

Applied Bayesian Analysis : NCSU ST 540

Midterm2

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Test section - VAR(1) in JAGS

This section is a test section where we generate and fit a vector autoregressive model - $VAR(1) \in \mathbf{R}^6$ given by

$$y_t = \nu + \rho * y_{t-1} + \epsilon$$

$$\epsilon \sim N(0, \Sigma)$$

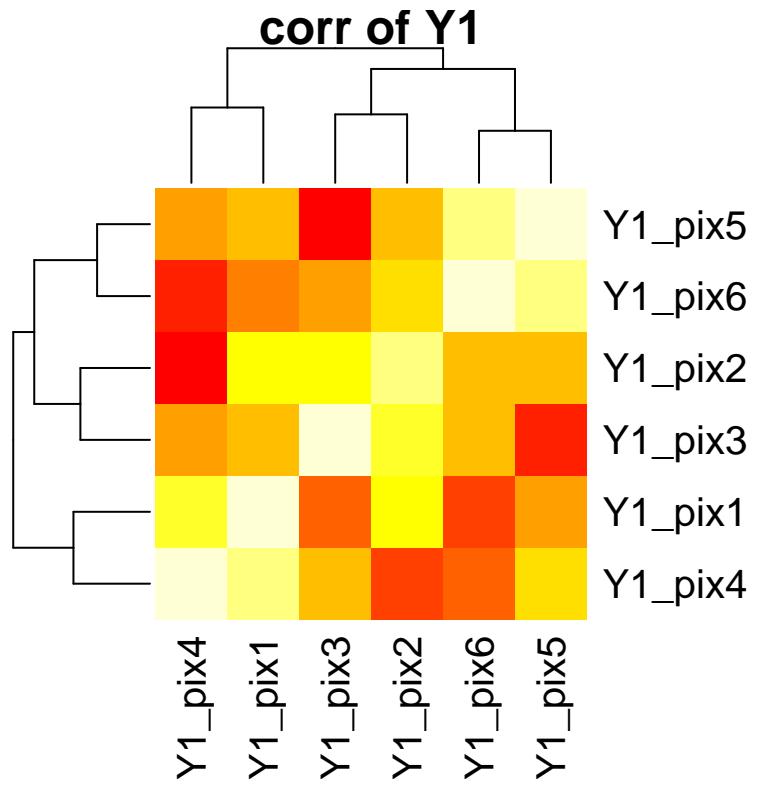
We use the $y1$ data to calculate a NaN firendly sample covariance and then we find the nearest positive semidefinite matrix to use to generate data for the model.

Notes - imputation is not working for this model - this section seeks to find the parameters that best explain the data

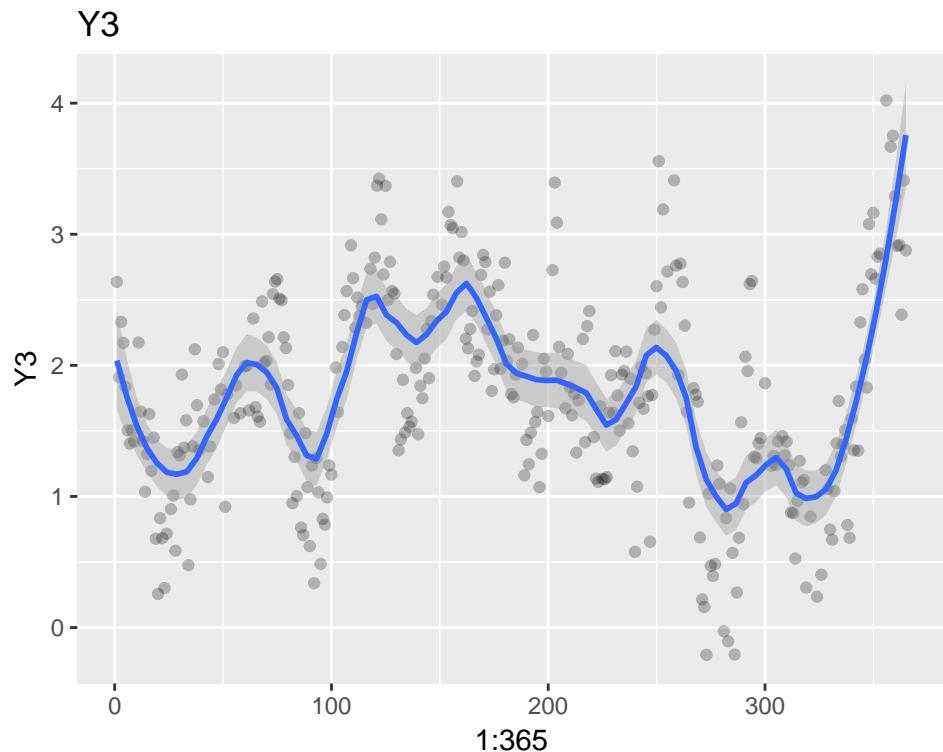
```
library(rjags)
library(coda)
library(modeest)
library(MASS)
load("E2.RData")

nSamples <- 10000
n.chains <- 2

cor.y1 <- cor(Y1, use = "pairwise.complete.obs")
cov.y1 <- cov(Y1, use = "pairwise.complete.obs")
heatmap(cor.y1, main = "corr of Y1")
```



```
ggplot(data.frame(Y3 = Y3), aes(x = 1:365,
  y = Y3)) + geom_point(alpha = 0.25) +
  geom_smooth(method = "loess", span = 0.22) +
  ggtitle("Y3")
```



```

N <- nrow(Y1)
p = 6
Y1.scaled <- scale(Y1)
# Try to simulate using the corr
#install.packages("Matrix")
library("Matrix")

sig <- nearPD(cov.y1)
N = 365
Sigma = sig$mat
rho = .6
nu = matrix(rep(.1,6), p, 1)
y = matrix(NA, N,p)
y[1,] = nu
for(t in 2:N)
{
  y[t,] = mvrnorm(1, nu + rho * y[t-1,], Sigma)
}

# Jags code to fit the model to the simulated data
model_code =
model
{
  # Likelihood
  for (t in 2:N)
  {
    y[t, ] ~ dmnorm(mu[t, ], precisionAR)
    mu[t, 1:p] <- nu + rho * y[t-1,]
  }
  precisionAR ~ dwish(I, p+1)
  Sigma <- inverse(precisionAR)

  # Priors
  rho ~ dunif(-1, 1)
  for(i in 1:p)
  {
    nu[i] ~ dnorm(0, 0.01)
  }
}
'

# Set up the data
model_data = list(N = N, p = p, y = y, I = diag(p))
# Choose the parameters to watch
model_parameters = c("Sigma", "nu", "rho" )

model <- jags.model(textConnection(model_code), data = model_data, n.chains = n.chains) #Compile

```

```

## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 364
##    Unobserved stochastic nodes: 8
##    Total graph size: 1153
##
## Initializing model

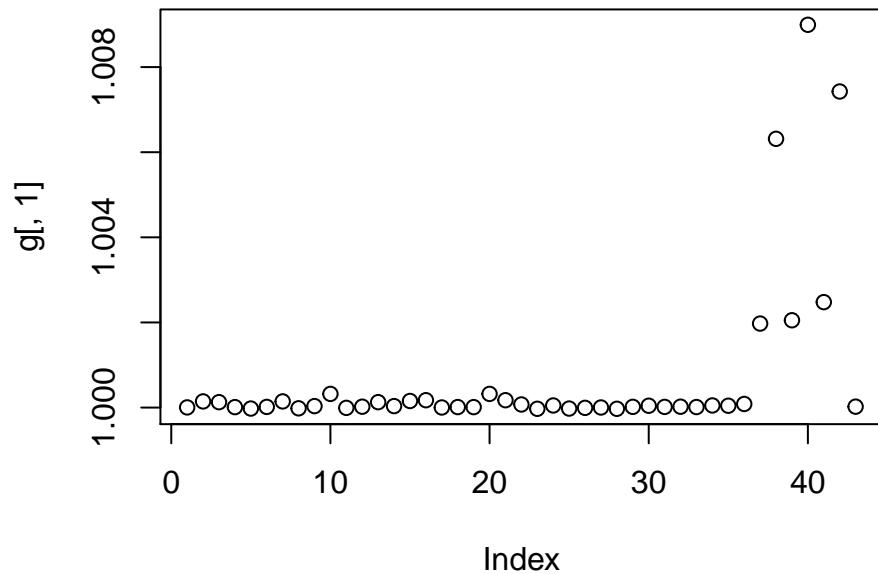
update(model, nSamples, progress.bar="none"); # Burnin
if(TRUE)
{
  out.coda <- coda.samples(model, variable.names=model_parameters,n.iter=2*nSamples)
  save(out.coda,file = "out.coda_JAGS_VAR1.RData")
}else{
  load("out.coda_JAGS_VAR1.RData")
}

#plot(out.coda )

if(n.chains > 1)
{
  g <- matrix(NA, nrow=nvar(out.coda), ncol=2)
  for (v in 1:nvar(out.coda)) {
    g[v,] <- gelman.diag(out.coda[,v])$psrf
  }
#multivariate - don't use if monitoring highly correlated variables
#gelman.srf <-gelman.diag(out.coda)
  count.coeff.gt <- sum(g[,1]>1.1)
  count.coeff.gt
  plot(g[,1],main="Gelman-Rubin ")
}

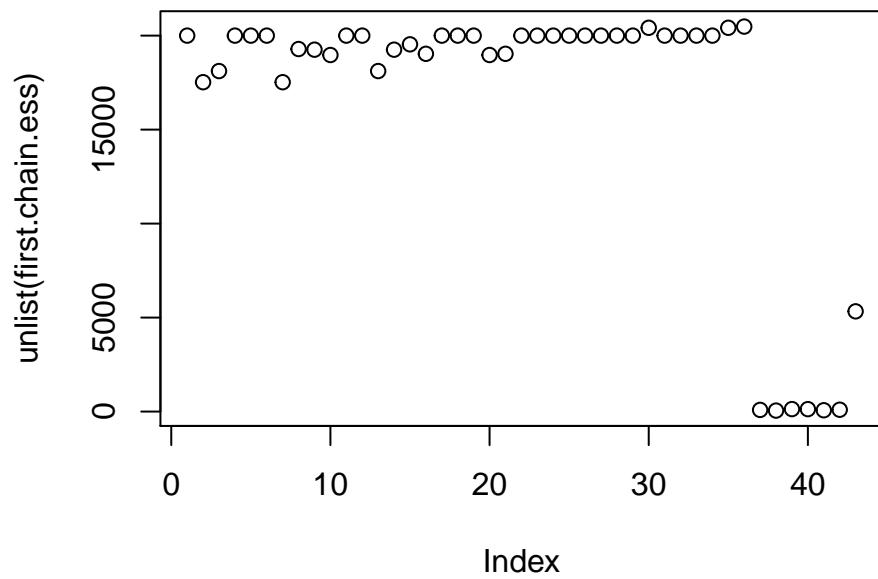
```

