ARTICLE IN PRESS

Cognition xxx (2014) xxx–xxx

Contents lists available at ScienceDirect

Cognition

journal homepage: www.elsevier.com/locate/COGNIT

Analyzing the history of *Cognition* using Topic Models

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ARTICLE INFO

Article history:
Available online xxxx

Keywords:
History of science
Topic Models
Framing topics

ABSTRACT

Very few articles have analyzed how cognitive science as a field has changed over the last six decades. We explore how *Cognition* changed over the last four decades using Topic Models. Topic Models assume that every word in every document is generated by one of a limited number of topics. Words that are likely to co-occur are likely to be generated by a single topic. We find a number of significant historical trends: the rise of moral cognition, eyetracking methods, and action, the fall of sentence processing, and the stability of development. We introduce the notion of framing topics, which frame content, rather than present the content itself. These framing topics suggest that over time Cognition turned from abstract theorizing to more experimental approaches.

1. Introduction

Many researchers are familiar with discussions during post-conference dinners speculating about which research areas are "hot" and lamenting that their own research area has fallen out of favor. Despite these all too common parlor debates, there is little to no empirical work analyzing how cognitive science as a field has changed over the last six decades (but see Leydesdorff & Goldstone, 2014, who analyze the interaction between cognitive science and related fields via citation analysis). Given that many articles have been digitized to be easily accessible electronically and that the abstract and title of most of these articles are free to download, it is now feasible to perform large, data-driven analyses of scientific trends. In this article, we describe one method for analyzing trends in scientific fields, focusing on the journal *Cognition* as part of this special issue.

What is a rigorous, data-driven method for analyzing trends in science? Perhaps the simplest approach would be to count how often particular words and phrases associated with a particular research area are used each year (e.g., "moral"), and analyze any resulting trends. Recently, Behrens, Fox, Laird, and Smith (2013) took this approach for analyzing publication patterns in cognitive neuroscience, and found that particular brain areas were positively correlated with high-impact journals (e.g., the fusiform gyrus). However, the word-based approach has several limitations. First, the choice of word trends is biased by the investigator's hypothesis, rather than the data. Second, there is a risk that changes in language use do not reflect academic interest itself, e.g. artificial intelligence still generates a lot of interest, but it is no longer referred to as artificial intelligence.[1] Finally, keyword-based approaches would fail to distinguish between two or more senses of a single word. For example, *movement* can refer to eye movement in eyetracking paradigms or to body movement in the study of action.

Rather than use words, Hall, Jurafsky, and Manning (2008) demonstrated that *Topic Models* (Blei, Ng, & Jordan, 2003; Griffiths, Steyvers, & Tenenbaum, 2007) present an appealing approach to track the rise and fall of specific research interests in general. Topic Models allow us to

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[1] As observed in the Google Books Ngram Viewer http://goo.gl/PUMKQP.

http://dx.doi.org/10.1016/j.cognition.2014.11.006

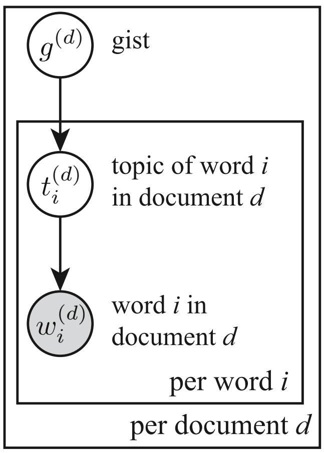
(a)

word	personal	force	depends	entirely	on	intention.	These	studies	also
lemma	personal	force	depends	entirely		intention		study	also
topic	moral	moral	experiment	experiment		moral		child	experiment

(b)

word	This	paper	proposes	a	new	theory	of	the	relationship	between	the	sentence	processing
lemma		paper	proposes		new	theory			relationship			sentence	processing
topic		theory	theory		theory	theory			theory			sentence	sentence

(c)



(d)

