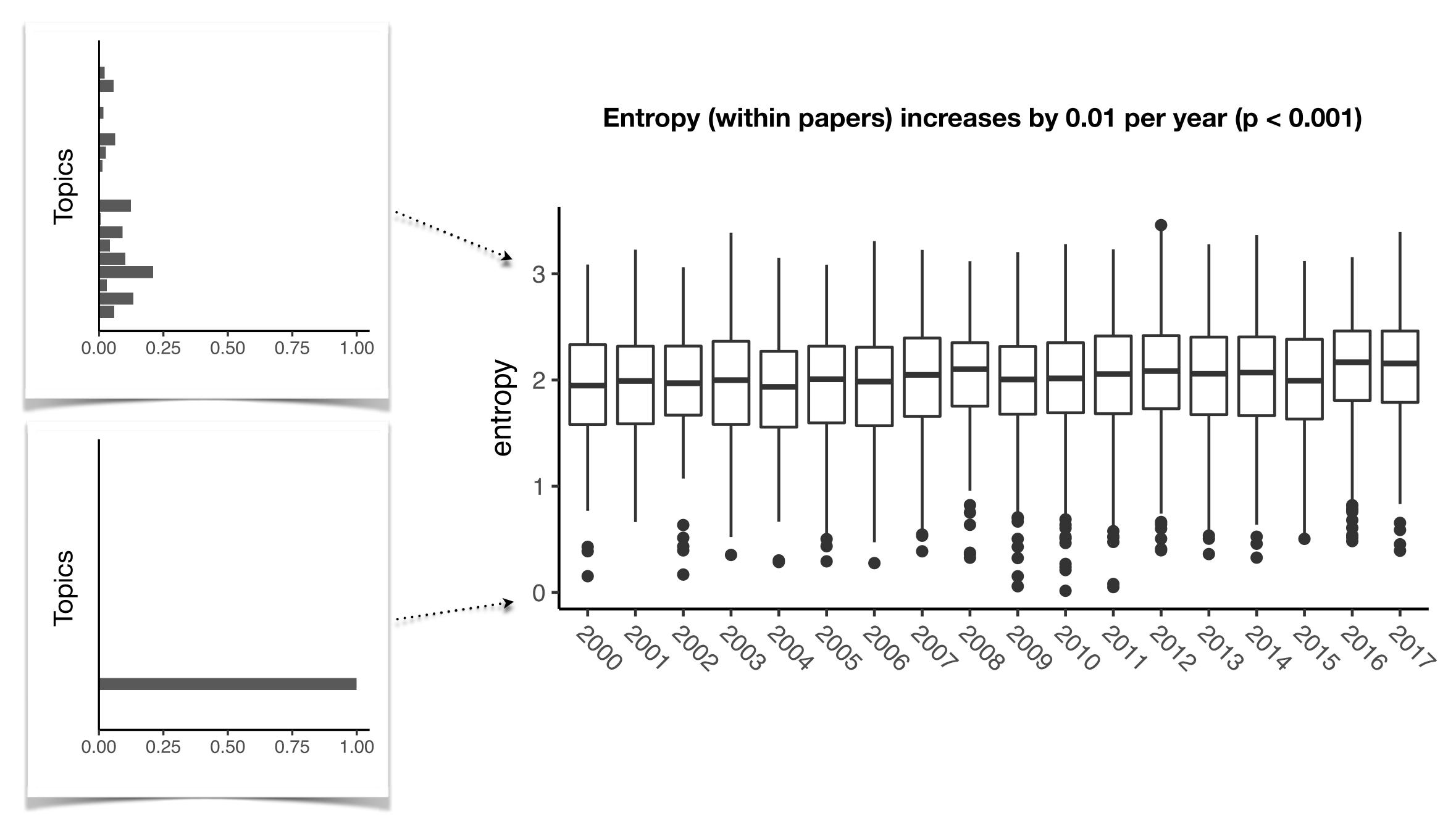
To bound the number of generations required for iterated learning to converge, we need to make some assumptions





