A Topic-Based Search, Visualization, and Exploration System

Abstract

From literature surveys to legal document collections, people try to organize and explore large amounts of documents. During these tasks, students and researchers commonly search for documents based on particular themes. In this paper we use a popular topic modeling algorithm, Latent Dirichlet Allocation, to derive topic distributions for articles. We allow users to specify personal topic distribution to contextualize the exploration experience. We introduce three types of exploration: *user model re-weighted keyword search*, *topic-based search* and *topic-based exploration*. We demonstrate these methods using the a scientific citation data set and a Wikipedia article collection. We also describe the user interaction model.

Introduction

In a variety of situations, from literature surveys to legal document collections, people try to organize and explore large amounts of documents. Current technology to search on documents are done based on keywords with minor extensions. Keyword-based search is useful when the user knows exactly what he or she is looking for. It is not particularly useful when a user wants to explore or learn a new topic. The difficulty with keyword based search is especially pronounced when, for example, a researcher wants to find out the state of the art in a particular area or a student would like to create a literature survey. In such situations, *topic-based search* can return more relevant results. Topic-based search is a classification of the search space to highlight topical relevance. In order to accomplish this, the topics underlying the document collection need to be extracted, and then they have to be represented in terms of those topics and ranked based on relevance to a particular topic.

In our system called *Grisham* we present various techniques for topic-based exploration and search of articles. Our work allows user to search for documents using three methods: First, users may perform a traditional keyword-based search for papers. The results are re-ranked based on a topic distribution specified by the user. Second, user may perform a *topic-based search* where the user specifies a topic she is interested in and documents will be returned ordered by their relevancy to the topic. Lastly, users may explore topically similar documents using a visual graph like interface. In all three methods, we adapt search results to personalize results.

This work is an implementation of a system that uses a novel search and exploration paradigm. The main contributions of this work are as follows:

- A search based on user-defined preferences. A user can interactively define a topic-based model for their search preferences.
- An implementation of ranking functions for topic-based search.
- A novel interaction model for topic-based exploration.

This paper is organized as follows. First, we give an introduction to topic models. Next, we describe the theoretical structure of *Grisham*. We then describe the user interface and the user interaction model. Finally, we conclude this paper with a discussion of related work.

Topic Models

Topic models are a set of models for the documents in a collection or corpus. They enable us to represent properties of a large corpus containing numerous words with a small set of *topics*, by extracting the underlying topical structure of the corpus and representing the documents according to these topics. We can then use these representations for organizing, summarizing, and searching the corpus. Traditionally, topic models assume each word occurrence within a document is independent. This is the assumption of "bag of words" models. Latent Dirichlet Allocation or LDA (Blei, Ng, and Jordan 2003) is a well known, generative, probabilistic topic model for a corpus. A probabilistic generative model assumes data as *observations* that originate from a generative probabilistic process that includes *hidden* variables. The hidden variable are typically inferred via *posterior inference*. In posterior inference, one tries to identify the posterior distribution of the hidden variables that are conditioned on the observations. Loosely speaking, one can consider posterior inference as the reverse of the generative process. LDA assumes that there exists a set of *latent* (hidden) topics for a give corpus. A topic is defined as a distribution over the corpus vocabulary. The topics are assumed to be generated from a *Dirichlet* distribution with a set of parameters. For example, a topic about *whales* will have words related to whales and related topics (e.g., *blue whales*, *killer whales*, *whaling*, etc.) with high probability and words related to other unrelated topics (e.g., *sports*, *medicine*, etc.) with low probability—assuming the corpus is built from a subset of articles from the topics *whales*, *sports*, and *medicine*. In addition, each document in the corpus is described by a latent topic distribution and the words in a document are generated from the document specific topic distribution. The document topic distributions are also assumed to be generated from another *Dirichlet* distribution with a set of parameters. In real life, we only observe documents and their words. As in any generative probabilistic model, the latent variables in the LDA model are typically identified by posterior inference.

