

# Visualizing Topic Models

Allison J.B. Chaney and David M. Blei

Department of Computer Science  
Princeton University, Princeton, NJ USA  
achaney@cs.princeton.edu, blei@cs.princeton.edu

## Abstract

Managing large collections of documents is an important problem for many areas of science, industry, and culture. Probabilistic topic modeling offers a promising solution. Topic modeling is an unsupervised machine learning method that learns the underlying themes in a large collection of otherwise unorganized documents. This discovered structure summarizes and organizes the documents. However, topic models are high-level statistical tools—a user must scrutinize numerical distributions to understand and explore their results. In this paper, we present a method for visualizing topic models. Our method creates a navigator of the documents, allowing users to explore the hidden structure that a topic model discovers. These browsing interfaces reveal meaningful patterns in a collection, helping end-users explore and understand its contents in new ways. We provide open source software of our method.

Understanding and navigating large collections of documents has become an important activity in many spheres. However, many document collections are not coherently organized and organizing them by hand is impractical. We need automated ways to discover and visualize the structure of a collection in order to more easily explore its contents.

*Probabilistic topic modeling* is a set of machine learning tools that may provide a solution (Blei and Lafferty 2009). Topic modeling algorithms discover a hidden thematic structure in a collection of documents; they find salient themes and represent each document as a combination of themes.

However, topic models are high-level statistical tools. A user must scrutinize numerical distributions to understand and explore their results; the raw output of the model is not enough to create an easily explored corpus.

We propose a method for using a fitted topic model to organize, summarize, visualize, and interact with a corpus. With our method, users can explore the corpus, moving between high level discovered summaries (the “topics”) and the documents themselves, as Figure 1 illustrates.

Our design is centered around the idea that the model both summarizes and organizes the collection. Our method translates these representations into a visual system for exploring a collection, but visualizing this structure is not enough. The discovered structure induces relationships—between topics and articles, and between articles and articles—which lead to interactions in the visualization.

Thus, we have three main goals in designing the visualization: summarize the corpus for the user; reveal the relationships between the content and summaries; and, reveal the relationships across content. We aim to present these in a ways that are accessible and useful to a spectrum of users, not just machine learning experts.

## Related Work

Several solutions to the problem of understanding large document corpora include Exemplar-based Visualization (Chen et al. 2009), ThemeRiver (Havre, Hetzler, and Nowell 2000), and FacetAtlas (Cao et al. 2010). These visualizations help users understand the corpus as a whole, but do not enable exploration of individual documents. Our visualization provides both a high-level summary of the corpus and links between the summary and individual documents.

Previous topic modeling research has focused on building new topic models and improving algorithms for fitting them. Researchers have typically used browsers to evaluate model algorithms (Newman et al. 2006; Gretarsson et al. 2011; Gardener et al. 2010). These browsers emphasize topics, giving little attention to documents. Further, they include little visual representation, relying mostly on numbers to convey meaning.

We present a way of using topic models to help learn about and discover items in a corpus. Our navigator presents the output of a topic model in an interface that illuminates a given corpus to non-technical users.

## Probabilistic Topic Models

We review topic modeling, focusing on *latent Dirichlet allocation* (LDA) (Blei, Ng, and Jordan 2003), which is one of the simplest probabilistic topic models. LDA decomposes a collection of documents into *topics*—biased probability distributions over terms—and represents each document with a (weighted) subset of the topics. When fit to a set of documents, the topics are interpretable as themes in the collection, and the document representations indicate which themes each document is about. Thus, the learned topics summarize the collection, and the document representations organize the corpus into overlapping groups.

LDA is a statistical model of a collection of texts. *Hidden random variables* encode its thematic structure. The assumptions LDA makes can be articulated by its *probabilistic generative process*, the imaginary process by which the collection arose.