Gelman–Rubin



```
chains.ess <- lapply(out.coda, effectiveSize)
first.chain.ess <- chains.ess[1]
plot(unlist(first.chain.ess), main="Effective Sample Size")
```

Effective Sample Size

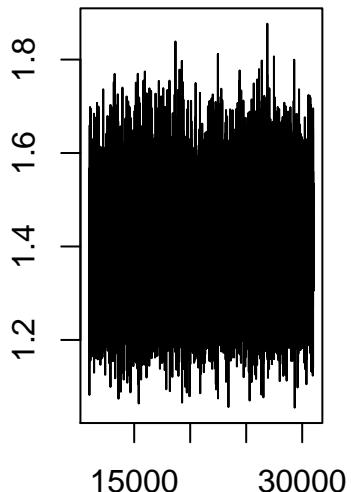


```

chain <- out.coda[[1]]
posterior.means <- list()
posterior.modes <- list()
for( i in 1:length(colnames(chain)) )
{
  colname <- colnames(chain)[i]
  plot(chain[,i])
  samples <- chain[,i]
  posterior.means[colname] <- mean(samples)
  posterior.modes[colname] <- mlv(samples)$M
}

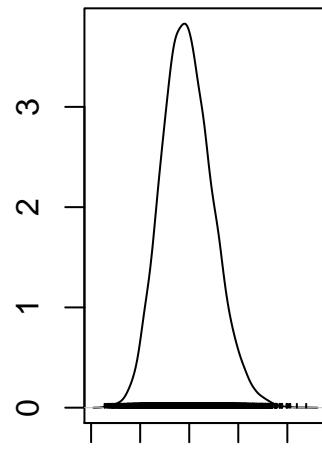
```