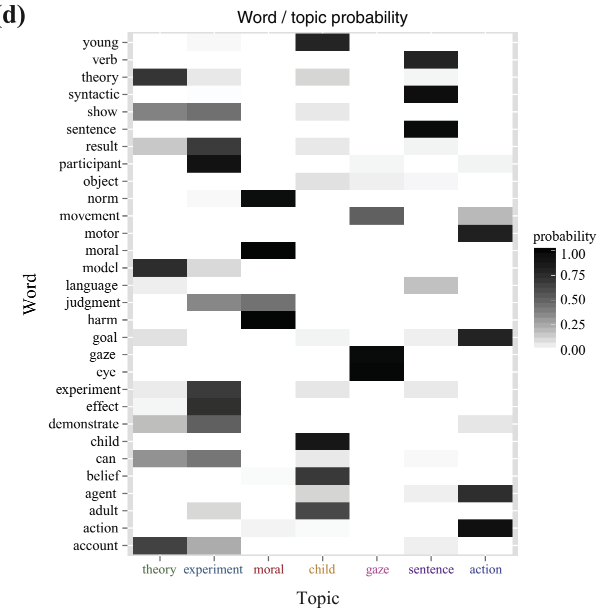


Fig. 1. Modeling word meaning using Topic Models. (a and b) Nine and twelve word excerpts from Greene et al. (2009) and Gibson (1998), respectively. The first row is the original text. The second row is the text after being processed through the lemmatizer. The third row is the topic assigned to each word by the model. (c) A graphical model representation of the Topic Model. Each node is a variable in the model and edges encode probabilistic dependencies between the two variables. Each rectangle is a called a "plate", where the variables and edges in the rectangle are copied multiple times (e.g., the inner rectangle represents each word in the current document and each word's topic). Shaded nodes denote that the variable was observed. (d) A word-topic matrix from our trained Topic Model limited to seven topics and their most probable words. Note how the gaze topic focuses on words related to eyetracking methods and that some words (e.g., movement) are probable in multiple topics (e.g., eye and action), capturing different senses of the same word.

see how topics, rather than words, trend over time. We followed their approach by analyzing the titles and abstracts of 34 years of *Cognition* articles to track trends in research topics. We discuss how topics such as *morality* surged, while others such as *developmental* remained stable. Additionally, we extend the work of Hall et al. (2008) in two ways. First, we propose a method for selecting which topics represent consistent trends, regardless of the number of topics used to build the model. Second, we show that interest may lie in what we label *framing topics*, topics that do not model any research domain, but contain words used to frame more contentful topics. Cognition's abstracts and titles support two framing topics: theory-centric and experimental.

2. Topic Models

Although there is no agreed upon representation of word meaning, Topic Models provide a relatively simple and practical method for exploring hypotheses about the meanings of words in documents. Topic Models assume that every word in every document is generated by one of a number of *topics* (see Fig. 1a and b for examples). Topics are (Dirichlet-distributed) mixtures of words (a topic specifies the probability of a word being produced by that topic), and documents are (Dirichlet-distributed) mixtures of topics. As illustrated in Fig. 1c, the model generates documents according to a hierarchical process. First, a mixture of topics (the *gist* of the document) is sampled from a Dirichlet distribution. Subsequently each word is sampled from the topics of the document. Documents are biased to be more likely to generate some topics rather than others, and topics are biased to be more likely to generate some words rather than others. Together, these biases lead the model when given a corpus of documents to converge[2] on solutions in which words that are likely to co-occur are generated by the same topic. For example, the "child"

[2] This is done using standard machine learning techniques, see Griffiths et al. (2007) for more details.

