

# Slice sampling and JAGS

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*Based on material by Søren Højsgaard*

## Slice sampling

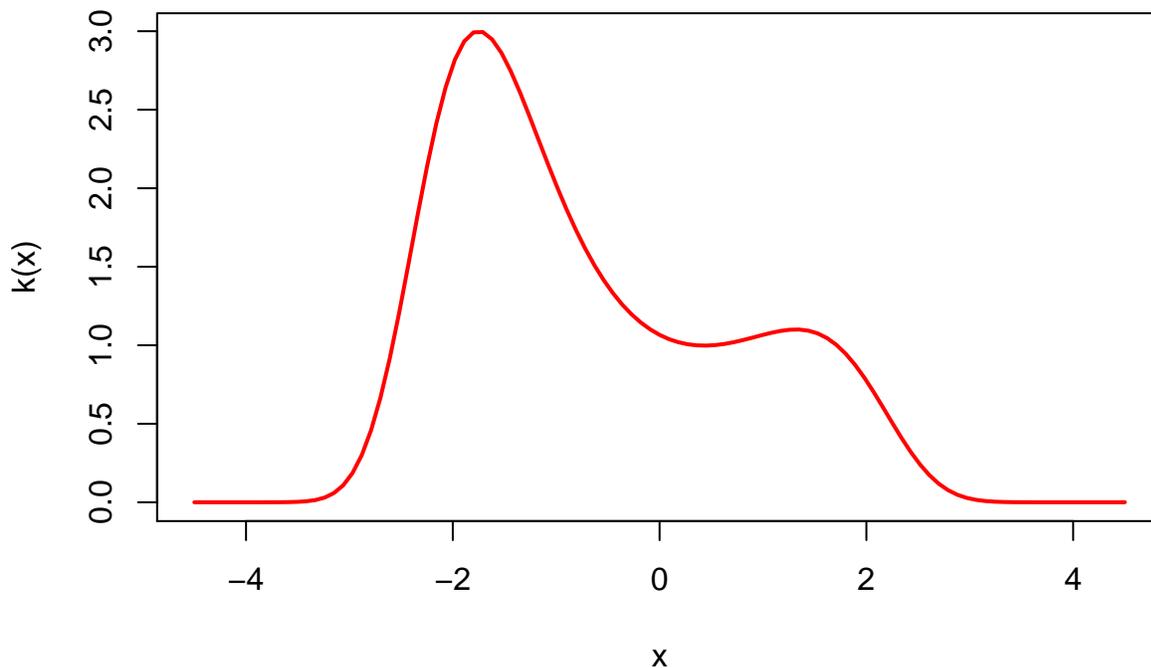
Suppose we want to sample from  $p(x_i|x_{-i})$  where  $x_{-i} = (x_1, \dots, x_{i-1}, x_{i+1}, \dots, x_K)$ .

Since  $x_{-i}$  is fixed we can regard  $p(x_i|x_{-i})$  as a function of  $x_i$  alone; call this function  $k_i(x_i)$  and recall that  $k_i(\cdot)$  is an unnormalized density.

Slice sampling is a simple approach for sampling from an unnormalized density.

---

```
k <- function(x, a=.4, b=.08){exp( a * (x - a)^2 - b * x^4)}  
curve(k(x), from = -4.5, to = 4.5, lwd=2, col=2)
```