Unfortunately, in most of these generative models, posterior inference is intractable due to the high dimensionality of the latent variable space, and practitioners typically rely on approximate posterior inference alternatives. For the LDA model, people have used different approximate inference methods such as deterministic *optimization methods* (Blei, Ng, and Jordan 2003) and *sampling methods* (Griffiths and Steyvers 2004) for the inference. Blei, Ng, and Jordan employed variational methods to find approximations to the posterior distribution of latent variables, by posing a family of lower bounds on the log likelihood indexed by a set of variational parameters. The variational parameters are then identified by a deterministic optimization procedure that seeks to find an optimal lower bound. Griffiths and Steyvers's method was based on Gibbs sampling—a Markov chain Monte Carlo method that helps to approximate the intractable posterior integral as an empirical estimate of the samples generated from a Markov chain. In Gibbs sampling, one forms the Markov chain by repeatedly sampling each variable conditional on the most recently sampled values of the other variables (Geman and Geman 1984). In this paper, we use the scalable implementation of the online variational inference algorithm for LDA (Hoffman, Blei, and Bach 2010) by Řehůřek and Sojka 2010.

Due to the fully generative semantics, even at the level of documents, LDA is expected to overcome several drawbacks such as synonymy and polysemy of words where in earlier models, e.g., TF-IDF (Salton, Wong, and Yang 1975) and Latent Semantic Analysis (LSA, Dumais et al. 1995). In this paper, we are interested in the LDA model parameters such as the corpus-level latent topic distributions and document-level latent topic distributions. The latent document topic distributions are lower dimensional representations of documents (which traditionally are vocabulary-size term-frequency vectors) and useful for finding and grouping similar documents in a corpus. The latent topics in a corpus, which are distributions over the vocabulary terms, are helpful in visualizing the prevalent thematic structure of a corpus and exploring documents related to a specific theme of interest. In the *Grisham* section, we describe how we exploit these model parameters.

Now we describe the notation we use in this paper. For a given corpus, let D be the number of documents in the corpus and V be the number of terms in the corpus vocabulary. The number of topics K in the corpus is a constant and known. For $d = 1, 2, \dots, D$, we denote the K dimensional vector θ_d^* as the estimate of document d's latent distribution on the topics identified via an approximate posterior inference algorithm. In addition, for $j = 1, 2, \dots, K$, we denote the V dimensional vector β_j^* as the estimate of jth topic distribution. This forms a $K \times V$ topic matrix, whose jth row is the jth topic and each element β_{jt}^* represents term t's probability for the jth topic.

Grisham

Grisham system is built to process articles, provide fast response to user queries and display descriptive results in a user interface. In this section we describe our pre-processing steps to extract topic models from the documents. We then discuss the *user model* behind each user search and *user model* re-weighted keyword search. Finally, we discuss our methods for topic-based search and exploration.

Data pre-processing and topic learning

Here we describe the main pre-processing steps we perform on a collection of articles for topic modeling and search. First, we tokenize articles with the help of the python Natural Language Toolkit (NLTK) [1] and a set of predefined regular expressions. Next, we standardize tokens by removing noise and stop-words. We use typical normalization techniques for word tokens such as *stemming*, in particular we use the popular Porter stemming algorithm (Porter 1980) implementation in NLTK. After building a vocabulary of corpus words, each document is represented as a sparse "bag of words". Last, we use the processed documents as input to the topic learning algorithm (Hoffman, Blei, and Bach 2010) which will in turn learn the latent topic structure of a corpus from the term co-occurrence frequencies of the corresponding documents.

User Model

When performing search, exploration and discovery over articles users may bring particular context to their search. Incorporating this information into the search process has been shown to be beneficial to users (Dou, Zhicheng and Song, Ruihua and Wen, Ji-Rong 2007; Ma, Zhongming and Pant, Gautam and Sheng, Olivia R. Liu 2007). We develop a user model that encapsulates the users personal context and integrates it into their search task.

