

# Latent Dirichlet Allocation for scientific topic extraction

Ivan Savov

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## Abstract

We learn a topic model from a large collection of scientific articles using Latent Dirichlet Allocation. The data set is the entire pdf contents of the Cornell Physics pre-print archive arXiv.org for the **quant-ph** category. We represent each document as an array of word counts from a fixed dictionary of size  $W = ?$ , which we determined by

We display the discovered topics and incorporate them into a rudimentary recommendation system.

**keywords:** LDA, topic model, collapsed variational bayes, domain knowledge,

## 1 Introduction

When I first learned about Latent Dirichlet Allocation I was totally amazed by the seemingly magical ability of this algorithm to automatically discern the topics underlying a collection of documents. Since then I have been thinking about how I can apply this method to

## 2 The model

LDA

## 3 The algorithm

First we begin by defining some quantities

We have the document set  $\mathcal{D} = \{d_1, d_2, \dots, d_D\}$ , where each document consists of a word count vector for the words taken from a fixed vocabulary  $\mathcal{W}$  of size  $W$ .

Our aim is to produce a set of topics  $\mathcal{T}$

$\gamma_{wjk}$ :  $= Pr(z = k | x = w, d = j)$ , the probability that word  $w$  in document  $j$  is assigned to the topic  $k$ .

$N_{wj}$ : # of times  $w$  appears in doc  $j$ .

$N_{wk} = \sum_{j \in \mathcal{D}} N_{wj} \gamma_{wjk} = \#$  of times  $w$  appears in topic  $k$ .

$N_{kj} = \sum_{w \in \mathcal{W}} N_{wj} \gamma_{wjk} = \#$  of times topic  $k$  appears in doc  $j$ .

$$N_k = \sum_{w \in \mathcal{W}} N_{wk} = \sum_{w \in \mathcal{W}} \sum_{j \in \mathcal{D}} N_{wj} \gamma_{wjk} \text{ \# words assigned to topic } k.$$

$$N_j = \sum_{k \in \mathcal{T}} N_{kj} = \sum_{k \in \mathcal{T}} \sum_{w \in \mathcal{W}} N_{wj} \gamma_{wjk} \text{ \# words in doc } j.$$

## 4 The data set

The good people who run the arXiv.org were kind enough to send me the entire collection of papers in the `quant-ph` repository. The papers contain nearly all the research in the physical sciences that is not particle physics.

```
ivan@flicker:/scratch/arxiv$ du -sh *
7.1G    pdf
2.1G    tex
ivan@flicker:/scratch/arxiv$ find pdf/ -type f | wc
31739   31739   730019
ivan@flicker:/scratch/arxiv$ find tex/ -type f | wc
21061   21061   470945
```

The `pdf/` directory contains the pdf versions of the papers and for some of these papers. For about 2/3 of these we also have the latex source code in the `tex/` directory.

Some more information about the dataset:

- Total number of documents: 31739
- Earliest date: 22 Dec 1994 (`pdf/9412/9412002v1.pdf`)
- Most recent: 30 Mar 2007 (`pdf/0703/0703278v1.pdf`)

### 4.1 Intended pre-processing

I plan to use the command `pdftotext` to convert the pdf documents to text files and then use the standard bag-of-words paradigm for each document.

I will do a first pass on the documents and remove stopwords. Given how large of a dataset is available I will try to run my algorithm without stemming in order to capture as much of the granularity of the data. If this proves to be ineffective then I will use stemming.

## 5 Project proposal

I will read the original 2003 paper by Blei, Ng and Jordan [?] and also perform a general literature review on topic models. In particular, I want to verify the results of the ICML09 paper [?] which state that all the different models of training LDA are equivalent and only differ by the setting of the hyper-parameters.

I will try to implement the Collapsed Variational Bayes technique of [?].

The results I would like to obtain is some meaningful cluster structure over the scientific topics.

## 6 Next steps

I will need to move the data to powerful workstation where I can do the pre-processing of the documents and perform the word counts.

Then, I must look into the algorithm which I will use for training.

## 7 Questions

## 8 Other ideas

### 8.1 Regular expressions

This could be a study of what you can do with different features. We can have as higher level features counts from regular expression matches. These features can themselves be refined over generations or by cross validation.

Come to think of it you can do all kinds of things with this. Regular expressions of the form "quantum (mechanics—physics)" for compound words that are synonymous.

Algorithm: Self-refining regular expression features

1. Start with word counts for a fixed list of words of size  $|W|$  and do regular LDA.
2. For each of the latent topics build all "two word" combinations.
3. Rerun LDA on the expanded feature space of size  $|W|^2 + |W|$ .
4. Find the important second order occurrences and discard all other features.
5. Try to compress multiple variations using regular expression language.  
Example: "a b", "a c", "a d" can be converted into regex "a (b—c—d)"
6. Go to step 3 but now number of features is  $|W| + \text{n\_of\_good\_reg\_exes}$

I am not sure if this will generate all possible word occurrences but I think reg-exes are pretty rich as feature set and their computation is all parallelizable so it doesn't matter if it is very expensive.

Can we let some genetic algorithm work on this instead?

### 8.2 Two data set correlations

You browse wikipedia about quantum informaiton topics and it suggests papers that are most similar to the subject — not so useful.

Maybe the opposite is better, as you browse the arXiv you get suggested links to articles on wikipedia that cover similar topics.

### 8.3 This paper covers

User interface idea: papers laid out on a table in such a way that the papers that cite each other overlap. All papers in the same "epoch" are visible at the same time and placement and paper size indicates relative importance.

(One way to think about this is where are the words of this each topic passed on from one generation to the next)

### 8.4 CUDA CUDA CUDA