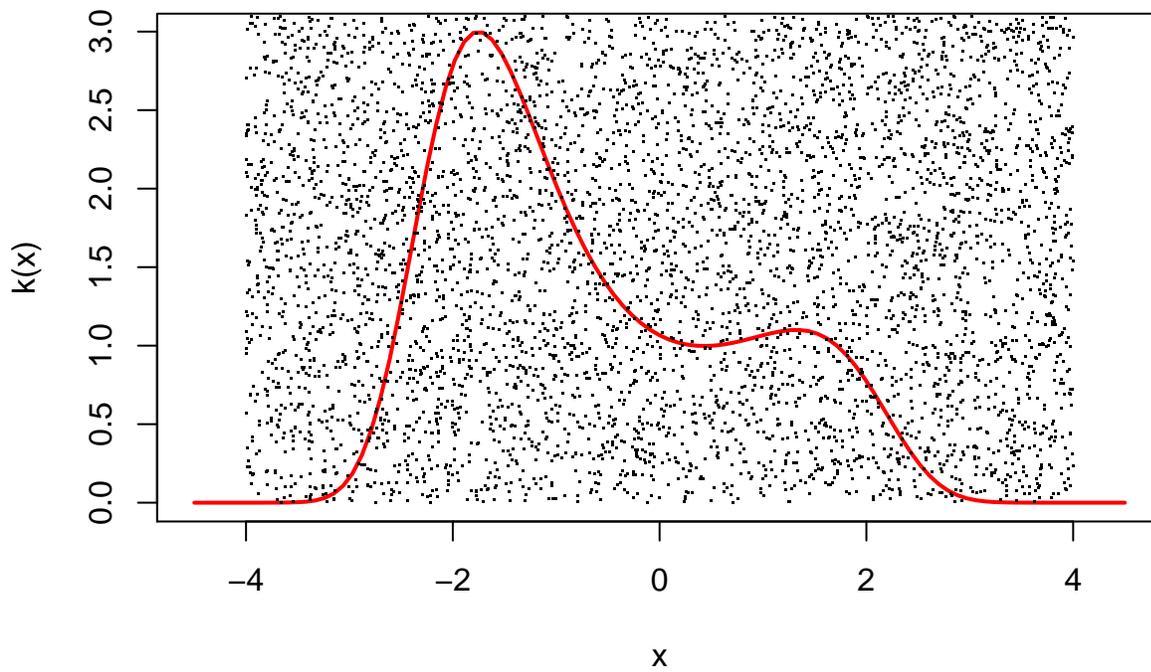


Notice:  $k(\cdot)$  is practically zero outside  $[-4, 4]$  and in this interval  $k(\cdot)$  takes values in, say  $[0, 3]$ .

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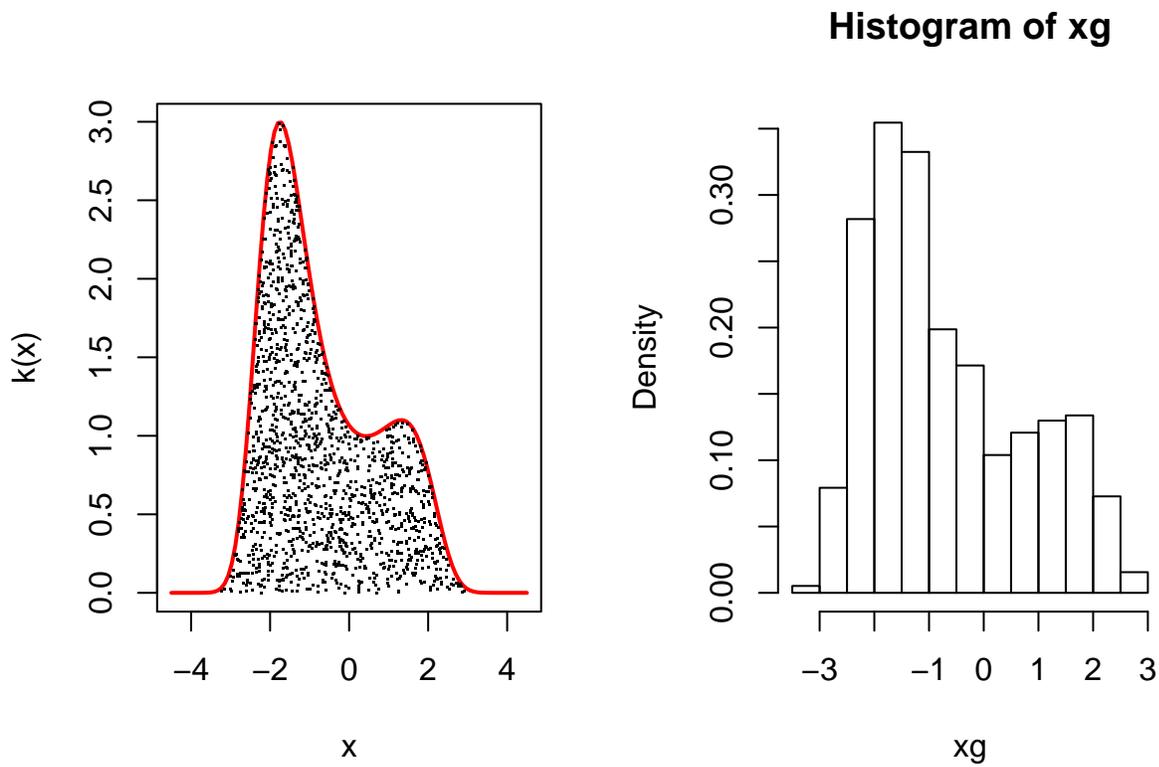
Slice sampling is based on the following idea: Sample uniformly in a “large enough” window:

```
N <- 5000  
xs <- runif(N, -4, 4)  
ys <- runif(N, 0, 3.1)  
curve(k(x), from = -4.5, to = 4.5, lwd=2, col=2)  
points(xs, ys, pch=".")
```