This model is a distribution of weights for each identified topic in a corpus. Formally, given a set of topics β_j^*s the user model is defined as

$$\mathcal{U} = \{u_0, \dots, u_K\}$$

where $u_j \in [0, 1]$, $\sum_{j=1}^{K} u_j = 1$, K is the number of topics in the corpus. We allow the user to interactively select the weights that correspond to each topic learned over the corpus. This allows the users to change preferences with each query for more desirable results.

[1] `http://www.nltk.org/`

User Model Reweighted Keyword Search

The user model is used to provide better feedback to the user. After a *keyword-based filter*, the document results of the search are re-ranked using the KL-divergence of each document and the user model. Formally, given the set of result documents $\mathcal{D}$:

$$KL(\mathcal{U}||\theta_d^*) = \sum_{j=1}^{K} u_j \ln \frac{u_j}{\theta_{dj}^*}. \tag{1}$$

where $d \in \mathcal{D}$ and θ_d^* is the topic proportion for document d from the LDA model.

Topic-Based Search

Another method of search is to identify the topics of real interest, observing the most *informative terms* in the estimated topics. To identify informative terms in a topic we can sort vocabulary terms in the order of their term probabilities. That is, each vector β_j^* in the topic matrix is sorted.

In literature, researchers have proposed several other methods for finding informative terms (Chuang, Manning, and Heer 2012) and evaluating topics (Mimno et al. 2011). In this paper, we use a visualization scheme called *word cloud* (Davis 2013), to visualize the most probable words in a topic. For example, see Figure 1 for the visualization of a topic that is extracted from a corpus, which is built from a subset of Wikipedia articles under the category *Whales*.

We can exploit the estimated document specific topic distributions of individual articles (θ_d^*) in a corpus, to rank them on relevance for given a topic. Let t be the index for the topic of interest. For each document $d = 1, 2, \ldots, D$ in the corpus, we can calculate (George et al. 2012)

$$m(d) = \ln \theta_{dt}^* + \sum_{j \neq t} \ln(1 - \theta_{dj}^*), \tag{2}$$

where $j = 1, 2, \ldots, K$ and each θ_{dt}^* is normalized, i.e., $\sum_{j=1}^{K} \theta_{dj}^* = 1$. We then sort the documents based on each $m(d)$ to rank them on relevance. Intuitively, we can see that Equation 2 will give a high value for a document, if the document is thematically related to the tth topic.

Topic-Based Exploration

If a user find an interesting document and she would like to find other similar documents she may use the topic-based method of exploration. To visualize the hidden topical content of the article we use the estimated document topic distribution, θ_d^*. For example, Figure 2 shows a Doughnut Chart[2] visualization for the Wikipedia article *Killer Whale*. It is an article listed under the Wikipedia category *Killer Whales*. Different slices of the doughnut chart represent different topics in the article *Killer Whale*. The size of a slice represents the probability of a topic given the article. For this illustration, we labeled all the topic distributions obtained via the LDA posterior inference, on a corpus that is built using a subset of Wikipedia articles under the category *Whales*. We used the topic word clouds and the Wikipedia subcategories under the category *Whales* for labeling. Once we find an interesting topic to pursue, we can explore all the relevant documents under that topic using the method described in the previous section.

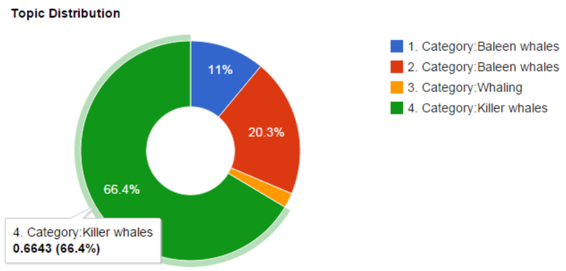


Figure 2: Visualization of the document specific topic distribution for the Wikipedia article *Killer Whale*.

