Interactive Visual Exploration of Topic Models using Graphs

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\begin{abstract}
Probabilistic topic modeling is a popular and powerful family of tools for uncovering thematic structure in large sets of unstructured text documents. While much attention has been directed towards the modeling algorithms and their various extensions, comparatively few studies have concerned how to present or visualize topic models in meaningful ways. In this paper, we present a novel design that uses graphs to visually communicate topic structure and meaning. By connecting topic nodes via descriptive keyterms, the graph representation reveals topic similarities, topic meaning and shared, ambiguous keyterms. At the same time, the graph can be used for information retrieval purposes, to find documents by topic or topic subsets. To exemplify the utility of the design, we illustrate its use for organizing and exploring corpora of financial patents.
\end{abstract}

1. Introduction

Across domains, we are faced with substantial and often overwhelming amounts of textual data, which present a need for tools to aid in organizing and understanding its content. Text mining techniques are widely used to computationally model human language and extract meaning. Granted, text mining has been successfully applied in many areas, yet, the intricacies of human language constitute an ever-present challenge to computational processing of text. Human involvement is still central to the text mining process. While computational modeling can scan vast data and extract information that is likely to be interesting, humans are uniquely capable of a deeper understanding \cite{RKPW08}. Acknowledging the essential roles of both computational and human information processing in text mining, the necessity for effective communication between the two parts becomes apparent. Visualization is a highly efficient communication channel, and the two-way communication enabled by interaction supports a more intimate understanding of the underlying model \cite{War04}.

This paper is concerned with probabilistic topic modeling and visual communication of modeling results. Topic modeling algorithms are used to discover latent topics in sets of documents, as a way of uncovering thematic structure. However, visualization of topic models is still a little researched area, which we seek to explore. This answers directly to concerns voiced by one of the authors of the original probabilistic topic modeling algorithm, David M. Blei, who states that “topic models provide new exploratory structure in large collections – how can we best exploit that structure to aid in discovery and exploration?” \cite{Ble12}. He further asserts that interface questions are “essential to topic modeling”, but that “making this structure useful requires careful attention to information visualization and [...] user interfaces”.

Our contribution is a new visualization design that aims to convey the meaning of found topics in an intuitive way, through a topic cloud, as well as how topics relate to each other. It is an interactive graph visualization that connects topics and descriptive keyterms, providing both corpus overview and thematic exploration of documents. A web-based implementation is available at: http://risklab.fi/demo/topics/. We illustrate the use of this visualization design through a case, in which topics in financial patent applications are modeled and presented for exploration to support domain experts in satisfying their information needs. The lack of proper tools to organize patents has come to be a pressing problem \cite{Elm07} that we seek to alleviate through the combination of computational processing and visual interfaces.

2. Probabilistic Topic Modeling

The family of probabilistic topic modeling algorithms has emerged as a widely popular approach to analyzing thematic structure in text. Latent Dirichlet Allocation (LDA) is the
most fundamental among them, having inspired a long array of variations [BL09]. Topic modeling is applicable especially to problems where there is little prior knowledge of the content of the text, i.e., where exploratory analysis is needed. LDA infers latent topics in an unsupervised manner, based on word co-occurrence in documents, and provides interpretable output in the form of probabilities. The algorithm takes the desired number of topics as input, assumes that each document may discuss several topics and attempts to identify coherent and meaningful topics by analyzing the terms in each document. By taking the context into account, LDA can help disambiguate single words.

There are two types of relations that are interesting for the presentation of LDA results: the topic-document relations and the topic-term relations. First, LDA provides a probability distribution over topics for each document, that is, to what degree a document relates to each of the topics. In the scope of this paper, this topic-document information is useful for retrieving documents based on topics of interest. Second, LDA provides topic assignments for each term in a document. The topics provided by LDA are defined by probability distributions over terms. The elementary way of representing the meaning of a topic is through its term probabilities directly, which are based on term frequencies for the topic. Such a representation is rather uninformative to a user, as it gives high ranking to common stop words (e.g., the, a, and) and terms that are general to the whole document corpus (in the case of patents: method, system etc.); better solutions for topic presentation are discussed in Section 3.1.