Keep those samples that fall under the curve.

```
good <- ys < k(xs)
xg <- xs[good]
yg <- ys[good]
par(mfrow=c(1, 2))
curve(k(x), -4.5, 4.5, lwd=2, col=2)
points(xg, yg, pch='.')
hist(xg, prob=TRUE)
```

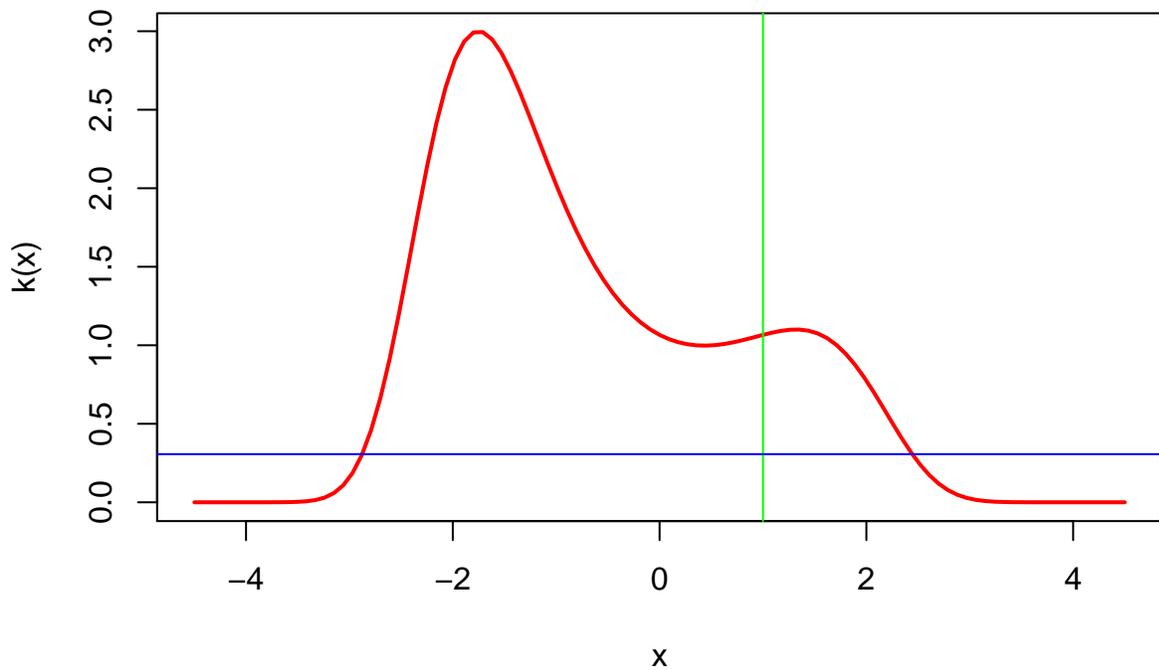


Algorithm goes as follows: Given sample  $x^t$ . Pick  $y$  uniformly in  $(0, k(x^t))$ .

```

set.seed(123)
xt <- 1; y <- runif(1, 0, k(xt))
curve(k(x), -4.5, 4.5, lwd=2, col=2)
abline(v=xt, col='green'); abline(h=y, col='blue')

```



Let set  $S = \{x : k(x) \geq y\}$  of  $x$ -values for which  $k(x)$  is larger than  $y$ . Sample  $x^{t+1}$  uniformly from  $S$ .

---

- Sample  $y$  uniformly from  $(0, k(x^t))$ . This  $y$  defines a horizontal “slice”  $S = \{x : k(x) \geq y\}$ .
- Find interval  $I = [L, R]$  containing all (or much) of the slice.
- Sample  $x^{t+1}$  uniformly from the part of the slice within  $I$ .