Another way to visualize a document is to look at its *paragraph* or *section* specific topic distributions. Each section or paragraph is written with careful attention in every peer review article or paper. While looking at an article or paper, one can easily identify which section or paragraph is of one's real interest. This intuition can be used to improve topic based exploration. We used the learned LDA model to estimate a section or paragraph's topic distribution using the Gensim LDA implementation (Řehůřek and Sojka 2010). This is an online task and is performed when a user selects a section or paragraph of an article, which is described in detail in the *Grisham* User Interface section.

Another interesting option to explore is how we can use an article's topic distribution for searching similar articles of interest. Recall that LDA enables us to transform documents in a corpus into vectors (θ_d^*) in a lower dimensional topic space of that corpus. One can then define similarity between two documents via any typical vector space similarities, e.g., cosine similarity.

User Interface

To demonstrate *Grisham*'s exploratory search we loaded scientific papers from the DBLP conference (Tang et al. 2008) and also Wikipedia articles downloaded using the MediaWiki API [3]. The *Grisham* website has a list of topics with a slider associated with each of them using which a user can specify the degree of interest in that particular topic. The weightage specified by each slider corresponds to the components of the user model. The user model is a profile of preference provided by the user before she makes any search.

Initially, all the extracted topics from the corpus are shown along with their most informative words (see Figure 3). This list is color coded to distinguish the relevance of topics as indicated by the user model — much like a heat map. The list is clickable and once a topic is clicked, relevant papers to that topic ranked based on the user model