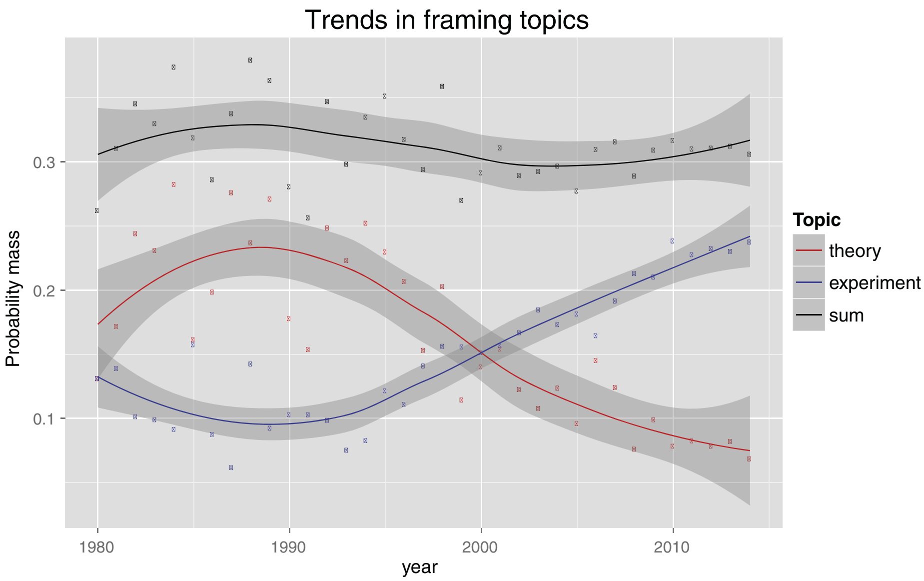


Fig. 2. Trends in the prevalence of the theory-framing topic (red), of the experiment-framing topic (blue), and the sum of the prevalence two topics (black). Although the prevalence of the two topics remains stable, the experiment-framing topic has become more prevalent while theory-framing declines. The curves are best-fit polynomial functions using the loess R function and shaded area around the curves denotes 95% confidence intervals.

topic from our analyses assigns high probability to development-related words (such as "child", "adult", "young", and "age" – see Fig. 1d). There is no explicit bias against having a single word generated by more than one topic, and indeed words like "object" in our models are likely to be generated by both a developmental-related topic, and by an eyetracking-related topic. Note that because the topic index is determined arbitrarily by the model, we use one of the words most likely to be generated by the topic to refer to the topic. For our results, the topic labels were robust regardless of the maximal number of topics used by the model.

Our main motivation for using Topic Models is pragmatic. They have been successfully used to analyze trends in other fields of science (notably trends in computational linguistics; Hall et al., 2008). We decided against using a related alternative to Topic Models, Dynamic Topic Models (Blei & Lafferty, 2006), which introduce additional biases regarding the development of topics over time (e.g., topics should change smoothly from year to year). The downside to constraining the development of topics is that the modeling results are more difficult to interpret. How would we know whether a trend found by the model is actually driven by trends in the data or due to the additionally imposed constraints? We also preferred to use Topic Models over another related model, Latent Semantic Analysis (LSA; Landauer & Dumais, 1997), which performs dimensionality reduction on a set of documents to extract a spatial representation of word meanings. The advantage of the Topic Model approach is in explicitly biasing topics to generate fewer words at high probability, and biasing documents to generate fewer topics at high probability. The topics inferred by the model are therefore more structured, and allow them to explain qualitative and quantitative aspects of word associations better than LSA (see Griffiths et al., 2007, for more details).

3. Analyzing trends in *Cognition*

3.1. Materials and methods

We retrieved[3] from ScienceDirect all the titles and abstracts of Cognition articles published between 1980 and 2014 (3104 abstracts), and loaded them to R (R Core Team, 2014). We cleaned the data by removing all punctuation, single-character words, HTML escape codes, English function words (e.g. *this*, *being*; using a stopword list from the *tm* library, Feinerer & Hornik, 2014), collapsing uppercase and lowercase distinctions, and converting all words to their lemmas, using the WordNet-based (Princeton University, 2010) NLTK lemmatizer (Bird, Loper, & Klein, 2009). Thus a fragment such as *"LSA, and Topic Models"* became *"lsa topic model"*. After the cleaning process was done, we excluded abstracts that had no words in the abstract (mostly non-articles such as short responses, indices and contents of volumes). The resulting set of 2512 abstracts had 107 words per abstract on average. We used the R lda library (Chang, 2012) to train Topic Models for multiple numbers of topics (between 30 and 50) using at most 1000 iterations. The hyperparameters, α and η, were both set to 0.1, which encourages the model to assign topics to documents such that each document is composed of a few topics and to learn topics that produce a few words with high probability, respectively. The main output of each model is an assignment of topics for every word in the dataset. For instance, a word vector of the form "*lsa topic model*" may be translated to "*2 2 10*", in which the first two words were generated by topic 2, and the third word by topic 10.

[3] Retrieved 2014-07-28.