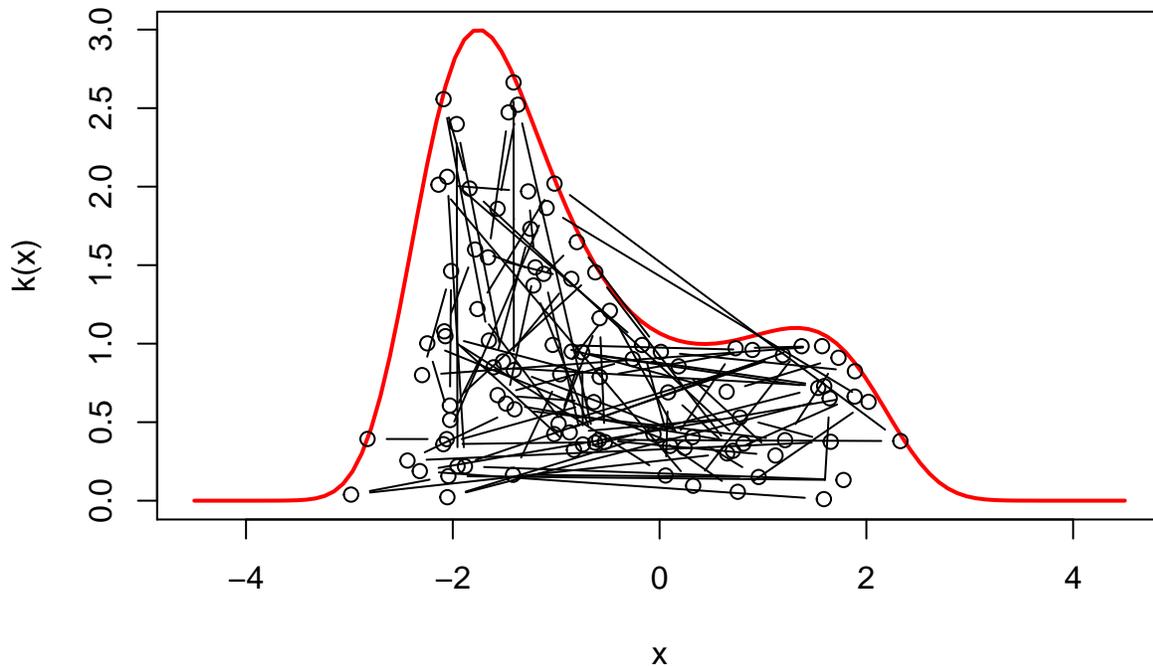
Various strategies exist for step two, but in any case it is problematic if the target is multimodal.

---

```
slicesample <- function(k, xc, w){
  kc <- k(xc)
  y <- runif(1, 0, kc)
  a <- runif(1) ## place w randomly around xc
  l <- xc - a*w
  u <- xc + (1 - a)*w
  kl <- k(l)
  while (kl > y){ ## expand interval to the left if necessary
    l <- l - w; kl <- k(l)
  }
  ku <- k(u)
  while(ku > y){ ## expand interval to the right if necessary
    u <- u + w; ku <- k(u)
  }
  xp <- runif(1, l, u) ## propose xp
  kp <- k(xp)
  while(kp < y){ ## shrink interval if possible
    if (xp < xc) l <- xp else u <- xp
    xp <- runif(1, l, u)
    kp <- k(xp)
  }
  return(list(x=xp, y=y))
}
```

---

```
N <- 100
y <- out <- rep(0, N)
x <- 1
for (i in 1:N){
  rslt <- slicesample(k, x, w=1)
  x <- rslt$x
  y[i] <- rslt$y
  out[i] <- x
}
curve(k(x), lwd=2, col=2, from = -4.5, to = 4.5)
lines(out[-N], y[-1], type = "b")
```



## Towards omnibus software

- With the slice sampling method, it is now clear why general purpose software can be constructed.
- JAGS (Just Another Gibbs Sampler) is one example of such software (another is STAN).
- JAGS builds on the BUGS language from WinBUGS (Windows only).
- From the WinBUGS website at Cambridge University:

The programs are reasonably easy to use and come with a wide range of examples. There is, however, a need for caution. A knowledge of Bayesian statistics is assumed, including recognition of the potential importance of prior distributions, and MCMC is inherently less robust than analytic statistical methods. There is no in-built protection against misuse.

