

# MCMC Sampling and JAGS

FW8051 Statistics for Ecologists

Department of Fisheries, Wildlife and Conservation Biology



Learning objectives:

- Gain insights into how MCMC sampling works
- Be able to implement your first Bayesian model in JAGS

Will borrow from...

## Markov Chain Monte Carlo in program **MARK**

Gary White, Ken Burnham & Evan Cooch

In our moose sighting example, we could determine the posterior distribution using calculus.

In many cases, there will be no closed form solution to:

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# MCMC

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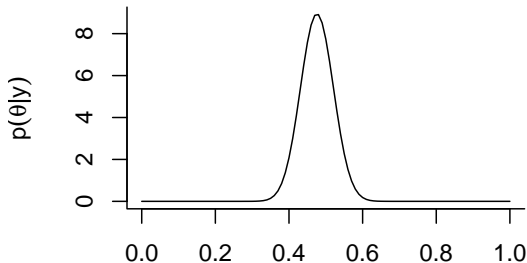
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MCMC = Markov Chain Monte Carlo is a way to draw a sequence of random variables that will converge in distribution to  $p(\theta|y)$

# MCMC Sampling

Goal: generate samples that we can use to summarize the **posterior distribution**,  $p(\theta|y)$



- Once we have these samples, we can estimate  $\theta$  by the mean (or median) of the samples.
- We can compute credible intervals using quantiles of the samples.

# Samplers

There are a variety of MCMC algorithms and samplers. We are going to consider 1 approach to gain some general insights into how these methods work.

# Metropolis Algorithm

$$p(\theta|y) = \frac{L(y|\theta)\pi(\theta)}{\int_{-\infty}^{\infty} L(y|\theta)\pi(\theta)}$$

Consider two possible values of  $\theta = \{\theta_1 \text{ and } \theta_2\}$ . Without the denominator, we cannot evaluate  $p(\theta_1|y)$  or  $p(\theta_2|y)$ .



# Metropolis Algorithm

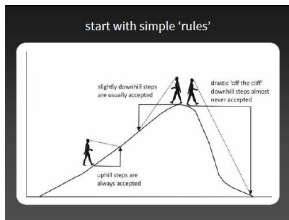
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We can, however, evaluate the relative likelihood of  $\theta_1$  and  $\theta_2$ :

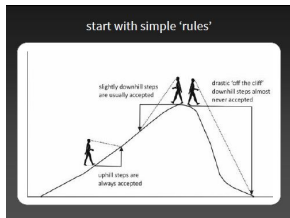
$$R = \frac{p(\theta_2|y)}{p(\theta_1|y)} = \frac{L(y|\theta_2)\pi(\theta_2)}{L(y|\theta_1)\pi(\theta_1)}$$

# Metropolis Algorithm



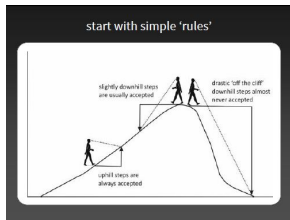
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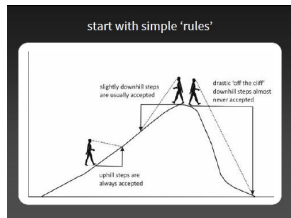
1. Initiate the Markov chain with an initial starting value,  $\theta_0$
2. Generate a new, proposed, value of  $\theta$  from a symmetric distribution centered on  $\theta_0$  (e.g.,  $\theta' = \text{rnorm}(\theta_0, \text{mean} = 0, \text{sd} = 1)$ ).

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3. Decide whether to accept or reject  $\theta'$ :
  - If  $R = \frac{p(\theta'|y)}{p(\theta_0|y)} > 1$ : **Accept** and set  $\theta_1 = \theta'$

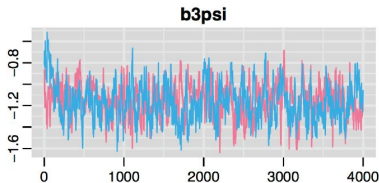
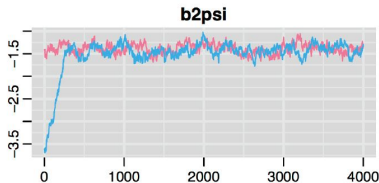
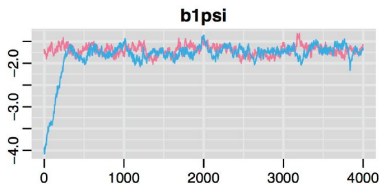
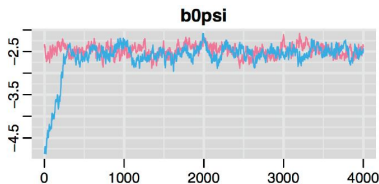
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  - If  $R = \frac{p(\theta'|y)}{p(\theta_0|y)} > 1$ : **Accept** and set  $\theta_1 = \theta'$
  - If  $R < 1$  accept  $\theta'$  with probability =  $R$ . Otherwise (i.e., if reject), set  $\theta_1 = \theta_0$
4. Back to step 2, and ...