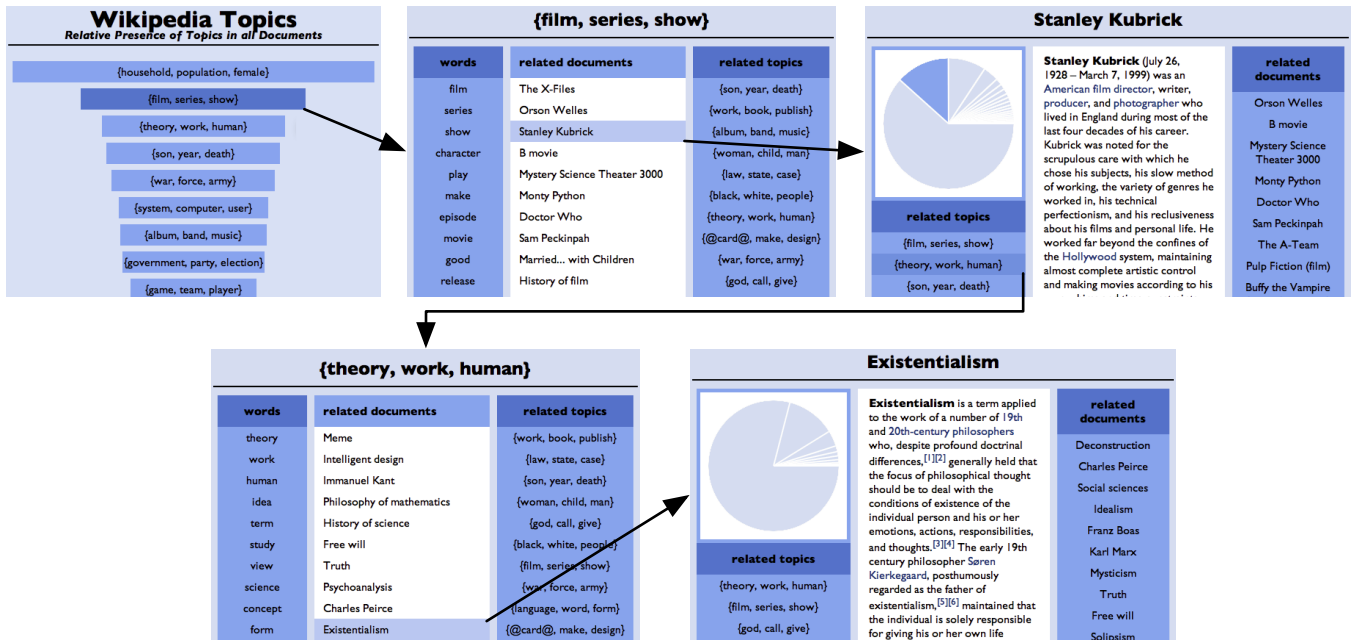


Figure 1: Navigating Wikipedia with a topic model. Beginning in the upper left, we see a set of topics, each of which is a theme discovered by a topic modeling algorithm. We click on a topic about film and television. We choose a document associated with this topic, which is the article about film director Stanley Kubrick. The page about this article includes its content and the topics that it is about. We explore a related topic about philosophy and psychology, and finally view a related article about Existentialism. This browsing structure—the themes and how the documents are organized according to them—is created by running a topic modeling algorithm on the raw text of Wikipedia and visualizing its output. This navigator can be found at <http://bit.ly/wiki100>.

1. For  $K$  topics, choose each topic distribution  $\beta_k$ .  
(Each  $\beta_k$  is a distribution over the vocabulary.)
2. For each document in the collection:
  - (a) Choose a distribution over topics  $\theta_d$ .  
(The variable  $\theta_d$  is a distribution over  $K$  elements.)
  - (b) For each word in the document
    - i. Choose a topic assignment  $z_n$  from  $\theta_d$ .  
(Each  $z_n$  is a number from 1 to  $K$ .)
    - ii. Choose a word  $w_n$  from the topic distribution  $\beta_{z_n}$ .  
(Notation  $\beta_{z_n}$  selects the  $z_n$ th topic from step 1.)

Notice that the same set of topics  $\{\beta_1, \dots, \beta_K\}$  is used for every document, but that each document exhibits those topics with different proportions  $\theta_d$ . This captures heterogeneity in documents: LDA can model that some articles are about “sports” and “business”, others are about “sports” and “health”, and that the topic of “sports” is similar in each. In statistics, this is known as a *mixed membership model*, where each data point exhibits multiple components.

Given a set of documents, the central problem for LDA is *posterior inference* of the variables, or determining the hidden thematic structure that best explains an observed collection of documents. This is akin to “reversing” the generative process to find the topics, topic proportions, and topic assignments that best explain the observed documents. Researchers have developed several algorithms for LDA inference, including Markov chain Monte Carlo sampling (Steyvers and Griffiths 2006) and optimization-based variational inference (Blei, Ng, and Jordan 2003). These algorithms take a collection of documents as input and return how the hidden topic variables decompose it.

Inference results in a set of interpretable topics  $\{\beta_1, \dots, \beta_K\}$  and a representation of each document of the collection according to those topics  $\{\theta_1, \dots, \theta_D\}$ .<sup>1</sup> One of the main applications of topic models is for exploratory data analysis, that is, to help browse, understand, and summarize otherwise unstructured collections. This is the application that motivates our work.

## Visualizing a Topic Model

Our goals are to use the topic model to summarize the corpus, reveal the relationships between documents and the discovered summary, and reveal the relationships between the documents themselves. We applied our method to 100,000 Wikipedia articles, which we will use as a running example.

Our visualization uses both the observed data from a corpus and the inferred topic model variables.<sup>2</sup> The topic model variables are the topics  $\beta_k$ , each of which is a distribution over a vocabulary, and the topic proportions  $\theta_d$ , one for each document and each of which is a distribution over the topics.