## JAGS

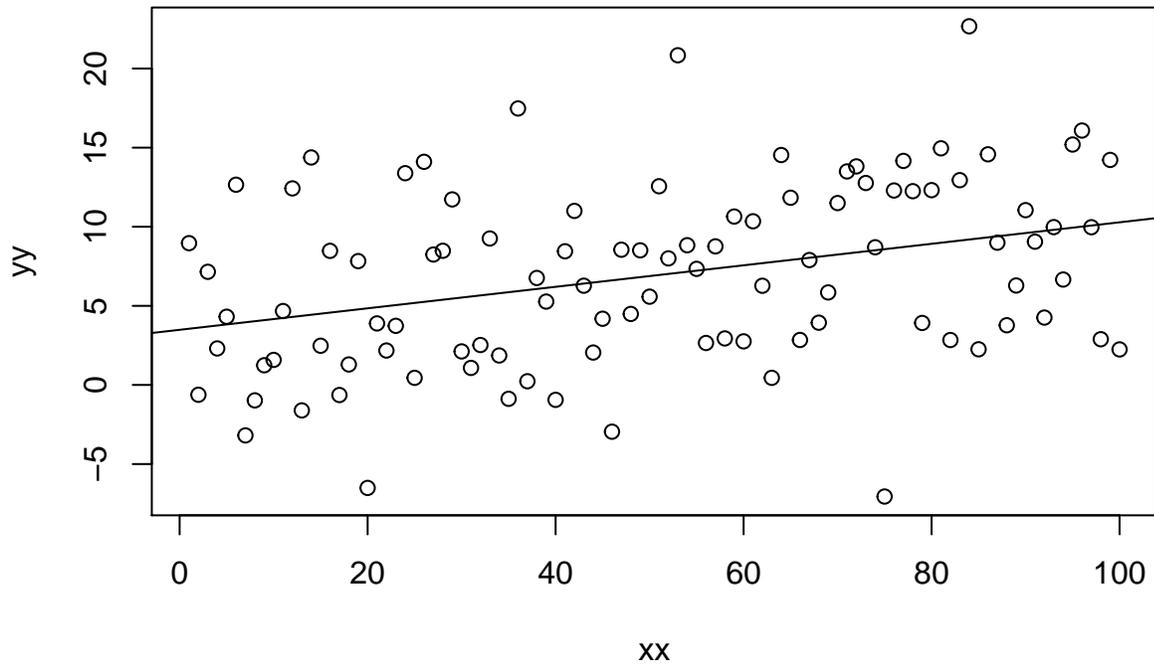
In JAGS you need to

- specify a model in a text file (can be written on the fly in R);
- supply the data;
- supply initial values (optional);
- compile the model;
- run the sampler;
- profit :-)

## Linear regression in JAGS

Let's do a Bayesian analysis of simple linear regression with the following fake data:

```
xx <- 1:100
yy <- rnorm(length(xx), 2+.1*xx, sd = 5)
plot(xx, yy)
abline(coef(lm(yy~xx)))
```



### Linear regression in JAGS (defining model)

```
cat("
model {
  for (i in 1:N) {
    Y[i] ~ dnorm(mu[i], tau)
    mu[i] <- alpha + beta * x[i]
  }
  alpha ~ dnorm(0.0, 1.0E-4)
  beta ~ dnorm(0.0, 1.0E-4)
  tau ~ dgamma(1.0E-3, 1.0E-3)
}
", file="linear.jag")
```

### Linear regression in JAGS (compiling model)

```
dat <- list(Y = yy, x = xx, N = length(yy))
ini <- list(alpha = 0, beta = 1, tau = 1)
library( rjags )
```

```
## Loading required package: coda
```

```
## Linked to JAGS 4.3.0
```

```
## Loaded modules: basemod,bugs
```

```
linmod <- jags.model("linear.jag",  
  data=dat,  
  n.adapt = 1000,  
  inits = ini,  
  n.chains = 1)
```

```
## Compiling model graph  
##   Resolving undeclared variables  
##   Allocating nodes  
## Graph information:  
##   Observed stochastic nodes: 100  
##   Unobserved stochastic nodes: 3  
##   Total graph size: 407  
##  
## Initializing model
```

```
print(linmod)
```