Trace of var1



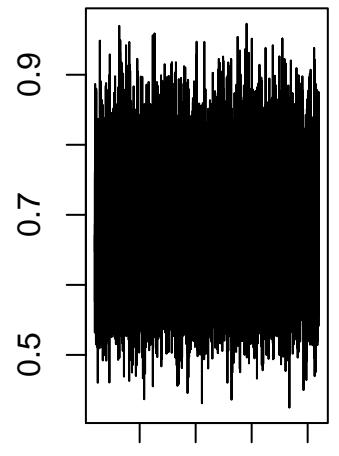
Iterations

Density of var1



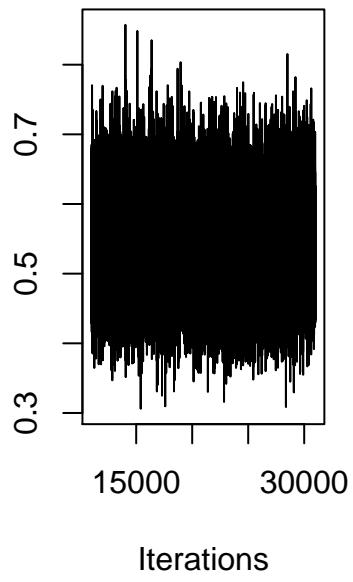
N = 20000 Bandwidth = 0.015

Trace of var1



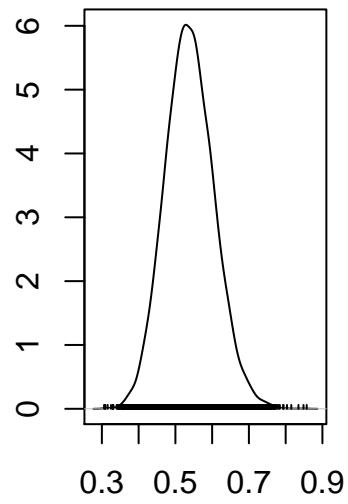
Iterations

Trace of var1



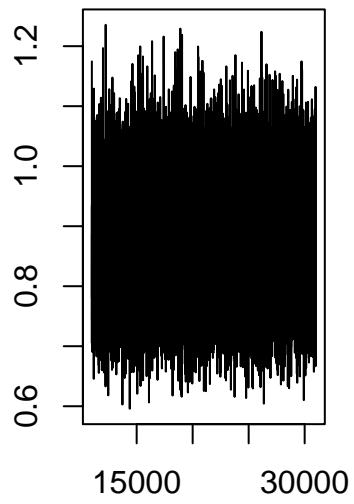
Iterations

Density of var1



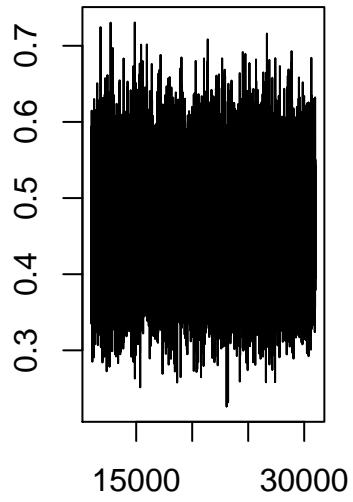
$N = 20000$ Bandwidth = 0.0096

Trace of var1



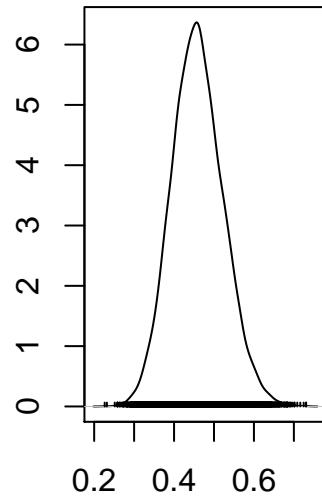
Iterations

Trace of var1



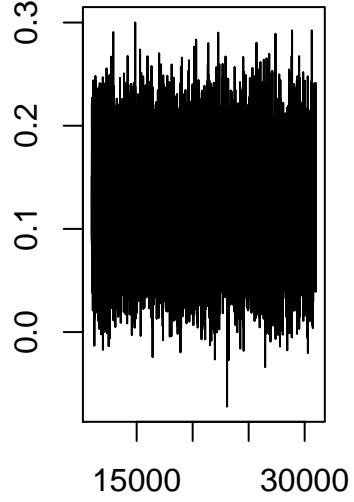
Iterations

Density of var1



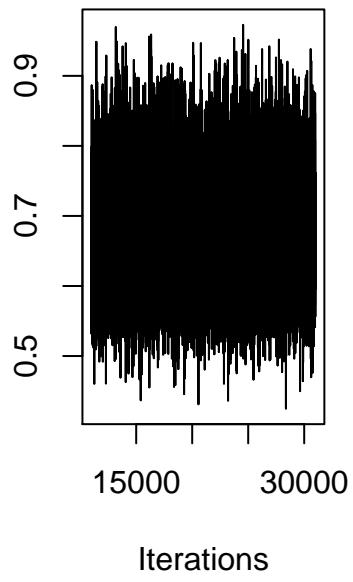
$N = 20000$ Bandwidth = 0.0094

Trace of var1



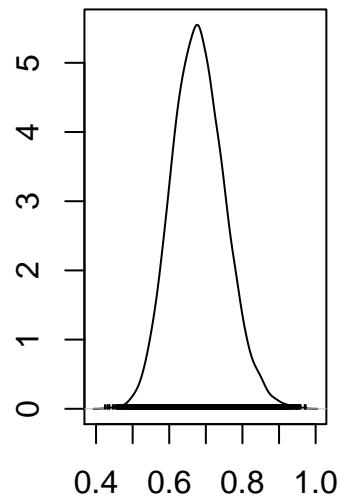
Iterations

Trace of var1



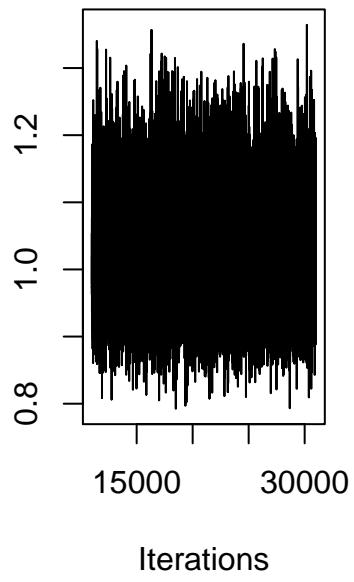
Iterations

Density of var1



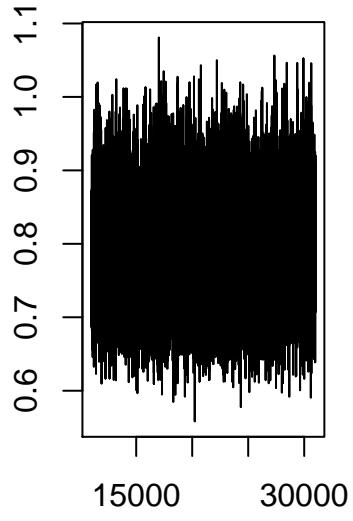
$N = 20000$ Bandwidth = 0.010

Trace of var1



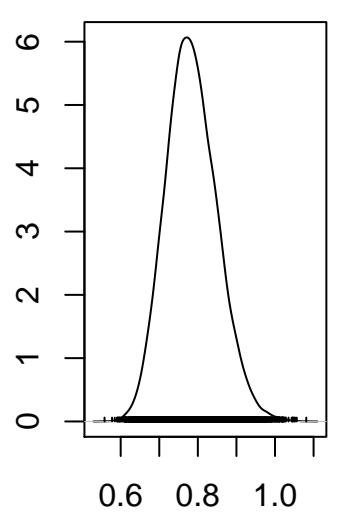
Iterations

Trace of var1



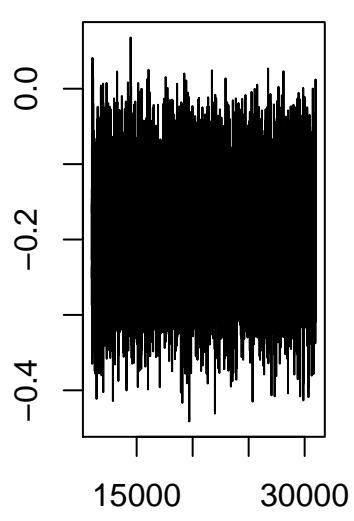
Iterations

Density of var1



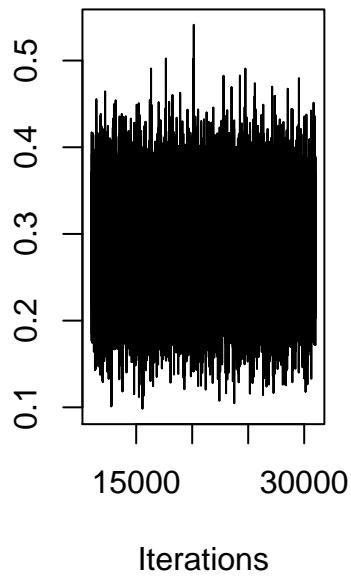
$N = 20000$ Bandwidth = 0.009

Trace of var1



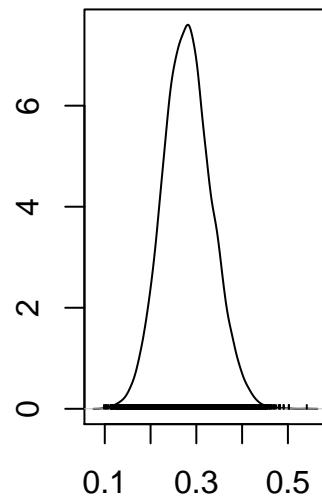
Iterations

Trace of var1



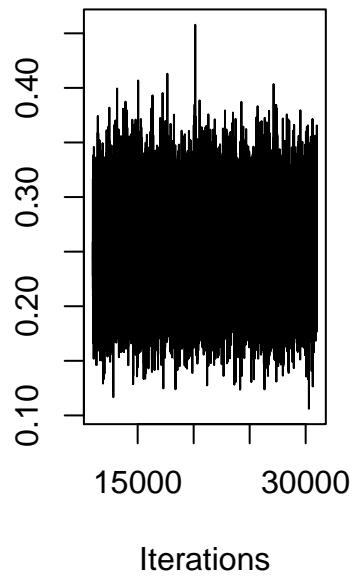
Iterations

Density of var1



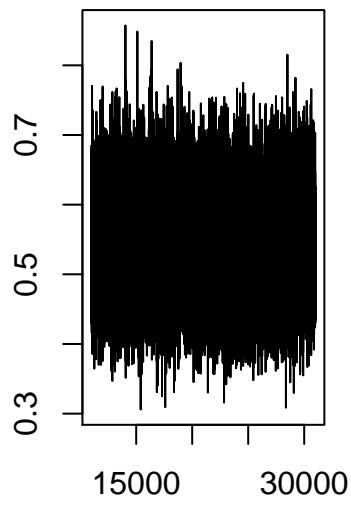
$N = 20000$ Bandwidth = 0.0071

Trace of var1



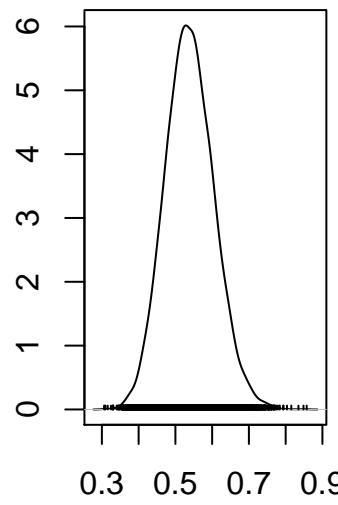
Iterations

Trace of var1



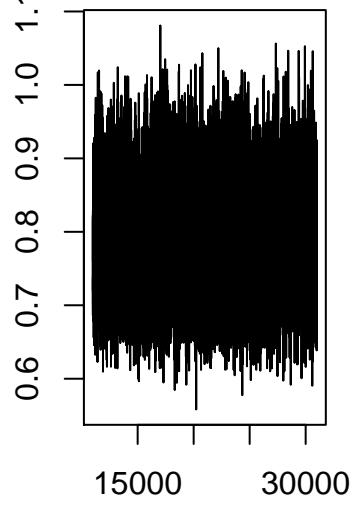
Iterations

Density of var1



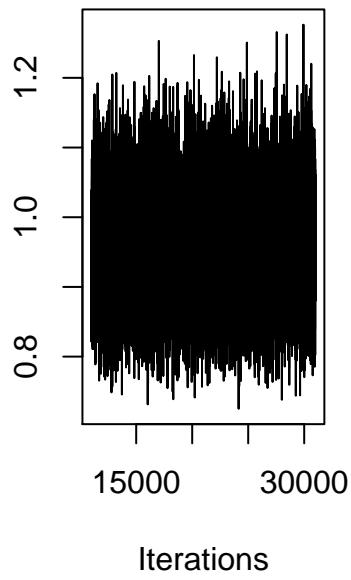
$N = 20000$ Bandwidth = 0.0096

Trace of var1



