Latent Dirichlet Allocation for scientific topic extraction

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December 16, 2009

Abstract

We experiment with an automated topic extraction algorithm based on a generative graphical model. Latent Dirichlet Allocation assumes that individual words that appear in a document collection are drawn form a family of distibutions associated with a fixed number of topics. We automatically learn these word-topic distributions from a collection of 20000 physics journal articles: the fulltext of the `arXiv.org/quant-ph` preprint archive between the years 1994 and 2007. We evaluate our results using the perplexity measure on the document collection.

keywords: LDA, topic model, Gibbs sampling, clustering

1 Introduction

There is a growing amount of unstructured data becoming freely available on the web and through various digitizaiton efforts. Due to the enormous scale of these data collections it is unrealistic to assume human supervision can play any significant role in their classification and curatorship. Clearly, automated largely-unsupervised machine learning techniques will be required in order to deal with the information oveload.

The subjects of classification, retreival and browsing have been central topics of research in the data mining community for the past decade, but there is still more work to be done. Recently, there has been a surge of interest in the machine learning community about "topic models" which attempt to automatically extract the subject matter from document collections [BNJ03, BL09]. These techniques are scalable to very large document collections and produce very informative results despite using the same old data mining paradigm of representing each document as bag of words.

For this project we will focus our attention on the *latent Dirichlet allocation* (LDA) model which is described in the seminal paper by Blei, Ng and Jordan [BNJ03]. We will use a Gibbs sampling approach to learn the LDA parameters which is very computationally efficient [GS04]. Computaitonal efficiency will be important since our data set contains rougly 20k documents and which are represented as word counts of over a dictionry of 10k words.

This report is structured as follows. In the next section we will provide some theoretical background on the LDA model. Afterwards, we will discuss the inference procedure we used to learn the model parameters. Section **??** is describes our data set and the preprocessing we performed. We descirbe the results of two experiments in seciton **??** and follow up with a some discussion and a conclusion.

2 The model

Terms to discuss MAP, PLSA, VB, CVB0 etc... LDA

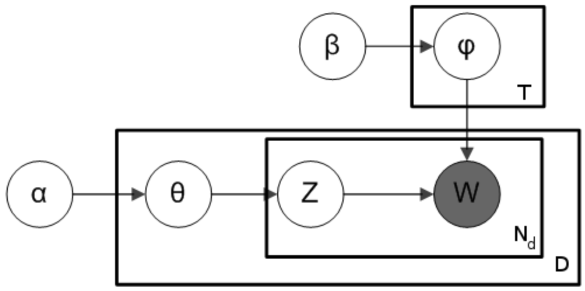

Figure 1: The graphical model behind LDA. θ is the distribution of topics for a document, β is the distribution of words for a given topic.

3 The inference algorithm

First we being by definiting some quantities

We have the document set $\mathcal{D} = \{d_1, d_2, \ldots, d_D\}$, 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 $\mathcal{T}$ where each topic is a probability distribution over words $\mathcal{W}$.

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

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

To achieve this we will have to learn...

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 arXiv is a prominent publication in the physicsl sciences and contains pre-print versions of most of the important research in several areas. Of particular interest is the field of quantum information science which is very well represented.

The raw data that was received consists of two directories. The first directory, `pdf/` of size 7.1GB condains 31739 pdf documents. The second directory `tex/` contains the

LaTeX source code of some of the papers (its size is 2.1G and it contains 21061 files). Since the source code of only about 2/3 of the papers was available, we decided to use the pdf version of the document collection.

Some more information about the raw dataset.

- Total number of pdf files: 31739
- Total number of papers: 20166 (multiple versions v1,v2)
- Number of files with unreadable/foreign fonts: 6
- Earliest date: 22 Dec 1994 (pdf/9412/9412002v1.pdf)
- Most recent: 30 Mar 2007 (pdf/0703/0703278v1.pdf)

4.1 Textual pre-processing

Since the intended feature vectors are word counts, we used the command-line utility `pdftotext` (part of `xpdf`) to convert the pdf documents to text files. The python script `preprocessing/pdftotext.py` accomplishes this and stores the output in the folder `data/text` while at the same time creating an inventory of all the available documents. At this stage, some documents were found to be unreadable or used foreign language fonts which were not recognized by xpdf. There were very few such documents so it was possible to manually remove them from the inventory.