[2] https://developers.google.com/chart

[3] https://www.mediawiki.org

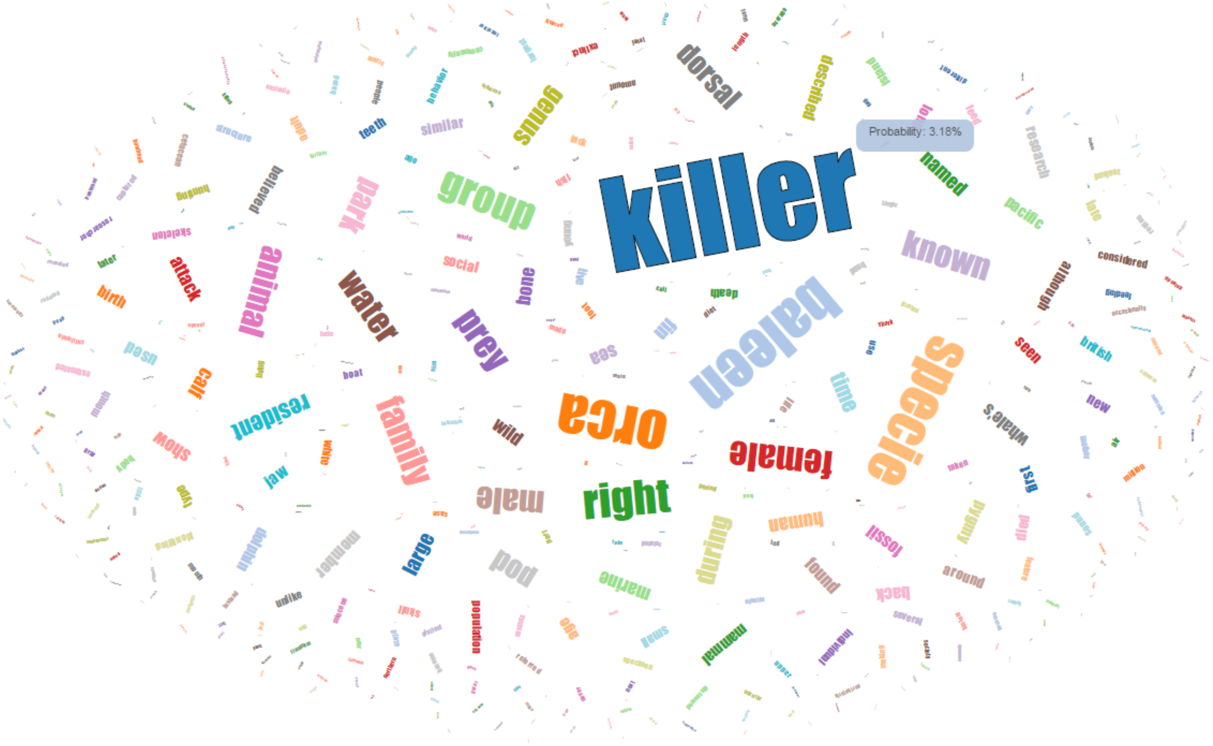


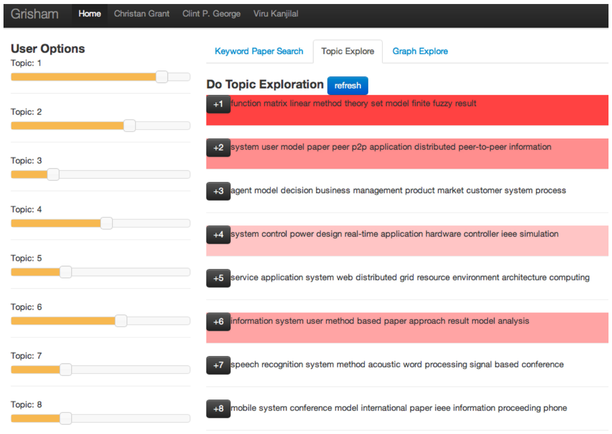
Figure 1: *Topic Word Cloud.* Words with high probabilities for the given topic are larger in size and words with low probabilities for the given topic are smaller in size. From the most probable words, we can infer that the topic mainly refers the Wikipedia category *Killer Whales*—one of the main categories from which, we downloaded the articles for the corpus.

are displayed. The user can look at this heat map to adjust their topic preferences. We use Equation 1 to calculate this preference on the *Grisham* browser. In the *Graph Explorer* interface the citations for the current paper is ranked using Equation 1. The citations of that paper that are most similar to the user model are ranked the highest.

In Figure 3, the *Keyword Paper Search* contains the interface for user model weighted keyword search. The user may enter one or more keywords representing topics, or author names etc. The keywords are searched in the title, abstract, and the author names of all the articles are listed. The results are re-weighted using the user model.

For topic exploration *Grisham* allows a user to click on a specific topic to see the informative words for that topic in a word cloud (Figure 1). By selecting a topic the user can explore more about the papers associated with the topic using Force-Directed Graph (Bostock, Ogievetsky, and Heer 2011) (Figure 4). A user can navigate to a particular document by clicking a document node (orange) in the graph.

On the document visualization page we show a doughnut chart with the topic distribution as well as a preview of the document contents. Clicking on the topics in the doughnut chart will take the user to the topic word cloud page. Selecting a section or paragraph changes the doughnut chart to reflect the topic distribution specific to that selection. The document visualization page for *Killer whale* is displayed in Figure 5.



User Options

Topic: 1

Topic: 2

Topic: 3

Topic: 4

Topic: 5

Topic: 6

Topic: 7

Topic: 8

Do Topic Exploration

+1 function matrix linear method theory set model finite fuzzy result

+2 system user model paper peer p2p application distributed peer-to-peer information

+3 agent model decision business management product market customer system process

+4 system control power design real-time application hardware controller ieee simulation

+5 service application system web distributed grid resource environment architecture computing