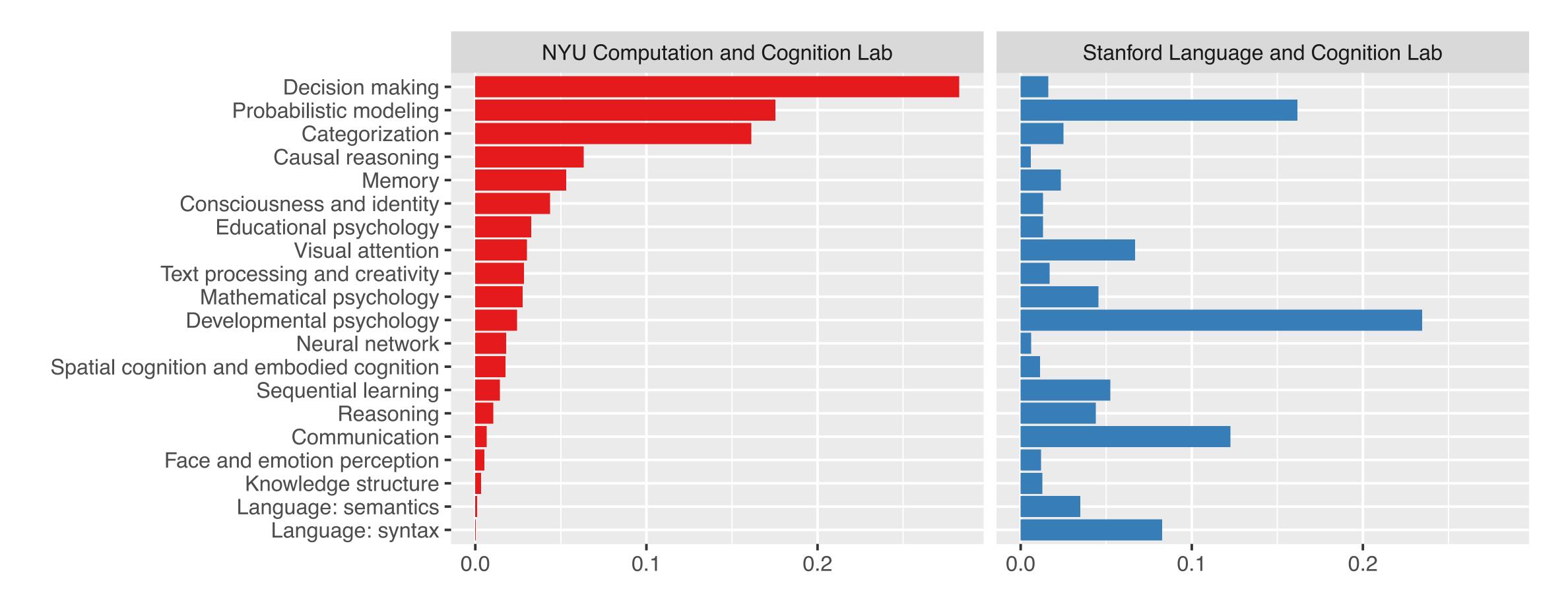


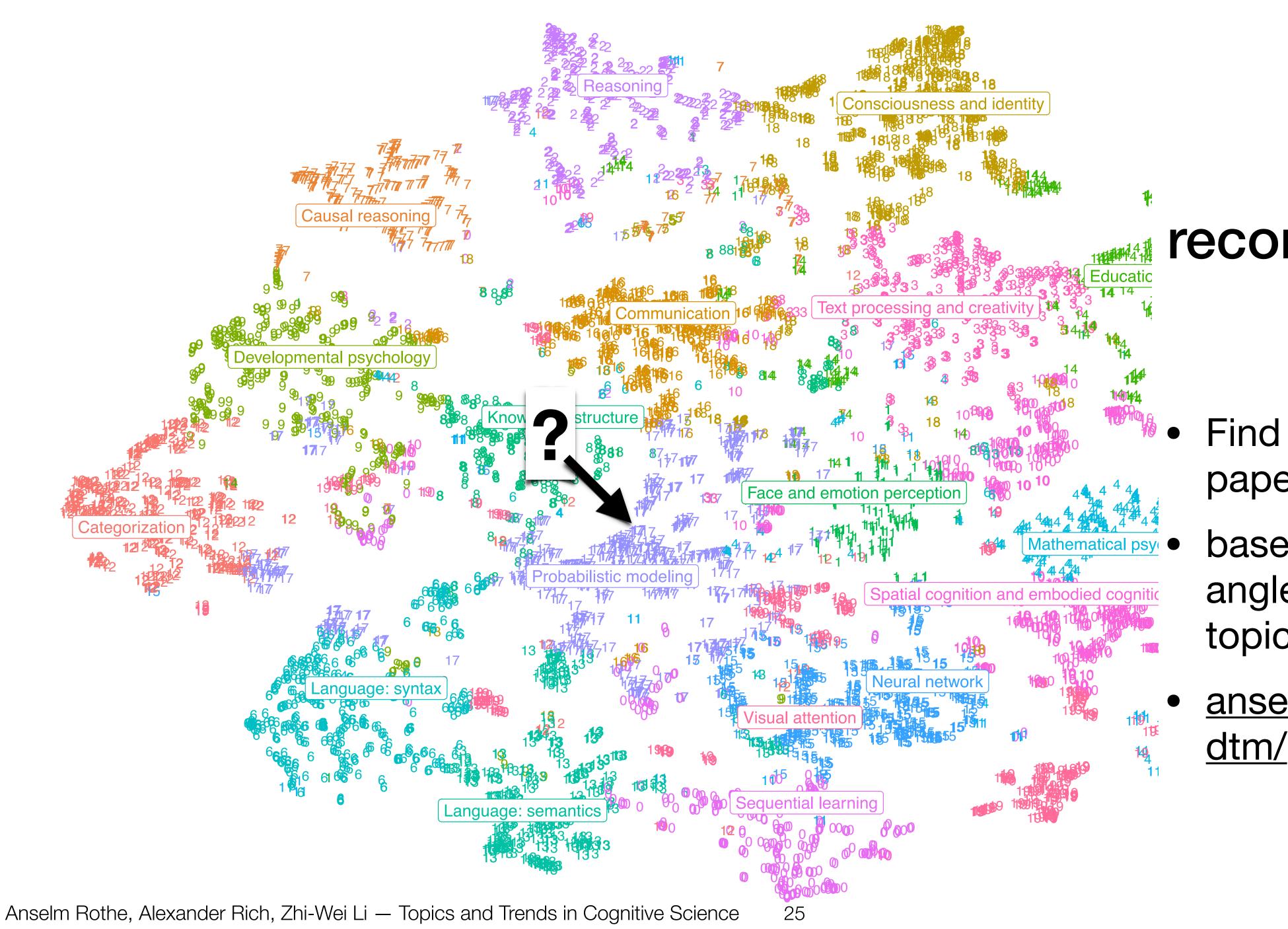




Compare labs

Average topic proportions across the CogSci papers published by the lab





Paper recommendation system

- Find the 6 most similar papers
- based on the cosine angle between their topic vectors
- anselmrothe.github.io/



Find similar papers!

Convergence Bounds for Language Evolution by Iterated Learnin

Convergence Bounds for Language Evolution by Iterated Learning

Similarity	Year	Title
0.996	2014	Percentile analysis for goodness-of-fit comparisons of models to data
0.995	2005	A Bayesian View of Language Evolution by Iterated Learning
0.993	2002	A probabilistic approach to semantic representation
0.993	2005	Modeling Individual Differences with Dirichlet Processes
0.993	2013	Inferring Subjective Prior Knowledge An Integrative Bayesian Approach
0.991	2009	Iterated learning in populations of Bayesian agents

Paper recommendation system

- Find the 6 most similar papers
- based on the cosine angle between their topic vectors
- anselmrothe.github.io/ dtm/

Summary & Discussion

- We used **Dynamic Topic Modeling** to get an overview over the last 18 years of CogSci publications
- "Probabilistic modeling" is on the rise
- The complexity (entropy) of the field is slowly increasing
- The "content" of topics was allowed to change over time
- The **number of topics** was fixed: 20 as a reasonable middle ground
 - Same as Blei & Lafferty 2006
 - Model log-likelihood improves with more topics (we tested up to 100)
- Future work: Enrich data set with google scholar citations + author + institution data
- Code and results: github.com/anselmrothe/dtm

