Latent Dirichlet Analysis (LDA) is a method used to model the generative process of creating discrete data such as text corpora. This model aims to capture the structure embodied by the word, document, and topic in text documents as well as other environments. LDA can take a large amount of data and create descriptions of that data. This method reduces the size of the data to these short descriptions while still maintaining the relationships necessary to carry out various inferences. The algorithm assumes a generative process for the creating of documents in a corpus D using N words. The topic for a particular word, $z\_n$, is modeled as Multinomial($\theta$), where $\theta \sim Dir(\alpha)$. Then, each word, $w\_n$, is chosen from a multinomial probability that is conditioned on the topic $z\_n$, P($w\_n | z\_n, \beta)$. (footnote for paper, pg. 996)

LDA is most well-known for its application in the analysis of text data. It is used to create topics for documents, classify documents based on these topics and to determine which documents are similar to one another. The algorithm can also be used in other problems that have a similar structure to the document generating method described above. For example, in Blei et.al, 2003, the authors used a data set where web site users provide information about movies they enjoy. In this example, the users are analogous to the documents and their preferred movies are “words”. Topics can be found by determining similar movies.

There are multiple alternative algorithms that can be used for text analysis. These include the term-frequency inverse-document-frequency matrix, latent semantic indexing (LSI) and the probabilistic latent semantic indexing (pLSI) model. In Section 7 of the paper, the authors present the results of document modeling and document classification. In this section, the authors’ results show that their implementation of LDA performs better than competing methods in terms of perplexity measure, where better generalization performance is defined by a smaller perplexity measure.

Perplexity measure is defined as:

\begin{center}

Exp(-\frac{\sum\_{d=1}^M log p(\textbf{w}\_d}{\sum\_{d=1}^M N\_d})

\end{center} (PUT THIS IN FOOTNOTES?)

In addition, this section demonstrates that other methods are prone to overfitting. As the number of topic increases, some of the alternative algorithms induce words that have small probabilities. This occurs because the documents in the corpus are divided into more collections. This can result in the perplexity measure becoming very large for these alternative algorithms. The problem comes from the requirement that the topic proportions in a future document must be seen in at least one of the training documents. On the other hand, LDA does not have this overfitting problem. For more detail, see Section 7 of Blei et al.

On the other hand, there are disadvantages of LDA as well. To begin with, LDA does not allow words to be assigned to multiple topics. Therefore, if LDA determines three topics for a corpus of documents, such as football, baseball and basketball, it would not be possible to assign a relevant word, such as sports, athlete, etc., that should be classified for topics. Another disadvantage of LDA is that exact inference of the posterior is impossible as a result of intractability. Thus, it is necessary for the user to implement an approximating technique such as variational inference, a Gibbs sampler, or another technique.

**References**

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