# Latent Dirichlet Ideas

Ivan Savov

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**Abstract**

During the last semester I worked on a small research project on the LDA topic model on a dataset of scientific documents. I feel my project has just scratching the surface of what is a fascinating subject which has plenty of interesting research topics to be explored. I also want to develop *practical* applications and demos that show what LDA can do.

**keywords:** LDA, topic model, Gibbs sampling, applications, hierarchical

## 1 Introduction

Topic models have received a lot of attention recently in the machine learning community [BNJ03, BL09]. This simple graphical model based on the multinomial distribution for word frequencies and its prior the Dirichlet probability density function has been acclaimed for its ability to magically find groups of words that seem to belong to the same subject matter.

The original model has been studied by several authors, and different techniques of inferring the probability distributions have been developed like collapsed variational Bayes [TNW07], Gibbs sampling [PNI$^+$08] and others [AWST]. Computational considerations have also been studied with several results about modifying the inference algorithms to scale [NSS06, NASW07] and to fit different hardware paradigms [MHSO09, YBQ].

The basic topic model of LDA has also been extended to involve hierarchical topic structures (hLDA [BGJT04]), authors and citations [RZGSS04], and many other variations [WWHB09, MM07, BGBZ07]. These LDA-inspired models are often more computationally intensive to learn, but often provide a natural match to a specific task.

On the applications side, we have had JSTOR search and categorizations [BL09], subject classification of newsgroups data and Google News. There hasn't been much research conducted on large datasets to my knowledge. No one has learned a topic model for the whole of wikipedia for example despite the fact that 5GB of text data (the current approximate size of wikipedia) can probably be crunched using a small number of machines.

Given my fascination with topics models, I feel like I should take a more active approach and actually code something up and run experiments instead of passively reading papers in order to keep up with what others have done.

More specifically, here is a list of tasks that I would like to accomplish during the next year.

1. Understand better the underlying principles that make LDA work. [arbilon, exp family, ]
2. Explore the "topic landscape" defined between topics by the K-L distance $KL(p_{t_1}(w \in Dict),\ p_{t_2}(w \in Dict))$.
3. Explore consistency of learned topics over multiple runs on the same data. (quality of matching between topics of different runs based on K-L distance)
4. Explore the topic landscape defined between topics from runs with different number of topics, i.e. which subset of topics from a $T = 100$ run are most similar to the first topic from a run with $T = 20$.
5. Produce a python library for automating LDA experiments (liblda). (preprocessing, word counts, dictionary generation, pluggable inference algorithms in C).
6. Write an inference algorithms that makes use of hardware acceleration in video cards.
7. Write a parallel inference algorithm for the LDA model that can be run on clusters.

# 2 Tasks

## 2.1 Theory

In order to place LDA in its historical context I think I should first learn about LSA, its precursor. Then, I want to re-read the latest version of the LDA review paper by Gregor Heinrich [Hei05], which is an amazing resume and discussion of LDA from first principles and with lots of details. Also I want to learn about the exponential family in general and more background material about the variational inference principles [WJ08].

## 2.2 Topic maps

distance between topics of the same run
visualization ?

## 2.3 Consistency

Evaluation of topic models have been difficult.

How similar are the topics extracted from a document collection between different runs of the inference algorithms. Are the topics extracted similar for Gibbs sampling and CVB based inference ? Play with $\alpha, \beta$ parameters on priors [Hei05, WM09].

To study this we want to repeat the approach in [ ?? ] which performs the Hungarian-algorithm for matching on the topics extracted from different runs. They claim to have about 80% of topics match between different runs.

## 2.4 Hierarchical topics

topic subtopic relationship ...

## 2.5 `liblda.py`

In order to run the experiments for .. pre-processing in python LDA C programs by Newman [New].

If I am going to be working on this project I need to cleanup the code. I want to refactor the whole code base into a self contained python library `liblda` with a simple API.

[Sav].

The user writes edits a config file which explains where the document collection lives and then the uses two-three simple commands to run an LDA experiment.

The results will be available (they already are kind of) as numpy arrays, so that more complex algorithms can be build on top of the basic LDA operations.

I want to follow the ideas of "loose coupling" and allow to swap out components like the underlying inference algorithm.

## 2.6 Parallel LDA

One aspect that I did not get a chance to look into deeper is the use of parallel algorithms for inference of the LDA model. One approach is to modify the Gibbs sampling or variational methods to permit loosely coupled parallel operation [NSS06, NASW07].

## 2.7 LDA on the GPU

Another approach is to use GPU based computation which is highly parallel and vectorized. CUDA (Compute Unified Device Architecture) is a simple API which allows for GPU programming on NVIDIA grpahics boards. The speedups reported are very impressive [MHSO09, YBQ].

# 3 Other less clear ideas

## 3.1 Regular expressions counts

In text analysis we invariably use word counts as the main "features" of documents. Since we have the full power and flexibility of python during the preprocessing stage, we could use instead regular expressions as features.

For example we could quantify how many matches to the reg ex "`H(.*)`" there are in each document. Certainly, for papers that deal with information theory this will be a highly informative feature.

Another possible use of regular expressions is to have a digram model with synonyms taken into account. For example we could count how many matches there are to this reglar expression "`quantum (mechanics|physics)`" instead of trying to keep track of the two options separately.

## 3.2 Two data set correlations

I have not seen in the literature any discussion about using LDA to automatically create links between two data collections. For example if we trained a topic model on wikipedia articles AND the arXiv, we would be able to automatically generate meaningful links between the two. As you browse the arXiv you could get suggested articles from wikipedia that cover similar topics.

## 3.3 Citation graph

One simple further step that can be taken to make use of the arXiv topic model is to extract the citation graph amongst the paper. This can be done with another regular expression of the form `quant-ph\d{7}` or from some third party source like Citeseer.

Having the citaiton graph would allows us to do a "page rank" type of calculation and extract a sense of importance for the papers in each topic.

## 3.4 Metadata

We should have the titles for each of these articles I think we need a little urllib2 script to get each of `http://arxiv.org/list/quant-ph/0003?show=1000` where 0003 corresponds to my folder 0003

I feel this is more of a beginning than an end to this project. I have gotten acquainted with the software and the data set and hopefully I can produce some worthwhile results in the coming months. All the source code and results associated with this project are available here [Sav].

# 4 Applications

In order to show off the power of LDA there should be

## 4.1 ArXiv browser

In particular I would like to use the extracted topics in order to develop an automated recommendation system or a "topic filter" which would help me keep track of which papers are posted on the arXiv every day that are relevant to my topics of research.

Other approaches for visualization and evaluation of topic models are suggested in [BGCG$^+$09].

## 4.2 Topic extraction as a service

Use our word counter and vocabulary picker, then just send us your count vectors. preserves privacy

## 4.3 Autotagging

run topic model,
present to user for him to tag topics,

apply these tags systemwide to all documents

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