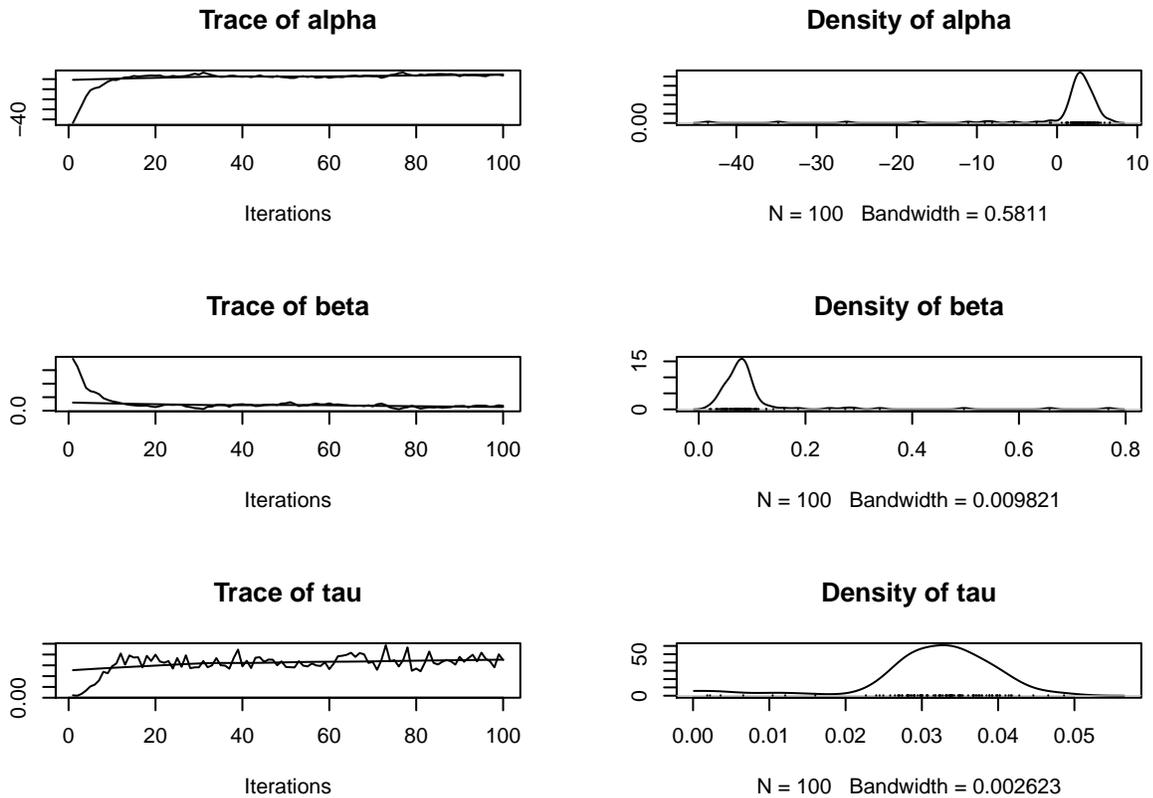
```
## JAGS model:  
##  
##  
## model {  
## for (i in 1:N) {  
## Y[i] ~ dnorm(mu[i], tau)  
## mu[i] <- alpha + beta * x[i]  
## }  
## alpha ~ dnorm(0.0, 1.0E-4)  
## beta ~ dnorm(0.0, 1.0E-4)  
## tau ~ dgamma(1.0E-3, 1.0E-3)  
## }  
## Fully observed variables:  
## N Y x
```

## Linear regression in JAGS (running sampler)

```
chain <- coda.samples(linmod,  
  var = c("alpha", "beta", "tau"),  
  n.iter = 100,  
  thin = 1 )
```

## Linear regression in JAGS (profiting)

```
plot(chain)
```



## Beetles in JAGS

- Note: A Cauchy distribution with scale  $\gamma$  is the same as a t-distribution with location 0, precision  $1/\gamma^2$  and degrees of freedom 1.

```
cat("
model {
for (i in 1:N) {
mu[i] <- alpha + beta * x[i]
p[i] <- exp(mu[i])/(1+exp(mu[i]))
Y[i] ~ dbin(p[i], 1)
}
alpha ~ dt(0.0, 1/(10^2), 1)
beta ~ dt(0.0, 1/(2^2), 1)
}
", file="logistic.jag")
```

## Beetles in JAGS

```
data_url <- "https://asta.math.aau.dk/course/bayes/2019/?file=beetles.dat"
beetles <- read.table(data_url)
dat <- list(Y = beetles[,2], x = beetles[,1], N = nrow(beetles))
ini <- list(
  list(alpha = 0, beta = 1),
```

```
list(alpha = 60, beta = -30))
logisticmod <- jags.model("logistic.jag",
  data=dat,
  n.adapt = 1000,
  inits = ini,
  n.chains = 2)
```

```
## Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 481
##   Unobserved stochastic nodes: 2
##   Total graph size: 1013
##
## Initializing model
```

