Scalable Topic Modeling: Online Learning, Diagnostics, and Recommendation

FINAL REPORT

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REPORT

The main activity of my research group is to build and develop the probabilistic pipeline. When solving problems with data, we take the following steps.

1. We make assumptions about our data, embedding it in a probability model containing hidden and observed random variables.

2. Given observations, we use inference algorithms to estimate the conditional distribution of the hidden variables. This is the central statistical and computational problem.

3. With the results of inference, we use our model to form predictions about the future, explore the data, or otherwise apply what we learned to solve a problem.

4. We criticize our model, understand where it went right and wrong, and repeat the process to revise it.

The pipeline cleanly divides the essential activities of data analysis and facilitates collaborative solutions to data science problems. Building models and using them are activities that require domain experts: They tell us what kinds of assumptions they want to make, and how they want to use the results of what we might discover from their data. Inference is a computational and statistics problem. Given the assumptions and data, the problem of estimating the conditional distribution is a well-defined mathematical problem. Model checking and application again requires the domain expert, who can identify what to expect and which areas of the problem are important to success.

For this project, we developed many aspects of this pipeline, particularly around scalable online learning, model checking, and recommendation systems. More broadly, we worked on computational algorithms for fitting models (scalable learning), algorithms for aiding domain experts to build models (model checking),
and real-world applications to test our ideas (recommendation). We went beyond the scope of the proposal in several ways, exploring applications as diverse as neuroscience, sociology, and genetics.

All of our research results are listed at the end of this report. I will highlight several publications of note.

The first is “Stochastic Variational Inference” (JMLR, 2013); this paper scaled up modern Bayesian computation, allowing us to fit many complex models to massive data. In one way, it is the culmination of this project.

The second is “Black Box Variational Inference” (AISTATS, 2014). While stochastic variational inference scaled Bayesian computation up to massive data, black box variational inference expands the scope of scalable Bayesian computation to models that were previously too difficult to work with.

Both of these algorithms, in retrospect, have had a significant impact. They are widely cited and widely implemented in open-source software packages. Many of our other publications for this project adapted these ideas including, notably, a paper in Proceedings of the National Academy of Sciences (Gopalan et al., 2013) on analyzing massive social networks.

Finally, I point out “Build, Compute Critique, Repeat: Data Analysis with Latent Variable Models” (Annual Review of Statistics, 2014). This is a review article that outlines the full perspective of modern applied probabilistic modeling, including inference, model checking, and applications.

Overall, this project was a success. Between 2011 and 2014, my group has significantly pushed the needle on modern Bayesian machine learning. We have developed new and impactful algorithms, stretched its scope to new applications, and further developed the craft of iterative criticism and model-building.

**Refereed Journal Articles**


**Refereed Conference Articles**


35. C. Wang and D. Blei. Collaborative topic modeling for recommending scientific articles. In *Knowledge Discovery and Data Mining*, 2011. **Best Student Paper Award.**


