Abstract

Variational algorithms are popularly used as an alternative to Markov chain Monte Carlo sampling to approximate posterior quantities in Bayesian inference. Variational inference proceeds by identifying a family of analytically tractable variational distributions, and the variational solution is obtained by minimizing Kullback–Leibler divergence to the true posterior distribution. Despite their popular usage, a general theory quantifying the quality of point estimates thus obtained is missing. We introduce a novel class of variational Bayes algorithms involving an inverse temperature parameter and study frequentist properties of point estimates obtained from the proposed variational objective function. We demonstrate that standard procedures, such as mean-field variational Bayes, lead to optimal point estimates in various models without and with latent variables.