Generalized Variational Inference

This paper introduces a generalized representation of Bayesian inference. It is derived axiomatically, recovering existing Bayesian methods as special cases. We use it to prove that variational inference (VI) with the variational family Q produces the uniquely optimal Q-constrained approximation to the exact Bayesian inference problem. Surprisingly, this implies that VI dominates any other Q-constrained approximation to the exact Bayesian inference problem. This means that alternative Q-constrained approximations like Expectation Propagation (Minka, 2001; Oppeer & Winther, 2000) can produce better posteriors than VI only by implicitly targeting more appropriate Bayesian inference problems. Inspired by this, we introduce Generalized Variational Inference (GVI), a modular approach for instead solving such alternative inference problems explicitly. We explore some applications of GVI, including robust inference and better approximate posterior variances. Lastly, we derive a black box inference scheme and demonstrate it on Bayesian Neural Networks and Deep Gaussian Processes, where GVI substantially outperforms competing methods.

Refreshments will be served following the seminar in 1181 Comstock Hall.