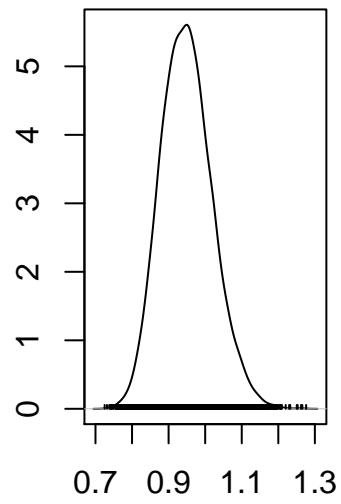
Iterations

Trace of var1



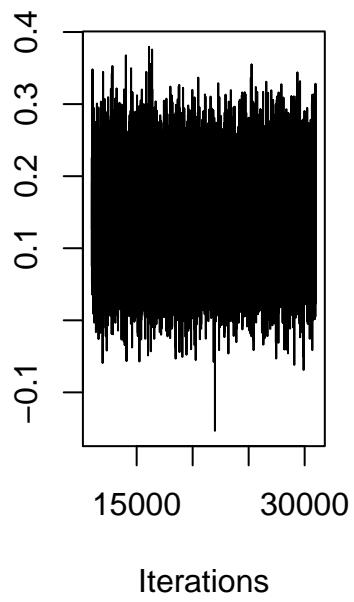
Iterations

Density of var1



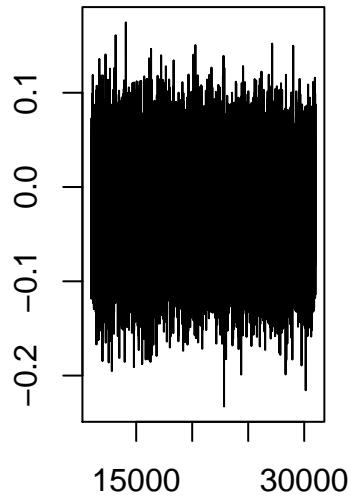
$N = 20000$ Bandwidth = 0.010

Trace of var1



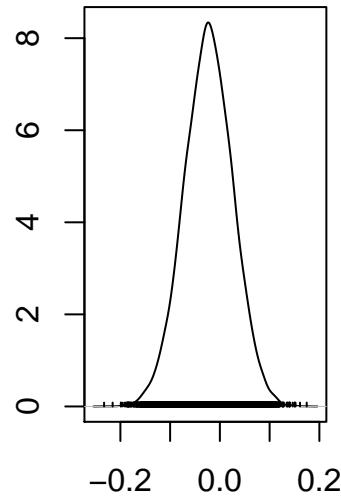
Iterations

Trace of var1



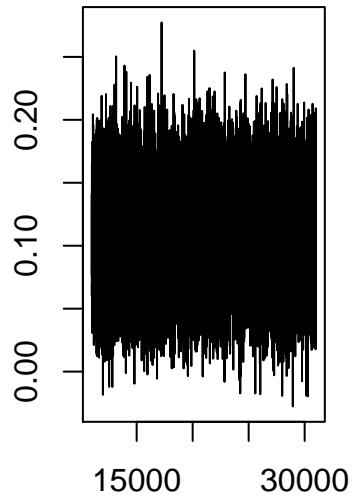
Iterations

Density of var1



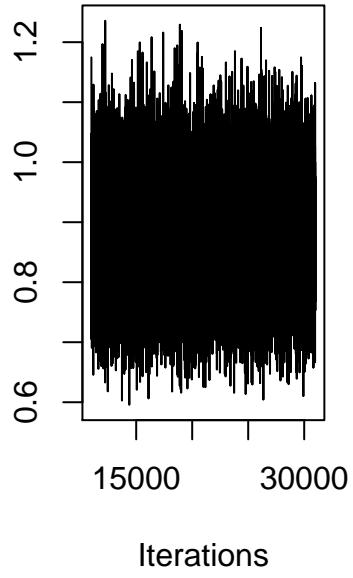
$N = 20000$ Bandwidth = 0.007

Trace of var1



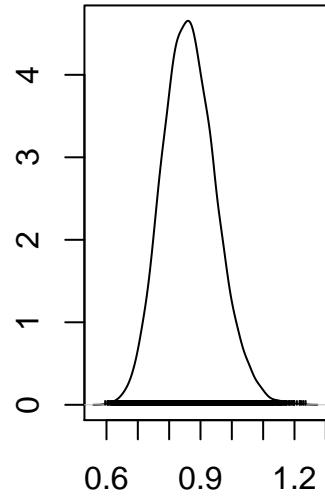
Iterations

Trace of var1



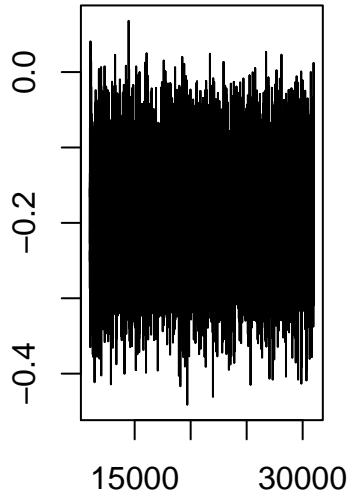
Iterations

Density of var1



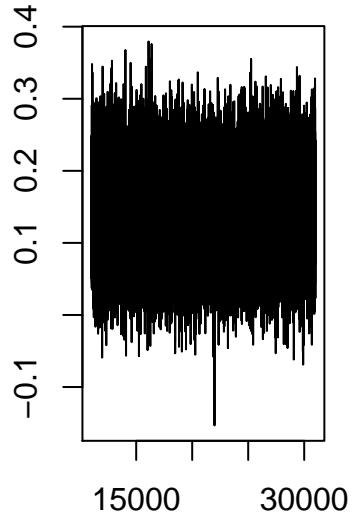
$N = 20000$ Bandwidth = 0.012

Trace of var1



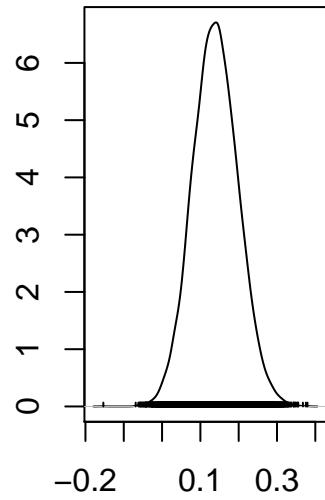
Iterations

Trace of var1



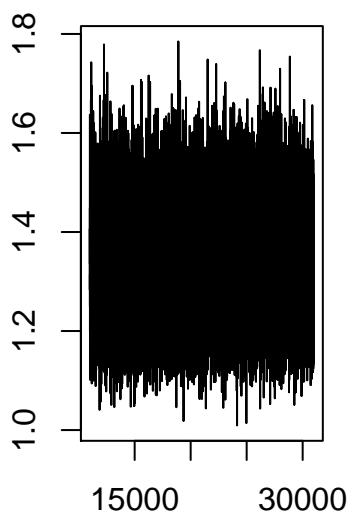
Iterations

Density of var1



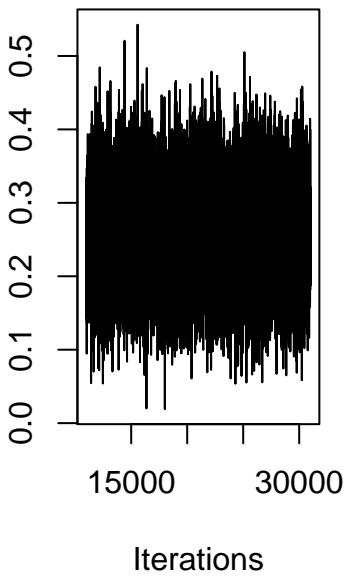
$N = 20000$ Bandwidth = 0.0086

Trace of var1



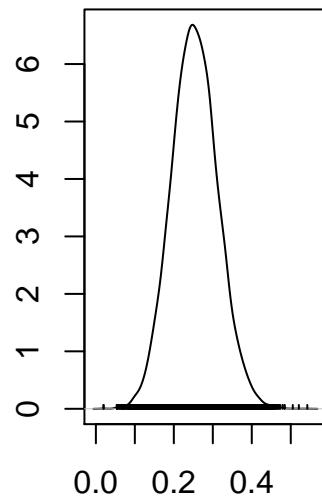
Iterations

Trace of var1



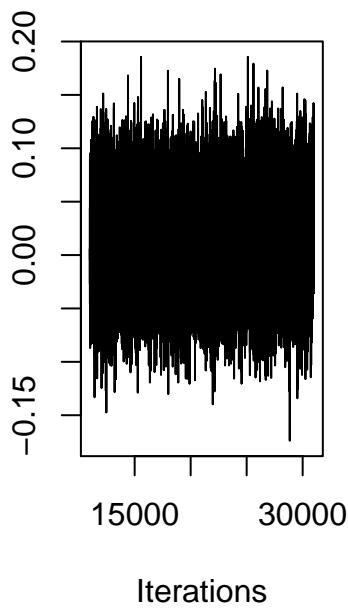
Iterations

Density of var1



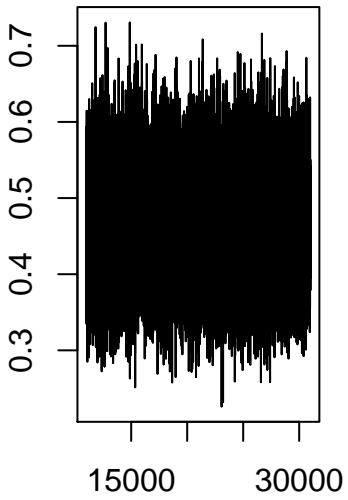
$N = 20000$ Bandwidth = 0.0086

Trace of var1



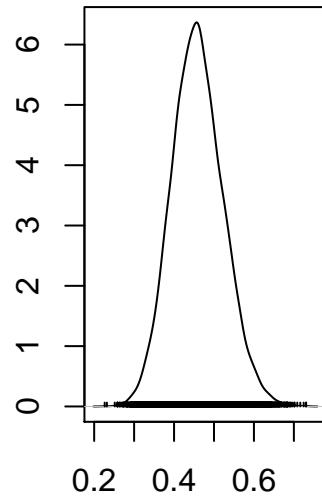
Iterations

Trace of var1



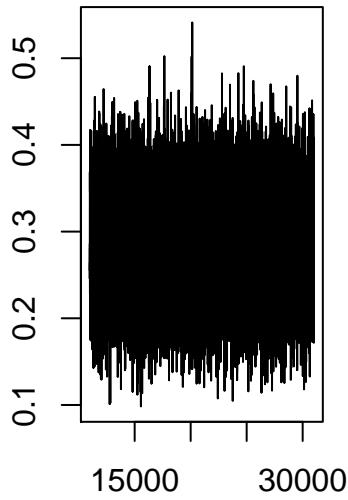
Iterations

Density of var1



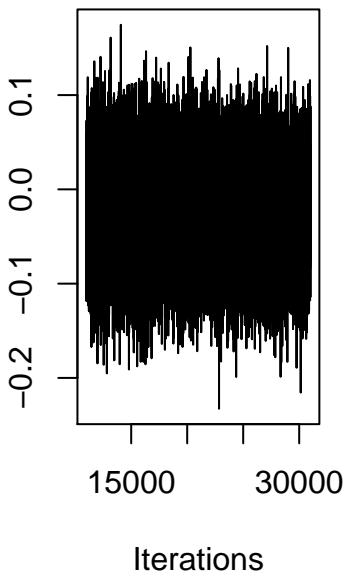
$N = 20000$ Bandwidth = 0.0094

Trace of var1



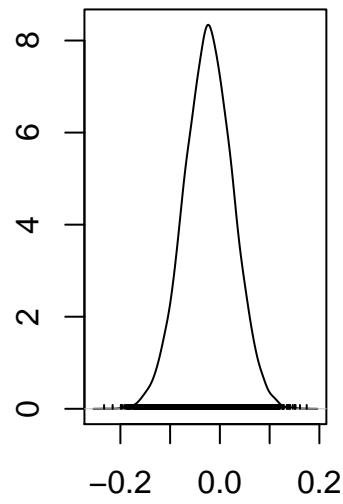
Iterations

Trace of var1



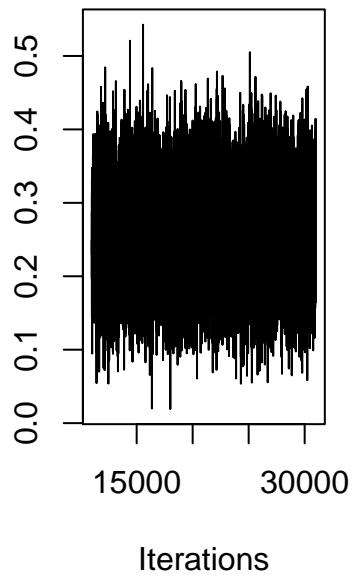
Iterations

Density of var1



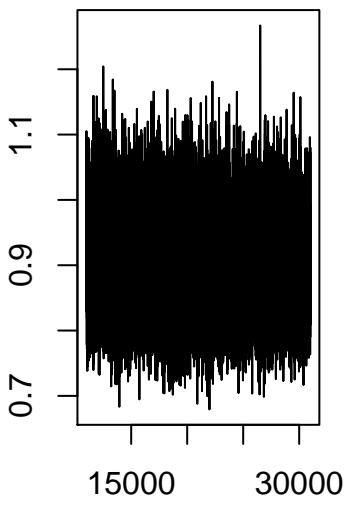
$N = 20000$ Bandwidth = 0.007'

