

# Reproducible workflows

- Reports from .R files
- e.g. 04\_5\_bootstrap\_p-value.R

# Main points McElreath Ch8

- **MCMC**: Monte Carlo Markov Chain
- Series of random numbers where each number **depends** on the previous one
- Sample less from low probability areas; more bang for your random buck
- Algorithms
  - Metropolis-Hastings
  - Gibbs sampling
  - **HMC**: Hamiltonian Monte Carlo
- We'll mostly use HMC

# MCMC algorithms

- Get an intuition for their behavior:
- <https://chi-feng.github.io/mcmc-demo/app.html#HamiltonianMC,standard>

# Bayesian tools

- Stan
  - Gelman group
  - Hamiltonian Monte Carlo
  - Betancourt (2017) A conceptual introduction to Hamiltonian Monte Carlo (<https://arxiv.org/abs/1701.02434A>)
  - open source
  - models with continuous parameters only
  - state of the art
- <http://mc-stan.org>

# Bayesian tools

- BUGS (Bayesian inference Using Gibbs Sampling) (and Metropolis-Hastings)
- <http://www.openbugs.info>
- Older, original standard tool for MCMC
- Exceedingly difficult to run on Mac
- Several newer tools are based on BUGS code style
- Lots of books and publications use BUGS
- Recommend: don't use anymore

# Bayesian tools

- JAGS (Just Another Gibbs Sampler)
- <http://mcmc-jags.sourceforge.net/>
  - cross platform, open source
  - basically the same as BUGS
  - often faster
  - highly recommended for models that can't be fit in Stan (e.g. discrete parameters)
  - easy install
- Best to run from R
  - Install R2jags package (install from R)

# Main points McElreath Ch8

- Using HMC via [Stan](#) to fit models
- Now getting posterior samples from HMC
- First use `map2stan` in `rethinking` to do HMC to follow examples. Same syntax as `sampost` or `map`
- [rstanarm](#) does the same
  - Stan group's linear models package
  - syntax like `lm`

# Main points McElreath Ch8

- **rstanarm** also uses Stan, HMC
  - Stan group's linear models package
  - syntax like `lm`
  - default priors

## **map2stan or sampost**

```
m1 <- map2stan(  
  alist(  
    y ~ dnorm(mu, sigma),  
    mu <- a + b*x,  
    a ~ dnorm(0, 100),  
    b ~ dnorm(0, 10),  
    sigma ~ dcauchy(0, 2)  
  ),  
  data=d1)
```

## **rstanarm**

```
m1 <- stan_glm(y ~ b, data=d1)
```



# Main points McElreath Ch8

- Good choice of priors (**weakly informative**) can be helpful to tame model fit
  - e.g. **Half-Cauchy** instead of uniform
- Look at MCMC **diagnostics** to judge convergence of fit
  - $\hat{r}$ ,  $n_{\text{eff}}$
  - plot chain traces ("time series")
- **Visualize** posteriors
  - histograms, pairs plot

# Chains

Random  
starts