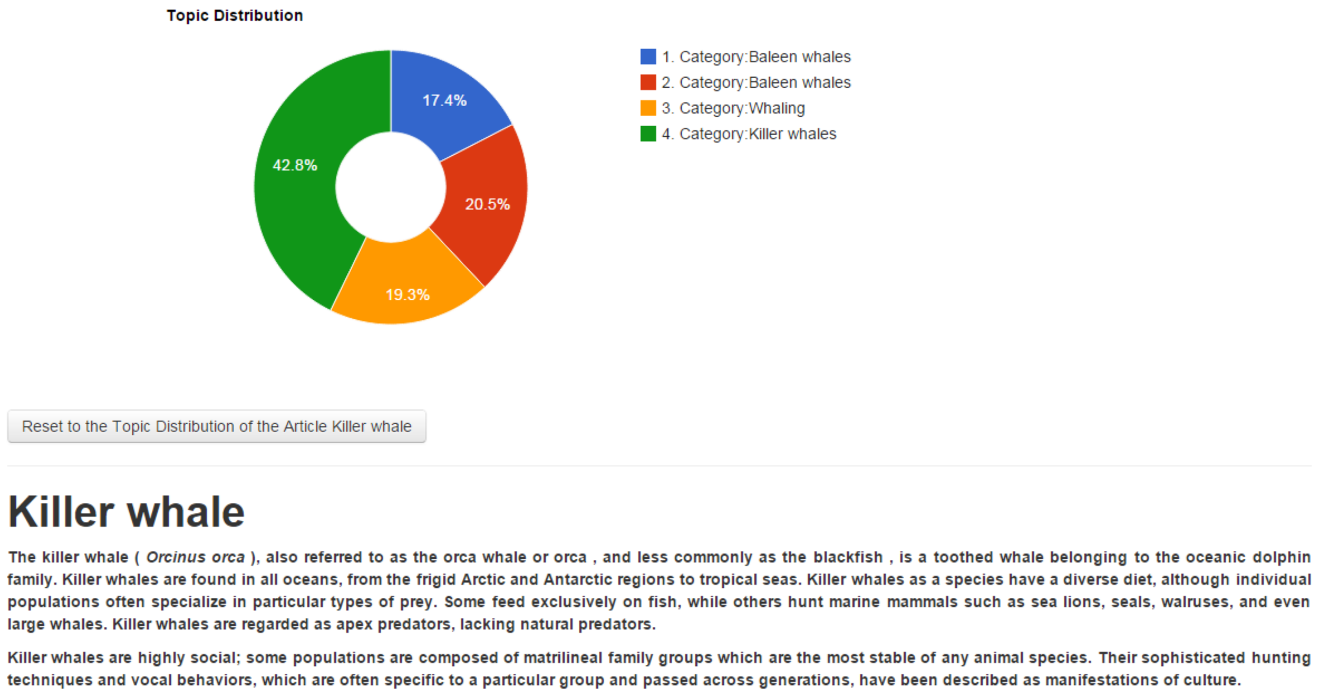
+6 information system user method based paper approach result model analysis

+7 speech recognition system method acoustic word processing signal based conference

+8 mobile system conference model international paper ieee information proceeding phone

Figure 3: The interface for examining the effect of changes to the user model on the topics.

One of the most interesting visualizations in the project is the *Graph Explore* interface which allows a user to conceptually drill down a graph of a paper and its citations in a recursive sequence. This is a common method of literature exploration; a user takes up a base paper and then reads up all the papers which have been cited in that base paper. These steps are recursively performed for each subsequent


Topic Distribution
17.4%
20.5%
19.3%
42.8%
🟦 1. Category:Baleen whales
🟥 2. Category:Baleen whales
🟧 3. Category:Whaling
🟩 4. Category:Killer whales
Reset to the Topic Distribution of the Article Killer whale

Killer whale

The killer whale (*Orcinus orca*), also referred to as the orca whale or orca , and less commonly as the blackfish , is a toothed whale belonging to the oceanic dolphin family. Killer whales are found in all oceans, from the frigid Arctic and Antarctic regions to tropical seas. Killer whales as a species have a diverse diet, although individual populations often specialize in particular types of prey. Some feed exclusively on fish, while others hunt marine mammals such as sea lions, seals, walruses, and even large whales. Killer whales are regarded as apex predators, lacking natural predators.

Killer whales are highly social; some populations are composed of matrilineal family groups which are the most stable of any animal species. Their sophisticated hunting techniques and vocal behaviors, which are often specific to a particular group and passed across generations, have been described as manifestations of culture.

Figure 5: Visualizing the topic distribution of the introduction section of the Wikipedia article *Killer Whale*. See Figure 2 for the topic distribution of the whole article.

paper until the user has found a sufficient amount of papers or they read all the papers in their collection.