3. Visualization of Topic Models

Despite the importance carried by visual representation in making topic models useful, the subject has seen limited research effort. Some tools that present topic modeling results rely heavily on text ordered in different fields, but use few visual aids to communicate structure (see, e.g., [CB12, GLL+10]). A few other notable tools can be found that use visualization more extensively, such as those by Chuang et al. [CMH12] and Gretarsson et al. [GOB+12]. Still, much room is left for further exploration of how visualization techniques can improve communication of topic modeling results, and results from text mining models in general. This exploration is also supported by Tufte’s [Tu83] design principle, to use graphics when words alone cannot communicate the message effectively, as structural information is as central to the analysis of text as semantics.

Our work extends that of Chuang et al. [CMH12], which we find to be the most promising previous example of topic model visualization. They visualize topic-keyterm relations through a matrix view, which provides some idea of topic distribution, similarities and meaning. Our approach may be seen as a graph visualization that uses a topic-keyterm matrix similar to theirs as an adjacency matrix. We argue that the force-directed graph visualization provides a view that more intuitively communicates topic similarity structure. In the following, we discuss the three main components of the interface: keyterm selection, graph representation and retrieval of documents.

3.1. Selecting informative topic keyterms

The raw topic-term probabilities provided by LDA are not suitable as a ranking to find terms that distinguish well between topics, as previously mentioned. Various measures have been proposed for reranking that provide better description of the topic meaning, such as a TFIDF-inspired term-score [BL09] and others that likewise penalize terms that are prevalent in many topics. Reranking the terms is essential to produce descriptive and distinguishing keyterms for presentation and visualization of topic meaning.

For the sake of interpretability, we use the conditional probability \( P(T|w) \) to score how distinguishing a term is of its topic. Given that a term \( w \) is observed, the probability of it belonging to topic \( T \) is a measure of how distinguishing \( w \) is of \( T \). We derive the measure as \( P(T|w) = P(w|T)P(T)/P(w) \) where \( P(w|T) \) is the term-topic probability distribution provided by LDA. The use of \( P(T|w) \) to identify informative terms is in line with [CMH12]. A threshold on the probability selects the top keyterms for each topic. Additionally, a limit on number of keyterms per topic may be enforced to avoid cluttering the visualization, or shared keyterms may be prioritized to shift focus towards topic relations rather than individual description.

3.2. Visualizing topics and keyterms as a graph

As our basic visualization technique, we use a graph with force-directed layout (using the D3 force algorithm [BOH11]). It provides a spatial metaphor for topic similarity in the corpus. The graph, as shown in Figure 1, consists of topic nodes connected to keyterm nodes only, which produces a fairly sparse graph for which force-directed layout can produce clear results. Topics are not directly connected to each other, rather only through their common keyterms. Still, the node positioning communicates general topic similarity structures, and the connecting keyterms provide qualitative detail on the nature of their relation. Visual connectedness is a strong means for communicating relationships [PR94]. The figure shows a (partial) overview of topics, where:

- the keyterm weighting is encoded by link opacity to communicate the strength of the relation
- node size is relative to the general frequency of the topic
- colors from a qualitative scale are used to better distinguish the topic neighborhoods.

Nodes can be dragged to alter their positions, which are then adjusted by the force-directed algorithm in real time. However, the automatic adjustment is slow enough to allow the
Figure 1: Overview of all topics. Topics that share keyterms are linked and reside closer, link strength represents how distinguishing a keyterm is of a topic, topic node size represents prevalence in the corpus.

user to move several nodes before a stable conformation is reached, which allows for interactive exploration of alternative locally optimal conformations and helps the user inspect the structure of the graph. Our implementation also allows zooming and panning to support exploration of many topics even on smaller screens.

The meaning of a topic is represented by the keyterms linked to it, each with the weighting discussed in the previous section. While the initial view of Figure 1 provides an overview of all topics, focusing on a single topic by hovering highlights its details, as in Figure 2. Highlighting fades all parts of the graph not connected to the topic to preventively direct the user and ease their inspection, in other terms, it provides context plus focus [CMS99]. The topic-specific term weighting can now also be encoded through keyterm font size, which enables simultaneous reading of term meaning and importance. Similar to a tag cloud, this creates an easy-to-read topic cloud.