Continue to sample until:

1. The distribution of  $\theta_1, \theta_2, \dots, \theta_M$  appears to have reached a steady state (i.e., reached **convergence**).
2. The MCMC sample,  $\theta_1, \theta_2, \dots, \theta_M$  is sufficiently large to summarize  $p(\theta|data)$



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There are no foolproof methods for detecting convergence.  
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- Discard the first  $n_{burnin}$  iterations (where the sampler has not yet converged)
- Calculate the Gelman-Rubin Statistic,  $R_{hat}$  = compares variance of between chains to within chains
  - Values near 1 suggest likely convergence
  - Should be less than 1.1 (general rule)

# Details

- With Metropolis or Metropolis-Hastings, need to consider how to generate good proposals
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JAGS will attempt to determine how best to sample once we give it a likelihood and set of prior distributions (one for each parameter).

# JAGS

Steps:

- Specify prior distributions and the likelihood of the data.
- Call JAGS from R to generate samples.
- Evaluate whether or not we think the samples have converged in distribution to  $p(\theta|y)$
- Use our samples to characterize the posterior distribution,  $p(\theta|data)$

# T-test

Mandible lengths in mm:

- 10 male and 10 female golden jackals
- From British Museum (Manly 1991)



```
males<-c(120, 107, 110, 116, 114, 111, 113, 117, 114, 112)
females<-c(110, 111, 107, 108, 110, 105, 107, 106, 111, 111)
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Do males and females have, on average, different mandible lengths?

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Do males and females have, on average, different mandible lengths?

$$H_0 : \mu_m = \mu_f$$

$$H_a : \mu_m \neq \mu_f$$

Likelihood:

- $y_{males} \sim N(\mu_m, \sigma^2)$
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- JAGS and WinBugs represent a normal distribution as  $N(\mu, \tau = 1/\sigma^2)$ ,  $\tau$  is called the **precision**



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Priors:

- $\mu_m \sim N(100, 0.001)$
- $\mu_f \sim N(100, 0.001)$
- $\sigma \sim \text{Uniform}(0, 30)$

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It is a good idea to check whether:

- your posterior looks different from your prior (i.e., if it was “informed by the data”)
- the posterior appears to have been constrained by your prior distribution
- your results change if you use a different prior

# JAGS

JAGS/BUGS (hereafter JAGS) code looks just like R code, but with some differences:

- JAGS code is not executed (just defines the model)
- Order does not matter (prior before likelihood, likelihood after prior, etc)

# JAGS

There are 6 types of objects

1. **Modeled data** defined with a  $\sim$  (“distributed as”). For example  $y \sim$  followed by a probability distribution. The variable  $y$  here is the response in our regression model.
2. **Unmodeled data**: objects that are not assigned probability distributions. Examples include predictors, constants, and index variables.
3. **Modeled parameters**: these are given informative “priors” that themselves depend on parameters called hyperparameters. These are what a frequentist would call random effects. We won’t consider till later in the course.
4. **Unmodeled parameters**: these are given uninformative priors. [So in truth all parameters are modeled].
5. **Derived quantities**: these objects are typically defined with the assignment arrow,  $<-$
6. **Looping indexes**:  $i, j$ , etc.

# JAGS

Types of objects for JAW example

1. Modeled data = **males, females**
2. Unmodeled data = **nmales, nfemales**
3. Modeled parameters (none in this example)
4. Unmodeled parameters = **mu.male, mu.female, sigma**
5. Derived quantities = **tau, mu.diff**
6. Looping indexes: **i** (used twice)

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Start simple, then build up.



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Lots of good tricks and tips in the Appendix of Kery's Introduction to WinBugs for Ecologists, especially:

Numbers: 2, 3, 4, 9, 11, 12 (use %T% in JAGS), 14, 16, 17, 20, 23, 24, 25, 26, 27

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Googling error messages is often useful for diagnosing problems.

Work with `12-BayesMCMC.R` to fit your first model in JAGS