MCMC Diagnostics

- **Mixing:** implies that the posterior is being explored efficiently. A chain with better mixing can be shorter and still provide accurate estimates of posterior quantities (e.g., posterior mean, variance, or credible intervals) with fewer samples. Mixing is related to autocorrelation or how dependent one sample is to the previous sample. Chains with poor mixing are often highly autocorrelated. For well-specified models, longer chains minimize the influence of poor mixing on inference. Somtimes mixing can be improved by adjusting the proposal distribution in Metropolis-Hastings, in Gibbs sampling there's nothing to change other than the model. Sometimes poor mixing can be an indicator of a poorly specified model (e.g., a model with non-identifiable components).

- **Thinning:** since Markov chains are inherently correlated, the tradition has been to "decorrelate" them by subsampling systematically (e.g., keeping only every 10th sample). Recent literature suggests that inappropriate amounts of thinning reduces the chain sample size so much in practice that posterior quantitites are better estimated without thinning. Link and Eaton (2012) provide a few very limited examples of where problems can occur.

- **Burn-In:** MCMC theory says that starting values don't affect inference. However, in practice, with finite computing time, it may take a while for the chain to reach the stationary distribution. View trace plots to visually assess burn-in period and truncate samples accordingly.

References

Link, W.A. and M.J. Eaton. (2012). On thinning of chains in MCMC. *Methods in Ecology and Evolution*, 3: 112-115.