Trace of var1



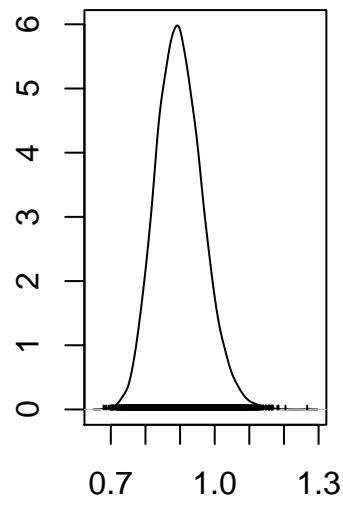
Iterations

Trace of var1



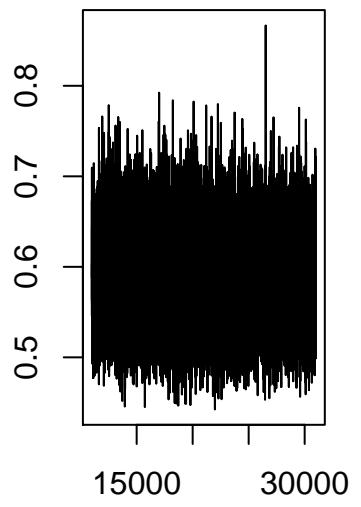
Iterations

Density of var1



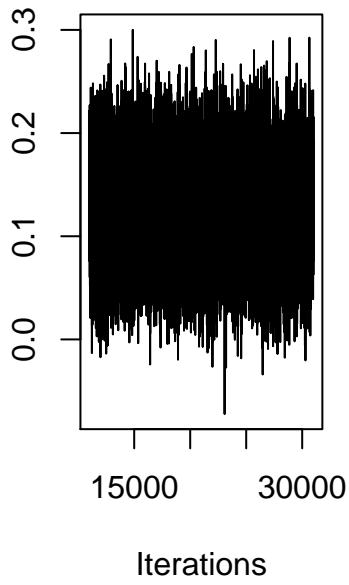
$N = 20000$ Bandwidth = 0.0098

Trace of var1



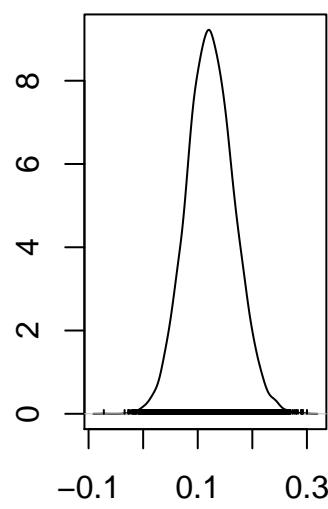
Iterations

Trace of var1



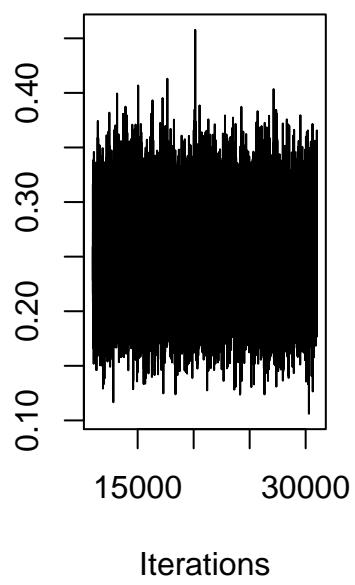
Iterations

Density of var1



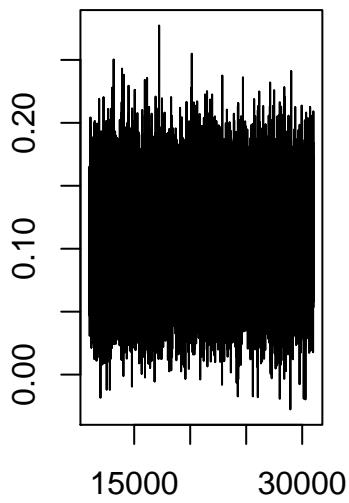
$N = 20000$ Bandwidth = 0.006

Trace of var1



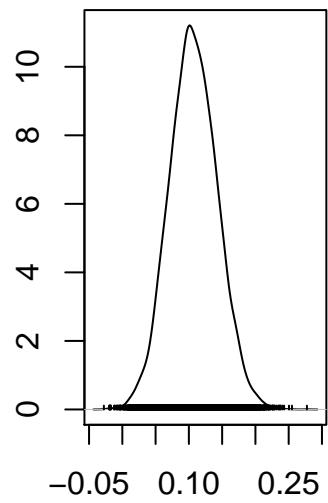
Iterations

Trace of var1



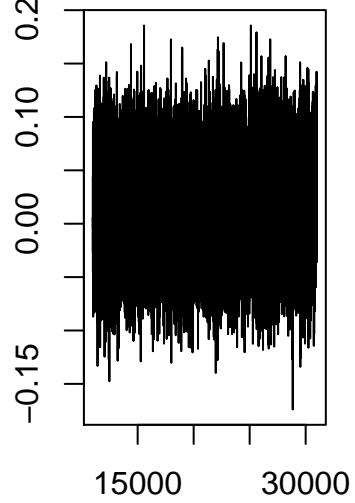
Iterations

Density of var1



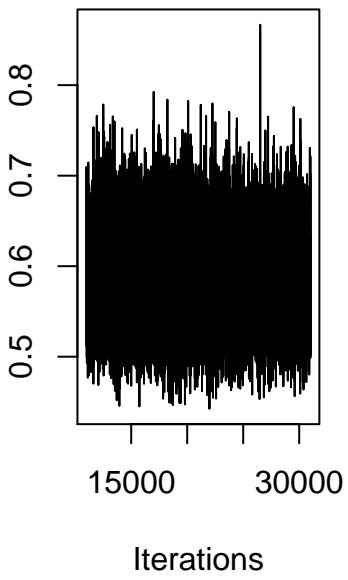
$N = 20000$ Bandwidth = 0.0052

Trace of var1



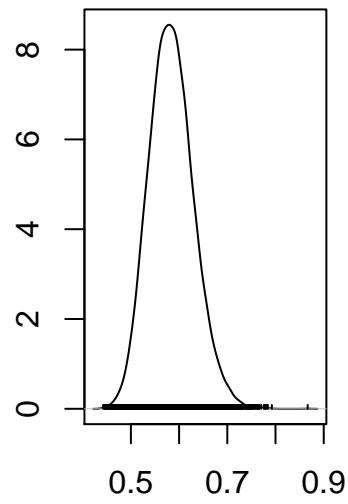
Iterations

Trace of var1



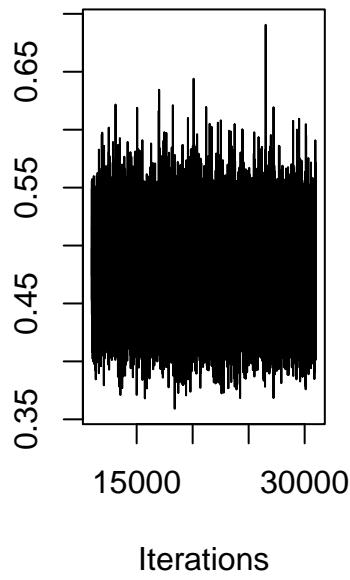
