

# Visualizing Topic Models Generated Using Latent Dirichlet Allocation

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**Abstract**—Topic Modeling is a set of statistical methods used to find "topics" in a given document corpus, where a *topic* is defined as a word distribution. Topic Modeling opens the doors to a set of interesting questions such as the various topics in documents & which documents are associated which kinds of topics. One of the problems with statistical methods is that the word distributions generated may not be interpretable by the user. Our project, *LDAExplore*, discusses the visualization designed, to look at topic models and how the user can interact with these statistical methods and provide feedback to improve the underlying model. Latent Dirichlet Allocation (LDA) is one of the basic methods to find such hidden topics that has been used in the project. To validate our design, we have used the *abstract's* of 322 *Information Visualization* papers, where every abstract is considered a *document* and generated topics which are then explored by users.

**Index Terms**—DataViz, InfoViz, LDA, Latent, Dirichlet Allocation, Parallel Coordinates, Treemap, Topic Modeling.

## 1 INTRODUCTION

A large body of human knowledge has traditionally been stored in the form of documents. These documents maybe in the form of books, magazines, journals. With the advent of the digital age, more and more content is stored digitally and with the cloud computing becoming increasingly common, we stored a lot of information online. We have websites that present this knowledge online in the form of HTML pages and are looking at this information being presented on mobile platforms such as IOS and Android in the form of apps. This growing knowledge base brings with it a unique set of challenges such as searching through a large set of documents for a specific piece of information, grouping similar documents together, looking at how these documents and their underlying content change over time. These changes could be the common theme or the language that is utilized in these documents.

*Topic Modelling* tries to automate the process of extracting topics from documents and annotate them with semantic information [2]. It is a set of statistical algorithms that extract correlated words from documents. These extracted word sets are called *Topics*. They are later annotated with semantic information, so that they are easily understood by people. For e.g. consider a word set extracted such as *visualization*, *sets*, *clusters*, *infoviz*, *interfaces* from a document then we have a general notion that this word set represents the topic *Information Visualization*. In this example, the "topic" generated using a topic modelling algorithm is the word set and *Information Visualization* is the semantic "topic name" annotated by the user. Latent Dirichlet Allocation (LDA) [1] is one of the common methods to perform topic modelling

on a given corpus of documents.

LDA generates viz. two types of distributions i.e. the topic distribution for each document in the set and the word distribution for each topic. The model works by computing the joint probability distribution of the words in each document to group words which appear together and form a single topic. These distributions can be changed by tweaking the underlying parameters. Our project, *LDAExplore*, tries to give visual cues about how these distributions look, and how the topics and documents are interrelated at the corpus level and for groups or individual documents. Also, it gives the users the ability query documents for specific words based on topics and see how correlated a topic is to a document. Some of the main concerns while creating the design are that visual should be able to work with a large set of documents while providing the ability to see individual and group relations. The number of topics, though, is considered to be a smaller set as compared to the number of documents.

## 2 RELATED WORK

There are quite a few ways of looking that the problem of how to represent distributions to show their interrelations. Some of the methods include looking at distributions graphs or sets [5]. In these visualizations, the distributions are converted to sets transforming them to a hierarchy of nodes. A standard technique to represent sets is to create an *Euler* diagram [5] or a variant of it. Region-based overlays can be used such as *Bubble Sets* and *Texture Splatting* or Line-based overlays like *LineSets* and *Kelp Diagrams* [5]. Some of the other methods include *Node-Link* diagrams and *Force-Directed* graphs. Standard Node-link diagrams include *Jigsaw*, *Anchored maps* and *PivotPaths*. These design patterns invariably limit the number of nodes that can be represented

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in a visual without applying some aggregation method which clusters nodes or edges together.

Topic-based, interactive visual analysis tool (TIARA) [3] shows topic distributions across documents across time. This helps users understand how content changes across time. *RoseRiver* is another analytics system to used to visualize how topics evolve [6]. The system uses a tree cut approach with a combination of a word cloud. The word cloud is a standard method to show a word set with word sizes varying according to their frequency (or probability). Higher frequency (or probability) words are given a larger size in the word cloud.

One of primary problems with topic modelling methods is that the "topic" generated by them, may not have clearly understood by the user. Sometimes, the words in the topic do not form a coherent group together, giving the user no idea of the larger (latent) topic. One of the solutions to this problem, is to introduce a human-in-the-loop paradigm where users can interact with the algorithm, providing feedback such that the underlying model can be modified to generate "better" or semantically correct topics. One example of such a system is *UTOPIAN* [7], which uses a force-directed graph to represent topics.

### 3 DESIGN CONSIDERATIONS

#### 3.1 Task Analysis

As described in the previous section, results after performing topic modelling, can be unintuitive. There are two basic requirements our project tries to achieve. The first is to provide the novice users ability the ability to understand the a method like LDA. The other is to provide advanced users with the options to explore the document set. This project provides the base design to achieve these goals while to keeping the design open, so that featured identified in the future can be added. *LDAExplore* is a visual tool that is designed to explore topics, their word distributions and the relations that exist between topics and documents. Following are the set of tasks which form the basis for our design.

##### 3.1.1 Visualize Topics

LDA generates a set of topic, each having its own individual word list. Each word has a probability of being associated with the topic. When the user interacts with a specific topic the relative importance of words will be displayed. This is one way for the user to identify an important topic.

##### 3.1.2 Overview of Document - Topic Relations

Once the user has a generic idea of how the topic look, user can then focus on the documents and topics correlations. The main purpose is to be able to see which topics have a higher density of documents, while which topics have a lower density. The density of documents gives the user an idea which topics are more or less important.

##### 3.1.3 Remove Topics from the Visual

When the user knows which topics are important, the rest of the visual can de-cluttered by removing excess topics from the visual.

#### 3.1.4 Filtering Documents

When the size of the corpus is large, the user will likely try to understand only a subset of the documents. Hence the user will filter the documents based on various criteria:-

- 1) The IDs of the documents. This will be helpful, if the user is aware of what documents are there in the corpus.
- 2) By top words in each document that associated with the topics having the highest probability of being related to the document.
- 3) The user may not know the documents, but may be able to identify some based on the *name* or *title* of the document. Thus, the user can filter out individual the documents.

#### 3.1.5 Perform set operations

While working with groups of documents, the user intuitively performs set operations such as *include* and *exclude*. *Include* gives the user, the ability to add a filtered set of documents to future filters. *Exclude* does the exact opposite, which is to remove the document set from any filter operations in the future. Once the document corpus has been explored, the user can export the filtered data for any post processing that is performed separately.

#### 3.1.6 Show & Cluster Similar Topics

To cluster documents which have a similar topic distribution.

#### 3.1.7 Cluster Documents & Display Topics

To display topics related to the clustered documents.

#### 3.1.8 Perform Cluster Operations

To allow operations on clusters such as merging & splitting of clusters which change the topics clusters or document clusters accordingly.

#### 3.1.9 Annotating Topics

Annotation of topics and documents / clusters.

### 3.2 Prototype Design

#### 3.2.1 Data Abstraction

#### 3.2.2 Task list and how they are performed

## 4 SYSTEM OVERVIEW

## 5 CASE STUDY

## 6 CONCLUSION

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