Some terms are shared among topics, which hints at their ambiguity. Ideally, a topic represents a meaningful context in which a term is used, through which the sense of the term is made clear. Hence, two topics sharing a term, as seen in Figure 3, might indicate that the term holds two different meanings in the corpus. Handling such ambiguity is a central purpose of topic models, but simple topic representations do not facilitate identification of such patterns by the user, while visualization easily can.

3.3. Finding documents by topic and keyterm
As the graph displays only topic nodes and a limited set of keyterm nodes, but no document information, it acts as an abstracted topical view of the corpus. All document information is accessible only through interaction, which means that scaling the corpus size does not affect the visualization.

By double clicking on nodes, any number and type of nodes can be selected to function as anchors for the underlying documents. This mechanism is used to drill down on the documents related to interesting topics, keyterms or their combinations. The titles of the documents are listed in a side panel linking to the full texts. Both focusing on nodes and selecting them follow the visual information seeking mantra [Shn96], by filtering information and providing details on demand, about topics, keyterms or related documents. Selecting a topic node ranks documents linked to it according to LDA’s topic-document distribution. Selecting a keyterm node of \( w \) ranks documents \( d \) according to \( P(d|w) \). The documents are ranked according to the joint probability when multiple nodes are selected.

4. Case: Visualizing Topics in Financial Patents
An example of abundant text data causing problems are patents. In particular, financial patents (or business method patents) have witnessed an explosion in numbers, referred to as the patent flood [Meu02], which has resulted from a decline of business method exception to patentability due to court decisions. It has led to the issuance of low-quality
patents, which further obstructs effective prior art search, creating uncertainty among inventors or would-be commercializers of innovations [Hal09]. The situation has directed considerable research effort in information retrieval towards patent search [TT11], which still, nevertheless, relies on visual analysis only to a very limited extent.

We demonstrate how topic modeling and our proposed visualization design could provide effective means for organizing and visualizing financial patents, by analysing a sample of 3954 abstracts of patent applications filed between 2001 and 2011. The patents are classified by the U.S. Patent and Trademark Office (USPTO) under patent subclass 705/35 defined as finance (e.g., banking, investment or credit). As a basic example, we construct a topic model consisting of 10 topics, for which an overview is shown in Figure 1. It is immediately clear that topic T1 is the most frequent in the corpus (largest node size) and that it is thematically central to the corpus (well connected to other topics and positioned near the center). The user can visually browse the structural properties of the model, and compare the prevalence, centrality and semantics of topics. While the keyterms function as initial guidance in browsing, they can be challenging to read in the more densely populated areas of the graph, and a focused view is required to ease their inspection. Figure 2 demonstrates this focused view on topic T3, with the rest of the graph faded in the background as visual context. It is now easy to interpret that T3 represents patents about loan services by reading its highlighted keyterms, weighted by how distinguishing they are of T3. For instance, we also identify T6 to discuss authentication systems. It is the task of the domain expert to infer meaning and higher-level descriptions for the topics, to further differentiate them and decide what best answers to their information needs. Topic modeling and our presentation is helpful as it can provide a more granular organization than the USPTO classifications.

The graph can be used to further explore the corpus, at the more detailed level of keyterms. As Figure 3 illustrates, the term mobile connected to T3 can be highlighted, upon which its connection to T6 is easier to identify. This view communicates that mobile is used in two senses in the corpus: in the contexts of loan services and authentication systems. This offers the user the possibility to disambiguate the term in search for related documents. By selecting T3 and mobile, patents mentioning mobile in the sense of T3 are found, ranked and presented to the user. This mechanism turns the visualization into a tool for information retrieval, not only for high-level browsing of the corpus.

5. Conclusions
We have discussed a new visualization design for presenting LDA models using graphs, in terms of topic structure and meaning, while retaining a certain level of abstraction. Its use is demonstrated by modeling the topics in a set of financial patent abstracts, where it can aid information search problems. We focused explicitly on model exploration, assuming the modeling results are satisfactory, although, real-world use of topic models requires assessment of model
quality by domain experts. Continued studies of this type of visualization should consider that topic modeling results are seldom perfect and the implications that might have on interface design.

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