Iterations

Density of var1



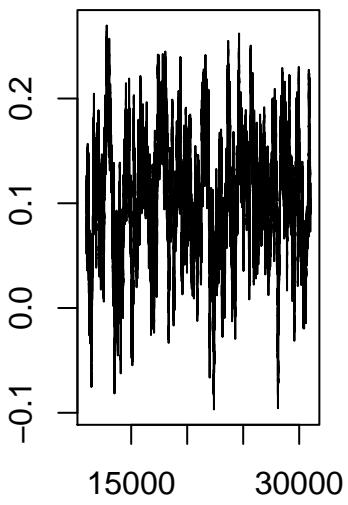
$N = 20000$ Bandwidth = 0.0067

Trace of var1



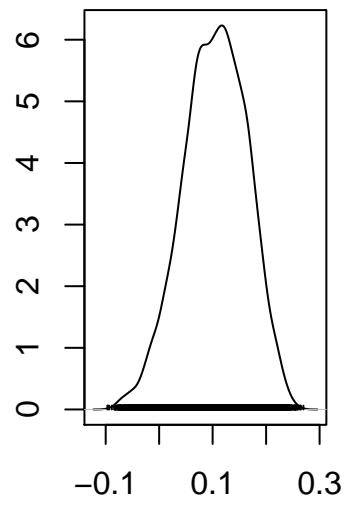
Iterations

Trace of var1



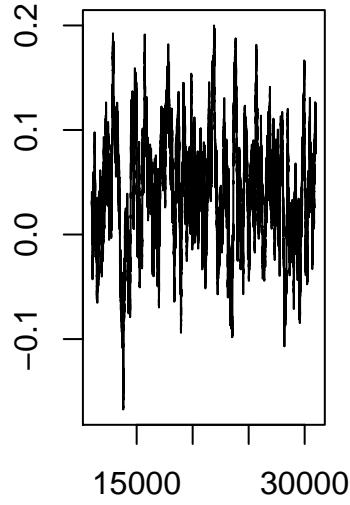
Iterations

Density of var1

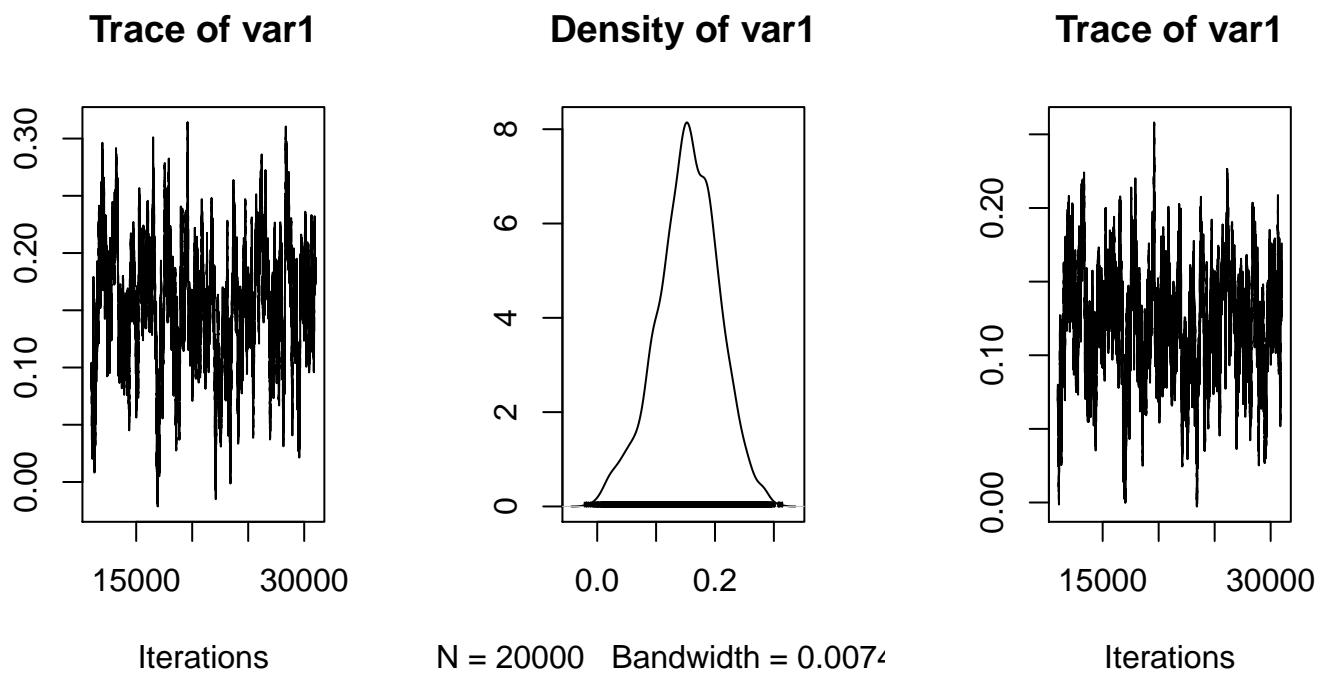
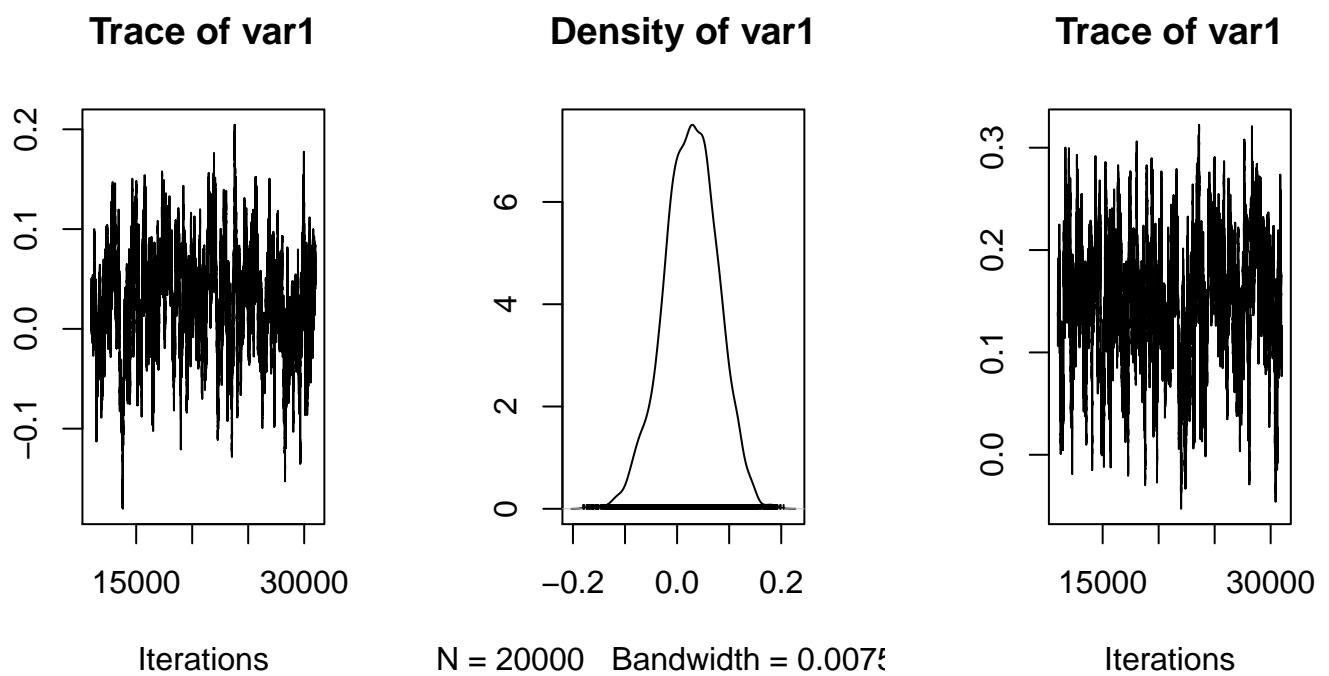


$N = 20000$ Bandwidth = 0.0087

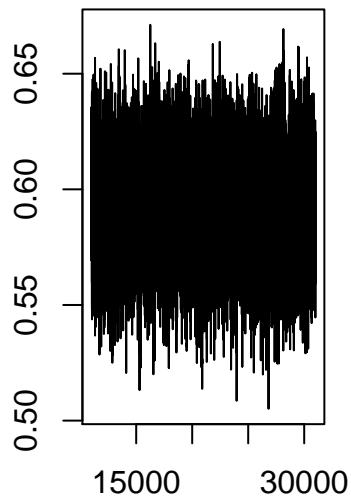
Trace of var1



Iterations

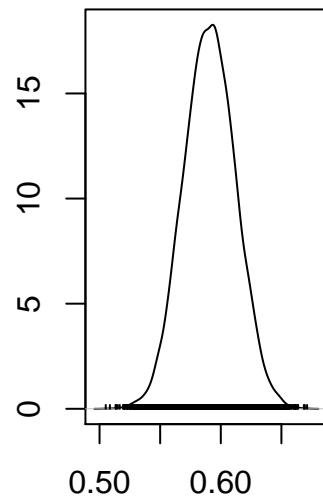


Trace of var1



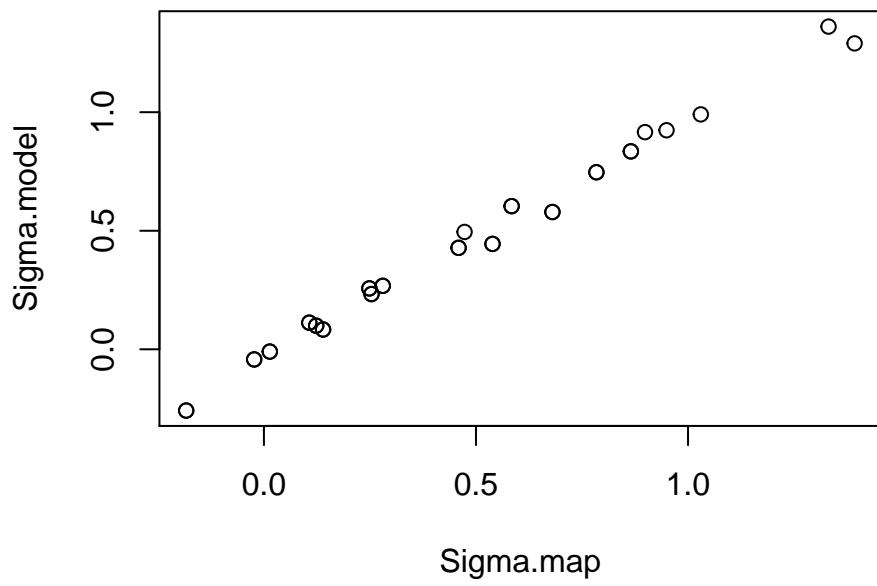
Iterations

Density of var1



$N = 20000$ Bandwidth = 0.003'

```
Sigma.map <- unlist(posterior.means)[1:36]
Sigma.model<- unlist(sig$mat)
plot(Sigma.map,Sigma.model)
```



```

rho.map <- unlist(posterior.means)[43]
nu.map <- unlist(posterior.means)[37:42]

