DAVID NOTT, **National University of Singapore**
Conditionally Structured Variational Gaussian Approximation with Importance Weights

We develop flexible variational inference methods for models with complex latent variable structure, such as generalized linear mixed models and state space models. Our approach first splits the variables in these models into ”global” parameters and ”local” latent variables. Variational approximations are then defined sequentially, through a marginal density for the global parameters and a conditional density for local variables given global parameters. Each term in our approximation is Gaussian, but we allow the conditional covariance matrix for the local parameters to depend on the global parameters, which leads to an approximation that is not jointly Gaussian. The approximations are motivated by the fact that in many hierarchical models there are global variance and dependence parameters which determine the scale and dependence structure of local latent variables in their conditional posterior given the global parameters. We also consider parsimonious parametrizations by using conditional independence structure, and improved estimation of the log marginal likelihood and variational density using importance weights. These methods are shown to improve significantly on Gaussian variational approximation methods for a similar computational cost. (Joint work with Linda Tan and Aishwarya Bhaskaran.)