The graph explore functionality allows a user to perform this in a more visually appealing manner. Once a user decides on a base paper (through any search scheme), the system shows a graph representation of its citations which are ranked based on her profile (*user model*). This will help her pursue the most relevant papers first. Clicking on any secondary paper will expand the graph further and list secondary citations ranked based on the *user model*.

Discussion and Related Work

There have been previous systems to use topic modeling as a basis of search and exploration.

A system of note is Yang et al. (Yang, Torget, and Mihalcea 2011) who applied topic modeling to collections of historical news papers to assist search. They found that the topics generated from topic models are are generally good, however once the sets of topics are generated, an expert opinion is required to name them. In *Grisham*, we allow users to select numbered topics for article-search based on topically relevant words.

Termite (Chuang, Manning, and Heer 2012) provides a visual analytic tool for assessing topic quality that allows for comparison of terms within and across latent topics. They introduce a saliency measure that enables the selection of relevant terms. For a particular topic, the system provides the word frequency distribution relative to the full corpus and shows the most representative terms according to the saliency measure.

A number of previous work (Chang et al. 2009; Mimno et al. 2011; Newman et al. 2010) depended heavily on experts examining lists of the most probable words in the topic and validating the models. Hall et al. (Hall, Jurafsky, and Manning 2008) applied unsupervised topic modeling to study historical trends in computational linguistics across 14,000 publications. The work required experts to validate the quality of the results. Only 36 out of 100 topics were retained, and there were 10 additional topics that were not produced by the model and had to be manually inserted.

Leake et al (Leake, Maguitman, and Reichherzer 2003) provide methods to aid concept mapping by suggesting relevant information in the context of topics models, represented as concept maps.

For visualizing the results, previous work (Chuang, Manning, and Heer 2012; Bertin 1983; Henry and Fekete 2007) use a matrix style view to surface the relationships between many terms. These tools are created for evaluating topic models. Interacting with such visualizations can be complex because the user should already have an intuition about the results in advance in order to properly generate necessary orderings.

Summary

We describe *Grisham*, a system for topic-based article search and exploration given a user model. This paper describes a promising search paradigm. Any researcher who would like to do exploratory search or literature reviews will find the system beneficial. We would like to perform user studies to obtain feedback on the effectiveness of the three

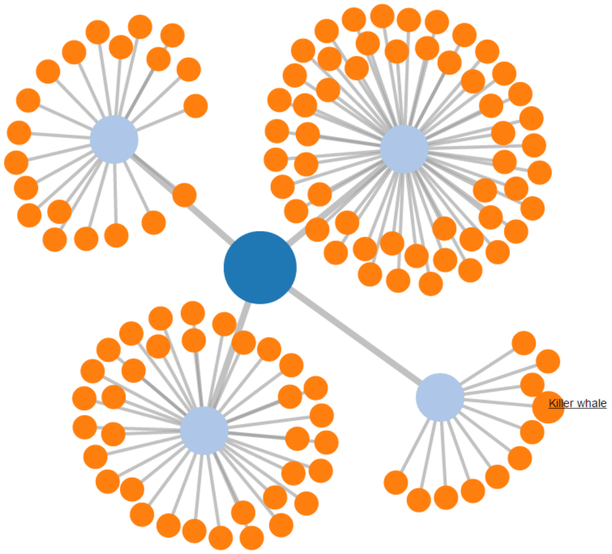


Figure 4: Visualizing *topic-based search* in *Grisham*, orange nodes represent documents and blue nodes represent the estimated topics in a corpus. For this illustration we only show four topics (light blue nodes). Topic names appear when the user hovers over a node.

search paradigms.

References

Bertin, J. 1983. Semiology of graphics: diagrams, networks, maps.

Blei, D. M.; Ng, A. Y.; and Jordan, M. I. 2003. Latent dirichlet allocation. Journal of Machine Learning Research 3:993–1022.