At this point we had 31732 documents in our "inventory", but some of these documents were different version of the same underlying paper (ex: `9412002v1.pdf`, `9412002v2.pdf`, etc.). We therefore ran `dupremover.py` which kept only the latest version. After this step, the total number of papers in our data set decreased to 20166.

Before we can perform any word counts, however, we had to deal with a typographical issue. Ligatures are linkages between the letters f, l and i in high quality fonts. Since LaTeX uses the computer modern fonts which have ligatures, the document collection was full of them. For example, when I write the word "affluent" it will not be treanlsated into the sequence of characters a,f,f,l,u,e,n,t but instead turn into a,ﬄ,u,e,n,t where ﬄ is a single unicode character. Can you see the difference between ﬄ and ffl? In order to deal with this issue, I did a preliminary pass using `makewordstream.py` expanding all ligatures to their consitituent letters. While I was at it, I also converted all words to lowercase ASCII.

4.2 Dictionary selection

The next step was to select a subset of all the words that occur in the document collection for which we will perform word count. I first pass was made on the documents to remove a standard list of stopwords (see `stopwords.py`). Given how large the dataset is we did not feel it was necessay to use word stemming; this way we can capture as much of the granularity of the data as possible.

The total number of unique words of 3 character or more at this step was 67075, and contained lots of non-words like "ijk", which probably refer to matrix indices. While 60k words is not an unreasonable dictionary size, it was deemed too large for our purposes and an effort was made to cut down on the dictionary size. The script `makevocab.py` goes through the word stream and counts total number of occurences for each word. It then rejects all words that occur less than 45 times in the corpus. We also impose a minimum occurence threshold of 10000, 6000 and 2000 for three, four and five letter words respectively.

The final pre-processing step selects the top 10011 words by overall frequency and stores it in the file `vocab.txt`. This figure was inspired by the paper [BL09], where they use a vocabulary of this size on a document collection roughly similar to our own.

4.3 Sparse matrix format

The input data that the `topicmodel` program expects is in a standard sparse matrix format which is generated by the script `Makedocword.pl`. The resultting file `docword.txt` contains one row for each unique word in each document. For example, consider the following exerpt:

```
#docword.txt
...
34 376 6
34 6767 5
...
```

These two lines indicate that the document with id=34 contains 6 occurences of word 376 and 5 occerences of word 6767. This is the standard bag-of-words paradigm for each document.

The following list summarizes the important details of the finalized data set at the stage when it is read to be fed to the Gibbs sampling inference algorithm.

- Size of vocabulary: $W = 10011$
- Total number of documents: $D = 20166$
- Total number of words in corpus: $N = 41202148$

5 Results

The natural application of topic models is the automated extraction of topics from the data set. Given that we have learned the

Another, more scientific method for evaluating the performance of a topic model is to calulate the perplexity.

$$pplex(\mathcal{D}) = \exp\left(-\frac{1}{N} \sum_{1}^{N} \log P(w_n|d_n) \right), \tag{1}$$

See how to classify new documents. Calculate perplexity and KL distance for different runs with same parameters

5.1 Informal evaluation of extracted topics

list them all....

5.2 Number of topics

5.3 Gibbs sampling chain length

Compare for different NITER and Ntopics The

I will read the original 2003 paper by Blei, Ng and Jordan [BNJ03] and also perform a general literature review on topic models. In particular, I want to verify the results of the ICML09 paper [AWST] 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 [TNW07].

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

run it and time it
check memory usage as it runs

6 Discussion and future work

6.1 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 $|W|$+ n_of_good_reg_exes

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

Can we let some genetic algorithm work on this instead?

6.2 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.

6.3 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)

6.4 CUDA

6.5 Citaiton graph

We can use a simple reg-ex to match things like
`quant-?ph\d{7}` and extract all citations to other papers on the archive. It won't be very complete, but you can still extract a sense of importance from it ! page rank ;)

7 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

8 Conclusion

We have demonstrated that

References

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