STAT 578: Advanced Bayesian Modeling

Week 7 – Lesson 1

Sampling with Markov Chains

Fall 2019

Dependent versus Independent Sampling

Recall: We seek to randomly draw posterior-distributed variates

$$\theta^1, \quad \theta^2, \quad \ldots, \quad \theta^S$$

to approximate various Bayesian tools.

Simulation methods based on independent sampling

- Are limited to special cases, or
- Are effective only in low dimensions, or
- Require special tailoring for efficiency (time-consuming).

Now allow samples

$$\theta^1, \quad \theta^2, \quad \ldots, \quad \theta^S$$

each drawn from the posterior but not independently.

Advantage: Admits a wider variety of simulation methods, including some that work well for complicated or high-dimensional models

Disadvantage: Usually requires more samples for a given accuracy

A dependent sample can be used to approximate Bayesian tools in the same way as an independent sample:

- Sample averages approximate posterior expectations.
- Sample quantiles approximate posterior quantiles.
- Forward sampling can approximate posterior predictive distributions.

Monte Carlo standard errors are usually larger than in independent case.

The most common methods generate a sequence of variates

$$\theta^1, \quad \theta^2, \quad \ldots, \quad \theta^S$$

with a **Markov property**: θ^s is conditionally independent of all other variates, given the adjacent variates (θ^{s-1} and θ^{s+1}).

We call the sequence a **Markov chain**. Using it for simulation is called **Markov chain Monte Carlo (MCMC)**.

JAGS and similar software packages implement forms of MCMC.