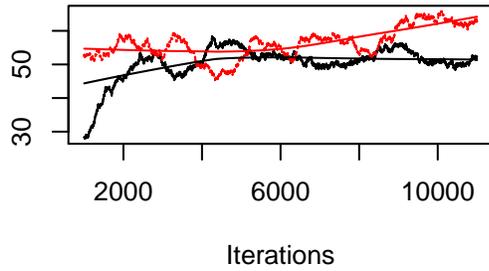
## Beetles in JAGS

```
chain <- coda.samples(logisticmod,
  var = c("alpha", "beta"),
  n.iter = 10000,
  thin = 1 )
```

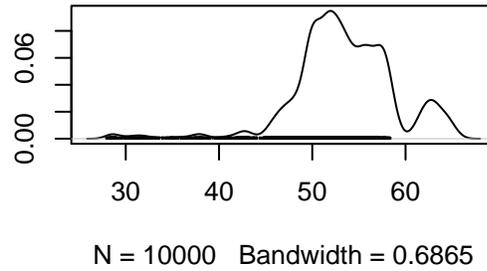
## Beetles in JAGS

```
plot(chain)
```

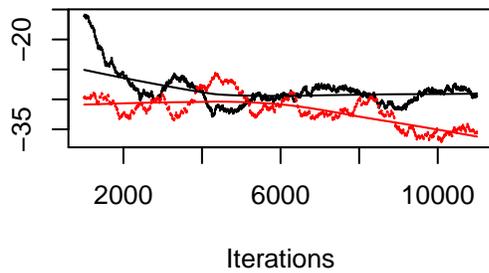
**Trace of alpha**



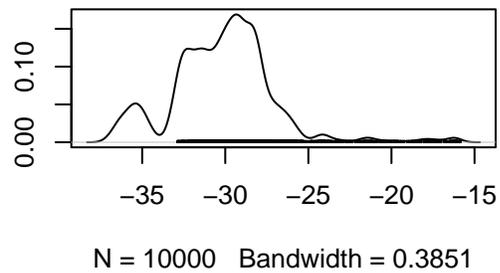
**Density of alpha**



**Trace of beta**



**Density of beta**

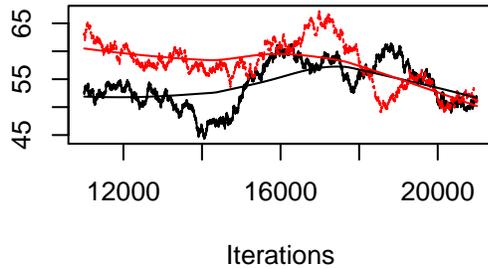


## Beetles in JAGS - Continuing the sampler

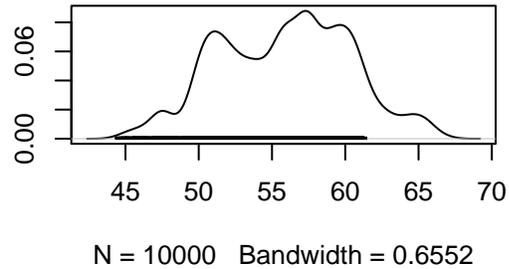
```
# Continuing sampling from earlier  
chain2 <- coda.samples(logisticmod,  
  var = c("alpha", "beta"),  
  n.iter = 10000,  
  thin = 1 )
```

```
plot(chain2)
```