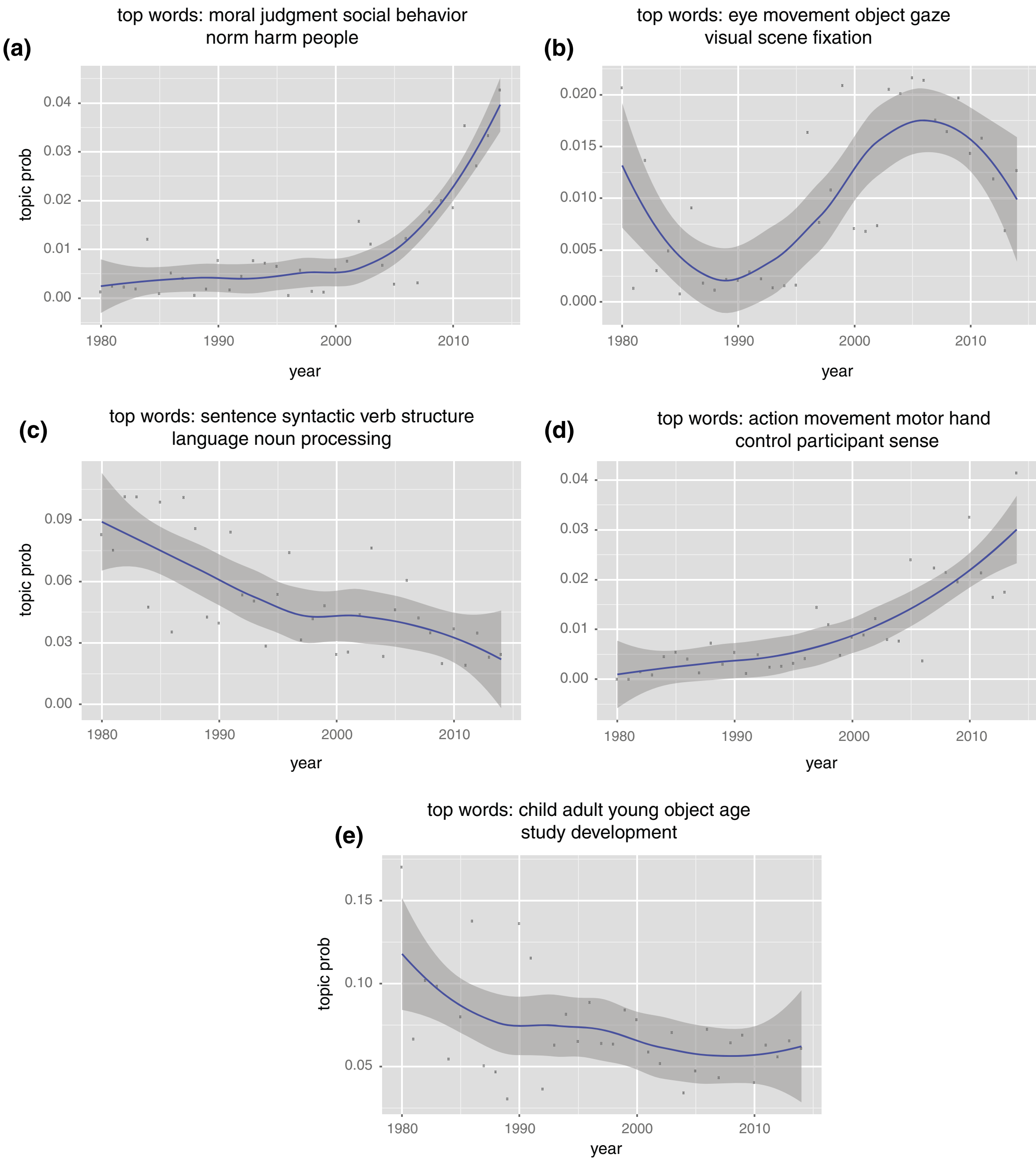


Fig. 3. Trends of topic prevalence in *Cognition* passing at least one criterion for the (a) moral, (b) gaze, (c) sentence (processing), (d) action, and (e) child topics. The curves are best-fit polynomial functions using the loess R function and shaded area around the curves denotes 95% confidence intervals. See text for more details.

To analyze trends in topics over time, we used the output from the model to calculate the weighted contribution of each topic t in each year y using Eq. (1). It calculates for each year the proportion of words generated by each topic, but controls for abstract length by dividing each word's contribution by the abstract's length. Thus, the yearly topic contribution estimate, $p_y(t)$, is defined to be

$$\frac{1}{|D_y|}\sum_{d\in D_y}\frac{|\{w\in d : topic(w)=t\}|}{|d|} \tag{1}$$

where t is a topic, w is a word in document d, and d is a document in D_y, the collection of documents published in year y.

