MCMC SAMPLERS

- Metropolis–Hastings algorithms (broad class of samplers, very general).
    - Most methods in the wild are some flavor of this.
- Reversible Jump MCMC (used in many phylogenetic packages).
    - Allows for posterior distributions with variable dimensionality.
- Usable non-mcmc methods: R-INLA - integrated nested Laplace approximation.
    - Great for structural equation modeling, much faster for some classes of models.

- Gibbs samplers.
  - Mostly surpassed, but still in wide use.
  - Can sample discrete parameters.
  - Requires particular types of priors.
  - Software: WinBugs, Bugs, Jags…
- Hamiltonian Monte Carlo samplers
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  - Can fit dynamic models using differential equations.
  - Software: PyMC3, Edward, Stan (rethinking engine)...

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WHAT MAKES THESE SAMPLERS DIFFERENT?

Basically the transition proposal distribution

$$P(\theta_{i+1} \mid \theta_i)$$

$$\downarrow$$

$$\theta_1 \to \theta_2 \to \theta_3 \to \theta_4 \to \cdots$$

We can visualize what is going on with different samplers:

https://chi-feng.github.io/mcmc-demo/app.html