```

Replicate JAGS in OpenBugs

VAR(1) on Y_1 with starting values, Y_2 and Y_3 incorporated imputation in OpenBugs

```

library(R2OpenBUGS)

openbugs_model <- function() {
  for (i in 2:N) {
    Y1[i, 1:p] ~ dmnorm(theta[i, 1:p],
                           precision[, ])
    for (j in 1:p) {
      theta[i, j] <- nu[j] + rho *
        Y1[i - 1, j]
    }
  }

  # Priors
  rho ~ dunif(-1, 1)

  for (j in 1:p) {
    nu[j] ~ dnorm(0, 0.01)
  }

  # Sigma[1:p, 1:p] <-
  # inverse(precision[1:p, 1:p])

  precision[1:p, 1:p] ~ dwish(R[, ],
                               k)

  k <- p + 1
  for (j1 in 1:p) {
    for (j2 in 1:p) {
      R[j1, j2] <- equals(j1, j2)
    }
  }
}

```

```

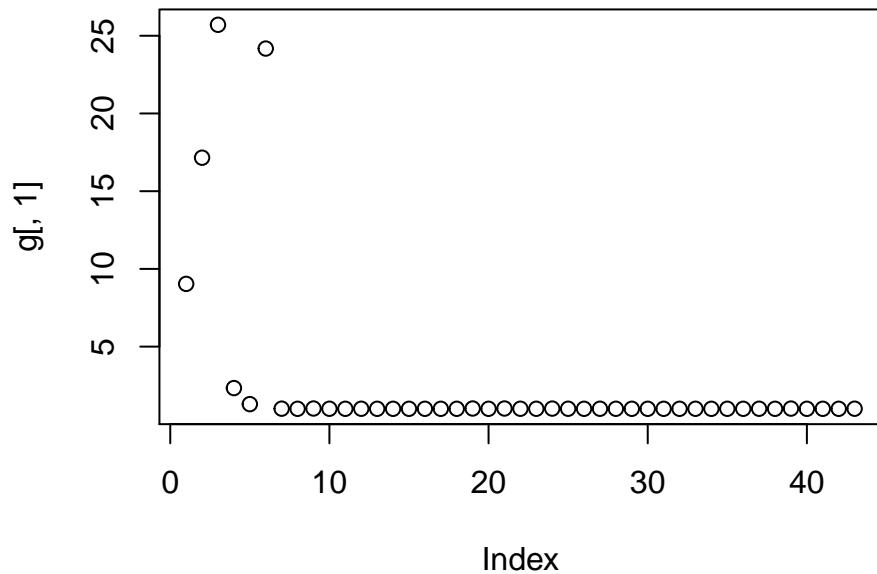
stacks_dat <- list(Y1 = scale(y), p = 6,
N = 365)
mlr_inits <- function() {
  list(rho = 0, precision = diag(p))
}
parameters.to.save = c("precision", "nu",
"rho")

samps <- bugs(data = stacks_dat, inits = mlr_inits,
parameters.to.save = parameters.to.save,
model.file = openbugs_model, codaPkg = TRUE,
n.chains = n.chains, n.burnin = 10000,
n.iter = 2 * nSamples, DIC = F) #, n.thin=10
out.coda <- read.bugs(samps)
save(out.coda, file = "out.coda_BUGS_VAR.RData")

if (n.chains > 1) {
  g <- matrix(NA, nrow = nvar(out.coda),
  ncol = 2)
  for (v in 1:nvar(out.coda)) {
    g[v, ] <- gelman.diag(out.coda[, v])$psrf
  }
  # multivariate - don't use if
  # monitoring highly correlated
  # variables gelman.srf
  # <-gelman.diag(out.coda)
  count.coeff.gt <- sum(g[, 1] > 1.1)
  count.coeff.gt
  plot(g[, 1], main = "Gelman-Rubin ")
}

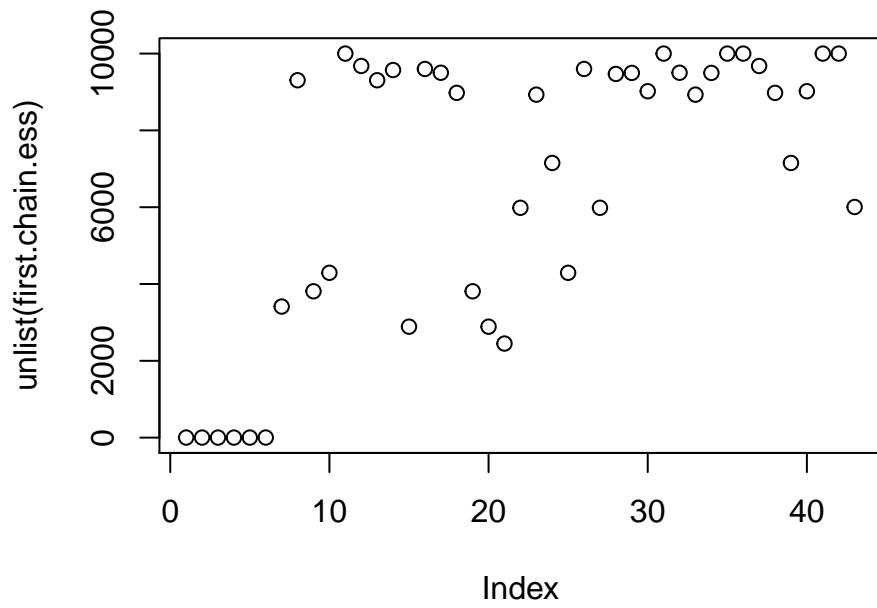
```

Gelman–Rubin



```
chains.ess <- lapply(out.coda, effectiveSize)
first.chain.ess <- chains.ess[1]
plot(unlist(first.chain.ess), main = "Effective Sample Size")
```

Effective Sample Size

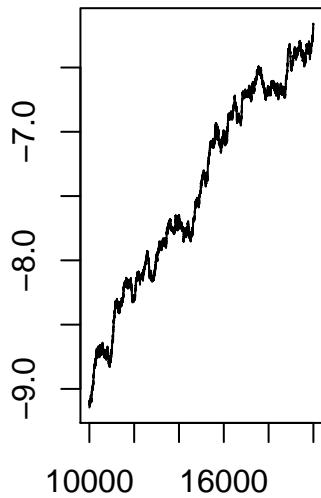


```

chain <- out.coda[[1]]
posterior.means <- list()
posterior.modes <- list()
for (i in 1:length(colnames(chain))) {
  colname <- colnames(chain)[i]
  plot(chain[, i])
  samples <- chain[, i]
  posterior.means[colname] <- mean(samples)
  posterior.modes[colname] <- mlv(samples)$M
}

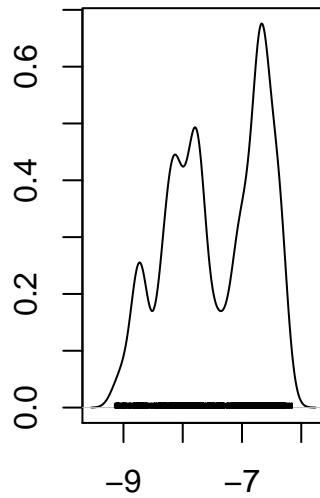
```