Because the choice of the number of topics can affect the topic trends, we needed a method for detecting which topic trends are likely to be meaningful and robust. After experimenting with a few methods and thresholds, we decided to include topics that were in the top 1–2.5/(number of topics) percentile of topics (top 10% for 25 topics, top 5% for 50 topics), or topics that had a significant trend ($R^2 > 0.4$) when trying to predict trends in topic contribution over the years, using a cubic-function regression. To prevent any influence of the particular choice of K (the number of topics learned by the model), we discuss only those topics that passed one of the above criteria for nearly every K. The presented results are the most conservative of the different options that we tried and thus, are most likely to be robust to the choice of K and thresholds.

3.2. Results and discussion

There were three types of topics inferred by the model that passed one of the above criteria: *framing* topics, topics with major trends, and topics that are stable, yet still occur relatively often. We discuss each of these in turn and then discuss some trends that were less robust (occurred roughly half of the time).

Framing topics do not concern any particular research domain, but contain words that are used to frame more contentful topics. They arise for the following reason: When using Topic Models, every word in a document has to be generated by some topic. For topics that are likely to generate words such as *development* and *child*, their interpretation is straightforward—the topic is related to developmental psychology. But some words such as *show* and *demonstrate* are not about any particular research interest. Instead, they are words that frame the content of the abstract. The model still has to generate these words, and it is biased against using the contentful topics to generate them, as every contentful topic will have to allocate some probability mass to content-framing words. Instead, in every model trained with more than 10 topics, one topic emerged that generated the framing context. In models with 30 or more topics, two framing topics emerged rather than one.

The two framing topics were the *theory-framing* topic, which generates words related to abstract theories of cognition, and the *experiment-framing* topic, which generates words related to empirical experiments testing aspects of cognition. Fig. 2 plots the yearly trend of each framing topic (red for *theory-framing* and blue for *experiment-framing*) along with the sum of the two trends (black). There is a clear downward trend for the theory-framing topic, whereas there is a clear upward trend for the experiment-framing topic. However, the trend of their sum remains stable over time. This suggests that over the last three decades, *Cognition* articles are increasingly framed in terms of experiments, rather than abstract theories. That is, over time the experiment-framing topic is replacing the theory-framing topic.

As shown in Fig. 3, we uncovered five topics that passed one of our criteria for nearly all K, a *moral* topic covering moral, social, and emotional aspects of cognition, a *gaze* topic covering eyetracking methodologies outside of vision (e.g., sentence processing or moral cognition), a *sentence (processing)* topic, an *action* topic, and a *child* topic. Although the *moral* topic has very low probability in *Cognition* during the 1980s and 1990s, its prominence has skyrocketed in the last decade from producing around 0.5% of the words in the mid-2000s to producing about 4% in 2014. This is a few years after groundbreaking work by Greene and Haidt. At the time of writing this article Greene, Sommerville, Nystrom, Darley, and Cohen (2001), and Haidt (2001) are widely cited (over 2000 citations each). The trend of the *gaze* topic is more complex. The most striking feature is the sharp increase in its popularity from nearly 0% at the early 1990s to almost 2% in the mid 2000s, which then plateaued (and possibly now is in a downward trend). The sharp increase in the 1990s seems to be due to the sudden popularity of using eyetracking as a method for analyzing language processing, which coincides with Tanenhaus, Spivey-Knowlton, Eberhard, and Sedivy (1995)'s seminal article. The *sentence* topic has been trending approximately linearly down in *Cognition* since the beginning of the 1980s, from nearly 9% to close to 3%. Conversely, *action* trends positively, from nearly 0% to about 3%. Although the *child* topic also passes the "frequently used" criterion, unlike the other discussed topics there are no notable trends. It has been generating approximately the same proportion of topics over the last few decades.

4. Summary and concluding remarks

In this article we used Topic Models to explore how different topics have trended over the history of Cognition. While one may expect specific topics would rise or fall, changes in framing topics reveal tendencies in the journal or field as a whole. One of the most robust trends in Cognition is the rise of the experimental approach at the expense of more abstract theorizing. We believe that Topic Models present a methodical way to analyze how scientific interest changes over time.

Acknowledgements

Both authors contributed equally to this article. This article greatly benefited from discussion with Steven Sloman. We thank Scott AnderBois, Elinor Amit, and Russell Church for their feedback on earlier versions of the manuscript.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.cognition.2014.11.006.

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Please cite this article in press as: Cohen Priva, U., & Austerweil, J. L. Analyzing the history of *Cognition* using Topic Models. *Cognition* (2014), http://dx.doi.org/10.1016/j.cognition.2014.11.006