We use multiple views to illuminate this complex structure and created a basic navigator that fully represents a corpus through the lens of an LDA analysis. In this section, we explain our design choices.

<sup>1</sup>That the topics are interpretable is an empirical finding; the name “topic model” is retrospective. Topic models correlate to curated thesauri (Steyvers and Griffiths 2006) and to human judgments of interpretability (Chang et al. 2009).

<sup>2</sup>Note that the we use variables to indicate their posterior expectations. This is to make the notation simple.

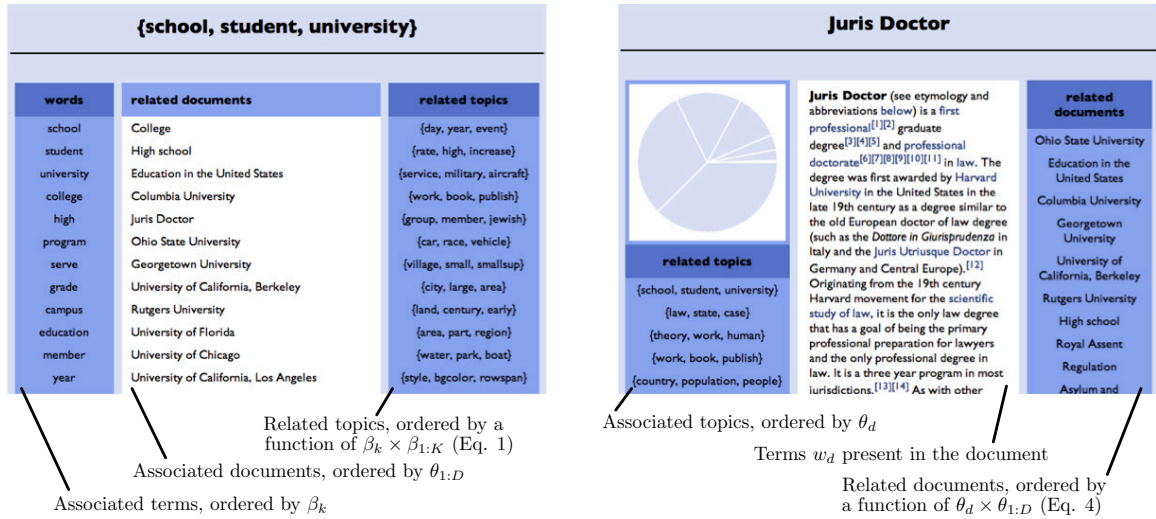


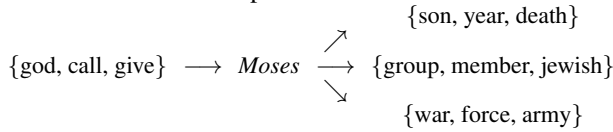
Figure 2: A topic page and document page from the navigator of Wikipedia. We have labeled how we compute each component of these pages from the output of the topic modeling algorithm.

## Visualizing the Elements of a Topic Model

The navigator has two main types of pages: one for displaying discovered topics and another for the documents. There are also overview pages, which illustrate the overall structure of the corpus; they are a launching point for browsing.

These pages display the corpus and the discovered structure. But this is not sufficient—we also use the topic model inference to find connections between these visualizations. With these connections, a user can move between summary and document-level presentations.

Hence, in our visualization every element on a page links a user to a new view. With these links, a user can easily traverse the network of relationships in a given corpus. For example, from a topic page a user can link to view a specific document. This document might link to several topics, each of which the user can explore:

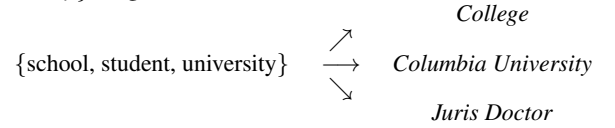


We illustrated another navigation example in Figure 1.

An advantage of this design is that every type of relationship has a representation and an interaction. This illuminates the structure of corpus to a user and helps her navigate that structure. Further, any variable may occur in multiple views; all relationships are many-to-many.

**Topic Pages** Topics summarize the corpus. In the output of an inference algorithm, they are probability distributions over the vocabulary. But topics tend to be sparse, so a good representation is as a set of words that have high probability. Given such a set, users can often conceive meaning in a topic model (Chang et al. 2009). For example, one can intuitively glean from the three words *{film, series, show}* (Figure 1) that this topic is about film and television. We illustrate example topic pages in Figure 2. In these pages, the terms are represented as a list of words in the left column, ordered by their topic-term probability  $\beta_{kv}$ .