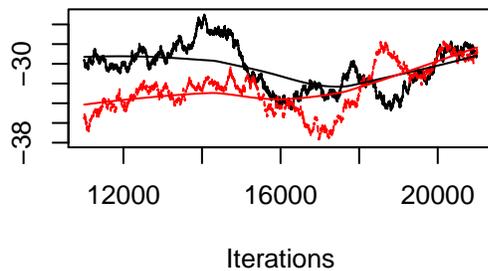
**Trace of alpha**



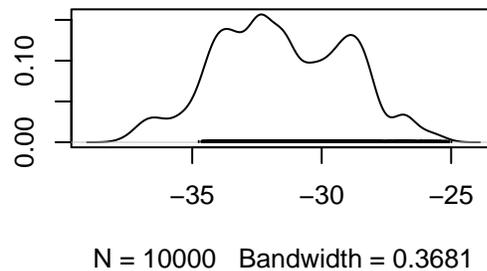
**Density of alpha**



**Trace of beta**



**Density of beta**



## Beetles in JAGS - Longer adaptation

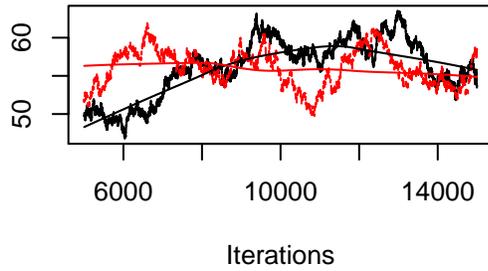
```
logisticmod <- jags.model("logistic.jag",  
  data=dat,  
  n.adapt = 5000,  
  inits = ini,  
  n.chains = 2)
```

```
## Compiling model graph  
##   Resolving undeclared variables  
##   Allocating nodes  
## Graph information:  
##   Observed stochastic nodes: 481  
##   Unobserved stochastic nodes: 2  
##   Total graph size: 1013  
##  
## Initializing model
```

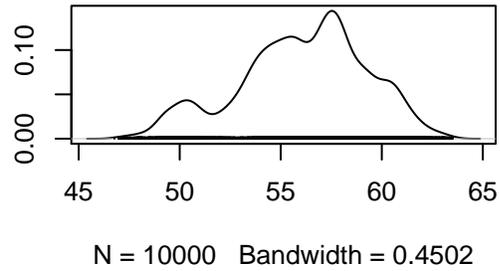
```
chain_new <- coda.samples(logisticmod,  
  var = c("alpha", "beta"),  
  n.iter = 10000,  
  thin = 1 )
```

```
plot(chain_new)
```

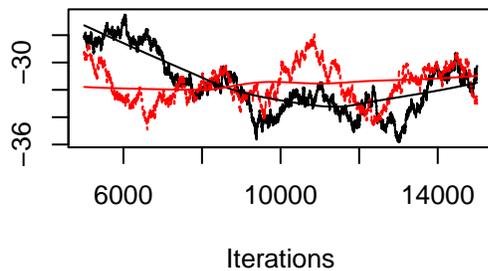
**Trace of alpha**



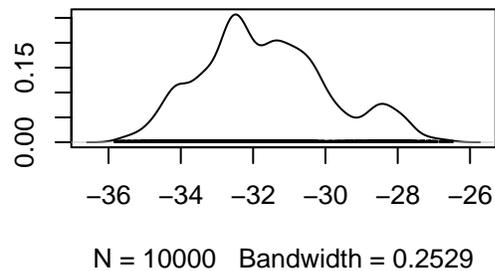
**Density of alpha**



**Trace of beta**



**Density of beta**



## Mixture in JAGS

```
cat("
model {
  # Likelihood:
  for( i in 1 : N ) {
    Y[i] ~ dnorm( mu[i] , 1 )
    mu[i] <- muvec[ Z[i] ]
    Z[i] ~ dcat( lambda[1:k] )
  }
  # Prior:
  for ( j in 1:k ) {
    muvec[j] ~ dnorm( 0 , 1.0E-10 )
  }
  lambda[1:k] ~ ddirch( rep(1, k ) )
}
", file="mixture.jag")
```

## Mixture in JAGS

```
data_url <- "https://asta.math.aau.dk/course/bayes/2019/?file=simmix.csv"
simmix <- read.csv(data_url)
k <- 3
dat <- list(Y = simmix[,1], k = k, N = nrow(simmix))
```

```

ini <- list(
  # list(lambda = rep(1/k, k), muvec = seq(-2,2,length.out = k)),
  list(lambda = rep(1/k, k), muvec = seq(-5,5,length.out = k))
mixturemod <- jags.model("mixture.jag",
  data=dat,
  n.adapt = 1000,
  inits = ini,
  n.chains = 1)

```

```

## Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 500
##   Unobserved stochastic nodes: 504
##   Total graph size: 1510
##
## Initializing model

```

## Mixture in JAGS

```

chain <- coda.samples(mixturemod,
  var = c("muvec", "lambda"),
  n.iter = 1000,
  thin = 1 )

```

## Mixture in JAGS

```

plot(chain)

```

