A fully Bayesian view of Latent Dirichlet Allocation

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Abstract

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1 Introduction

2 Related work

3 A conjugate prior for the Dirichlet distribution

4 Fully variational Bayes for Latent Dirichlet Allocation

5 Experiments

In order to evaluate our model we ran experiments over three corpus to compare the typical LDA and his formulation with Boojum prior . We used a 20 news groups dataset, a nips 2012 set of articles and a the reuter50 corpus. Each of them were divided into a training and test set corpus with a ration 80-20 percent respectively. We fit both a classical LDA model and the extented LDA using the training set. The test set was used to assert to convergence of the training phase by computing the perplexity of the model. To compute it we follow a fold-in procedure and use the approximation in (Asuncion, 2009) to compute the perplexity. Hence the topic-word distribution is fit on the learning set and the document-topic distribution is evaluated on the testing set, thus the perplexity of the model is computed as follow:

$$\log p(x^{test}) = \sum_{dw} N_{dw} \log \sum_{k} \hat{\theta}_{kd} \hat{\phi}_{wk}$$

$$perplexity(x^{test}) = \exp(-\frac{\log p(x^{test})}{\sum_d Nd})$$

Preliminary work. Under review by AISTATS 2016. Do not distribute.

Each inference procedure was run over 50 iterations and reproduced 10 times to provide a stability measure. Therefore, the figure shows the mean perplexity for each run and his variance.

6 Discussion

Acknowledgements

Use unnumbered third level headings for the acknowledgements. All acknowledgements go at the end of the paper. Be sure to omit any identifying information in the initial double-blind submission!

References

Asuncion, Arthur, et al. "On smoothing and inference for topic models." Proceedings of the Twenty-Fifth Conference on Uncertainty in Artificial Intelligence. AUAI Press, 2009.