Bostock, M.; Ogievetsky, V.; and Heer, J. 2011. D3: Data-driven documents. IEEE Trans. Visualization & Comp. Graphics (Proc. InfoVis).

Chang, J.; Gerrish, S.; Wang, C.; Boyd-graber, J. L.; and Blei, D. M. 2009. Reading tea leaves: How humans interpret topic models. In Advances in neural information processing systems, 288–296.

Chuang, J.; Manning, C. D.; and Heer, J. 2012. Termite: Visualization techniques for assessing textual topic models. In Advanced Visual Interfaces.

Davis, J. 2013. D3: Word cloud. online.

Dou, Zhicheng and Song, Ruihua and Wen, Ji-Rong. 2007. A large-scale Evaluation and Analysis of Personalized Search Strategies. In Proceedings of the 16th international conference on World Wide Web, WWW '07, 581–590. New York, NY, USA: ACM.

Dumais, S.; Furnas, G.; Landauer, T.; Deerwester, S.; Deerwester, S.; et al. 1995. Latent semantic indexing. In Proceedings of the Text Retrieval Conference.

Geman, S., and Geman, D. 1984. Stochastic relaxation, Gibbs distributions, and the Bayesian restoration of images. IEEE Transactions on Pattern Analysis and Machine Intelligence 6:721–741.

George, C.; Wang, D.; Wilson, J.; Epstein, L.; Garland, P.; and Suh, A. 2012. A machine learning based topic exploration and categorization on surveys. In Machine Learning and Applications (ICMLA), 2012 11th International Conference on, volume 2, 7–12.

Griffiths, T. L., and Steyvers, M. 2004. Finding scientific topics. Proceedings of the National Academy of Sciences 101:5228–5235.

Hall, D.; Jurafsky, D.; and Manning, C. D. 2008. Studying the history of ideas using topic models. In Proceedings of the conference on empirical methods in natural language processing, 363–371. Association for Computational Linguistics.

Henry, N., and Fekete, J.-D. 2007. Matlink: Enhanced matrix visualization for analyzing social networks. In Human-Computer Interaction–INTERACT 2007. Springer. 288–302.

Hoffman, M.; Blei, D. M.; and Bach, F. 2010. Online learning for latent dirichlet allocation. In NIPS.

Leake, D. B.; Maguitman, A. G.; and Reichherzer, T. 2003. Topic extraction and extension to support concept mapping. In FLAIRS Conference, 325–329.

Ma, Zhongming and Pant, Gautam and Sheng, Olivia R. Liu. 2007. Interest-based Personalized Search. ACM Trans. Inf. Syst. 25(1).

Mimno, D.; Wallach, H. M.; Talley, E.; Leenders, M.; and McCallum, A. 2011. Optimizing semantic coherence in topic models. In Proceedings of the Conference on Empirical Methods in Natural Language Processing, EMNLP '11, 262–272. Stroudsburg, PA, USA: Association for Computational Linguistics.

Newman, D.; Noh, Y.; Talley, E.; Karimi, S.; and Baldwin, T. 2010. Evaluating topic models for digital libraries. In Proceedings of the 10th annual joint conference on Digital libraries, 215–224. ACM.

Porter, M. 1980. An algorithm for suffix stripping. Program: electronic library and information systems 14(3):130–137.

Řehůřek, R., and Sojka, P. 2010. Software Framework for Topic Modelling with Large Corpora. In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks, 45–50. Valletta, Malta: ELRA.

Salton, G.; Wong, A.; and Yang, C. S. 1975. A vector space model for automatic indexing. Commun. ACM 18(11):613–620.

Tang, J.; Zhang, J.; Yao, L.; and Li, J. 2008. Extraction and mining of an academic social network. In Proceedings of the 17th international conference on World Wide Web, WWW '08, 1193–1194. New York, NY, USA: ACM.

Yang, T.; Torget, A.; and Mihalcea, R. 2011. Topic modeling on historical newspapers. ACL HLT 2011 96.