The center column of the view lists documents that exhibit the topic, ordered by inferred topic proportion  $\theta_{dk}$ . Document titles links to the corresponding document pages. We can see that the list of documents related to *{school, student, university}* (Figure 2) are tied to education and academics:

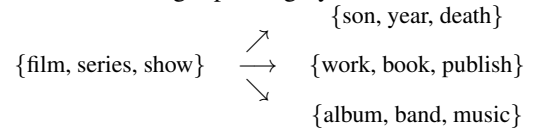


Finally, related topics are also listed with corresponding links, allowing a user to explore the high-level topic space. Topic similarity is not inferred directly with LDA, but can be computed from the topic distributions that it discovers. Related topics are shown in the right column of the topic page by pairwise topic dissimilarity score

$$\xi_{ij} = \sum_{v \in V} \mathbf{1}_{\mathbb{R}_{\neq 0}}(\beta_{iv}) \mathbf{1}_{\mathbb{R}_{\neq 0}}(\beta_{jv}) |\log(\beta_{iv}) - \log(\beta_{jv})| \quad (1)$$

where the indicator function  $\mathbf{1}_A(x)$  is defined as 1 if  $x \in A$  and 0 otherwise. This is related to the average log odds ratio of the probability of each term in the two topics. This metric finds topics that have similar distributions.

Continuing with the topic from Figure 1, this metric scores the following topics highly.



The original topic relates to film and television. The related topics cover a spectrum of concepts from other forms of media to human relationships and life events.

**Document Pages** Document pages render the original corpus. We show the document and the topics that it exhibits, ordered by their topic proportions  $\theta_{dk}$ . We also display these topics in a pie chart, showing their respective proportions within the document. For example, Figure 2 illustrates that



Figure 3: Topic overviews from a visualization of Wikipedia (left), the New York Times (center), and US Federal cases (right). All of these navigators are online (see the *Implementation and Study* section).

the *Juris Doctor* article is a third about academia, a third about law, and a third about other topics. Each rendering of a topic links to its respective page.

Finally, documents are associated with similar documents. Document similarity is not inferred directly with LDA, but is defined by the topic proportions:

$$\sigma_{ij} = \sum_{k \in K} \mathbf{1}_{\mathbb{R}_{\neq 0}}(\theta_{ik}) \mathbf{1}_{\mathbb{R}_{\neq 0}}(\theta_{jk}) |\log(\theta_{ik}) - \log(\theta_{jk})|. \quad (2)$$

This metric says that a document is similar to other documents that exhibit a similar combination of topics.

**Overview Pages** Overview pages are the entry points to exploring the corpus. In the simplest of these pages, we rank the topics by their relative presence in the corpus and display each in a bar with width proportional to the topic’s presence score  $p_k$ : the sum of the topic proportions for a given topic over all documents,

$$p_k = \sum_{d \in D} \theta_{dk}. \quad (3)$$

Examples of this view can be found in Figure 3. From this figure, we see that many documents are related to the topic  $\{\text{household, population, female}\}$ ; this is consistent with our observations of the corpus, which includes many Wikipedia articles on individual cities, towns, and townships.

## Implementation and Study

We provide an open source implementation of the topic modeling visualization. There are three steps in applying our method to visualizing a corpus: (1) run LDA inference on the corpus to obtain posterior expectations of the latent variables (2) generate a database and (3) create the web pages to navigate the corpus.

Any open-source LDA package can be used; we used LDA-C.<sup>3</sup> We implemented the remainder of the pipeline in python. It can be found at <http://code.google.com/p/tmve>.

We created three examples of navigators using our visualization. We analyzed 100,000 Wikipedia articles with a 50-topic LDA model (<http://bit.ly/wiki100>). We analyzed 61,000 US Federal Cases<sup>4</sup> with a 30-topic model (<http://bit.ly/case-demo>). We analyzed 3,000 New York Times articles with a 20-topic model (<http://bit.ly/nyt-demo>). A page from each of these three demos can be seen in Figure 3. One week after we released the source code, we received links to a navigator of arXiv (a large archive of scientific preprints) that was generated using our code; it is at <http://bit.ly/arxiv-demo>.

<sup>3</sup><http://www.cs.princeton.edu/blei/lda-c>

<sup>4</sup><http://www.infochimps.com/datasets/text-of-us-federal-cases>

**Preliminary User Study** We conducted a preliminary user study on seven individuals, asking for qualitative feedback on the Wikipedia navigator. The reviews were positive, all noting the value of presenting the high-level structure of a corpus with its low-level content. One reviewer felt it organized similar to how he thinks.

Six individuals responded that they discovered connections that would have remained obscure by using Wikipedia traditionally. For example, one user explored articles about economics and discovered countries with inflation or deflation problems of which he had previously been unaware.

## Acknowledgements

David M. Blei is supported by ONR 175-6343, NSF CAREER 0745520, AFOSR 09NL202, the Alfred P. Sloan foundation, and a grant from Google.

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