Trace of var1



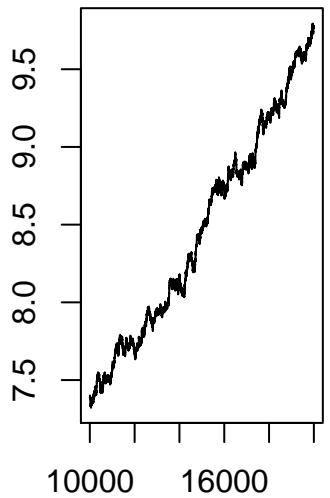
Iterations

Density of var1



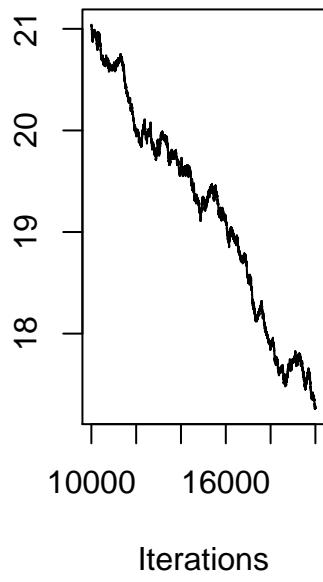
N = 10000 Bandwidth = 0.132

Trace of var1



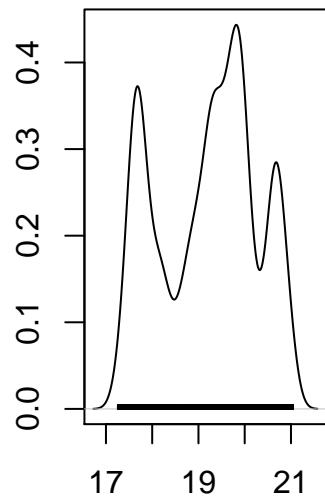
Iterations

Trace of var1



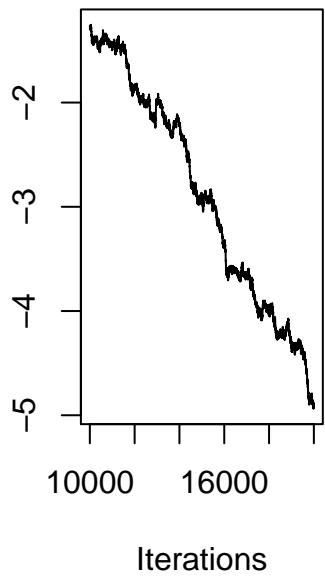
Iterations

Density of var1



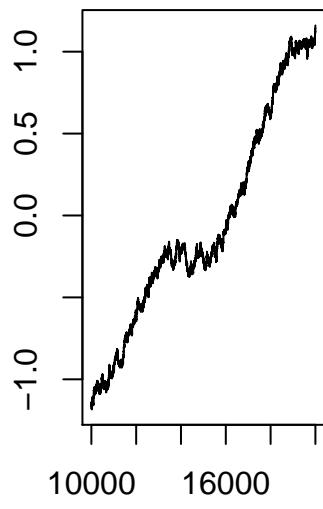
$N = 10000$ Bandwidth = 0.177

Trace of var1



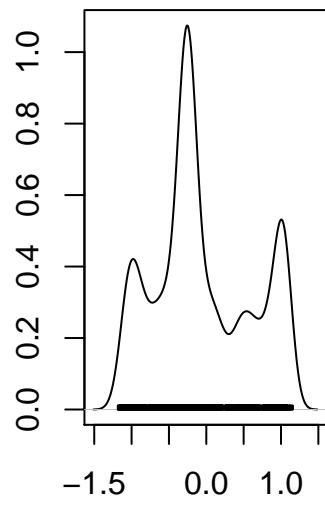
Iterations

Trace of var1



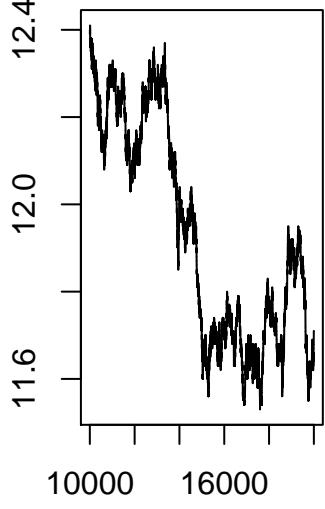
Iterations

Density of var1



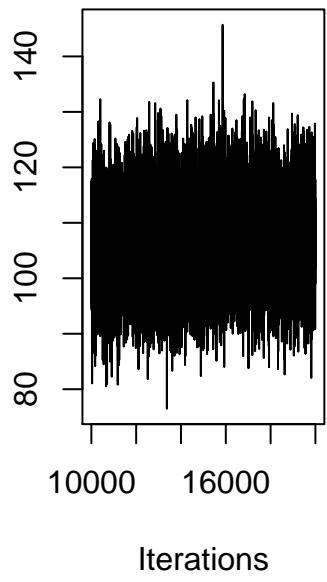
$N = 10000$ Bandwidth = 0.109

Trace of var1



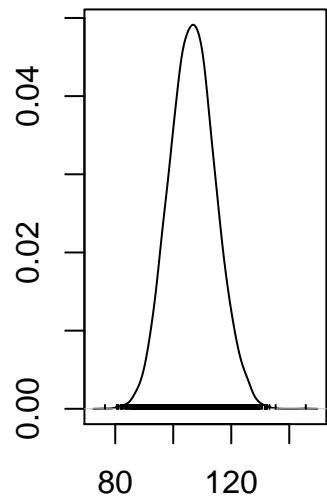
Iterations

Trace of var1



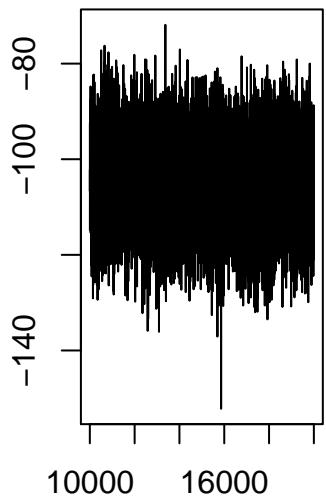
Iterations

Density of var1



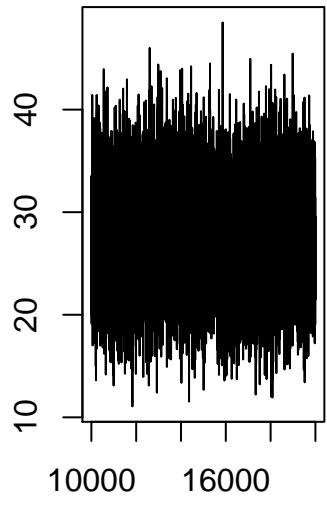
$N = 10000$ Bandwidth = 1.33

Trace of var1



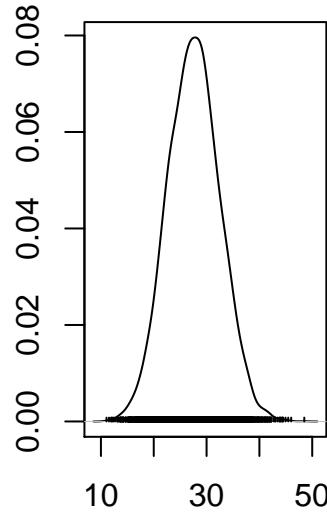
Iterations

Trace of var1



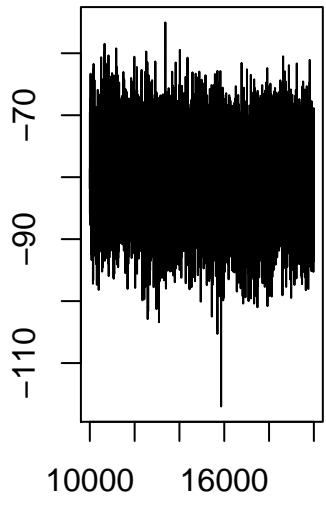
Iterations

Density of var1



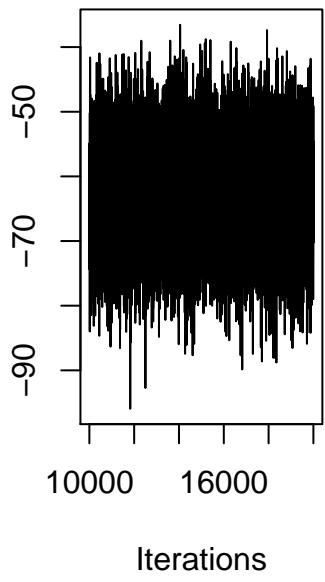
$N = 10000$ Bandwidth = 0.82

Trace of var1



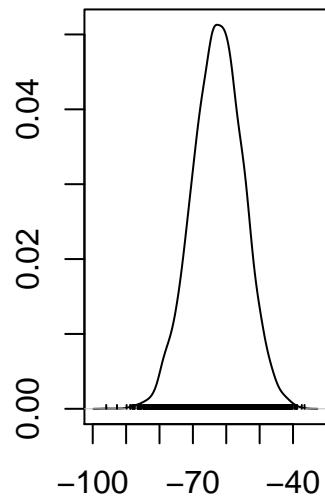
Iterations

Trace of var1



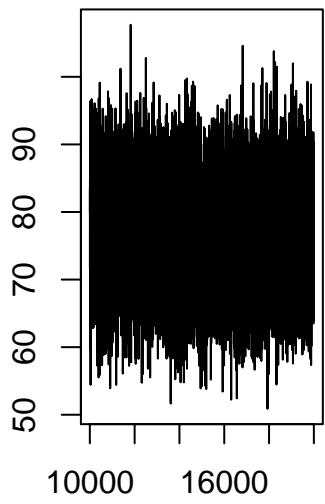
Iterations

Density of var1



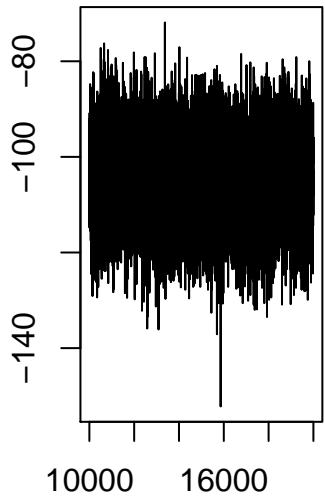
$N = 10000$ Bandwidth = 1.28

Trace of var1



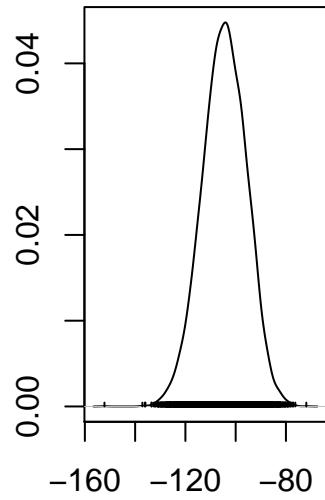
Iterations

Trace of var1



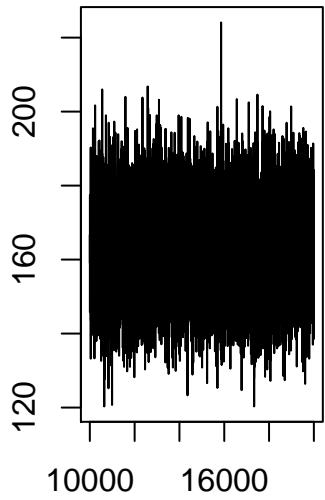
Iterations

Density of var1

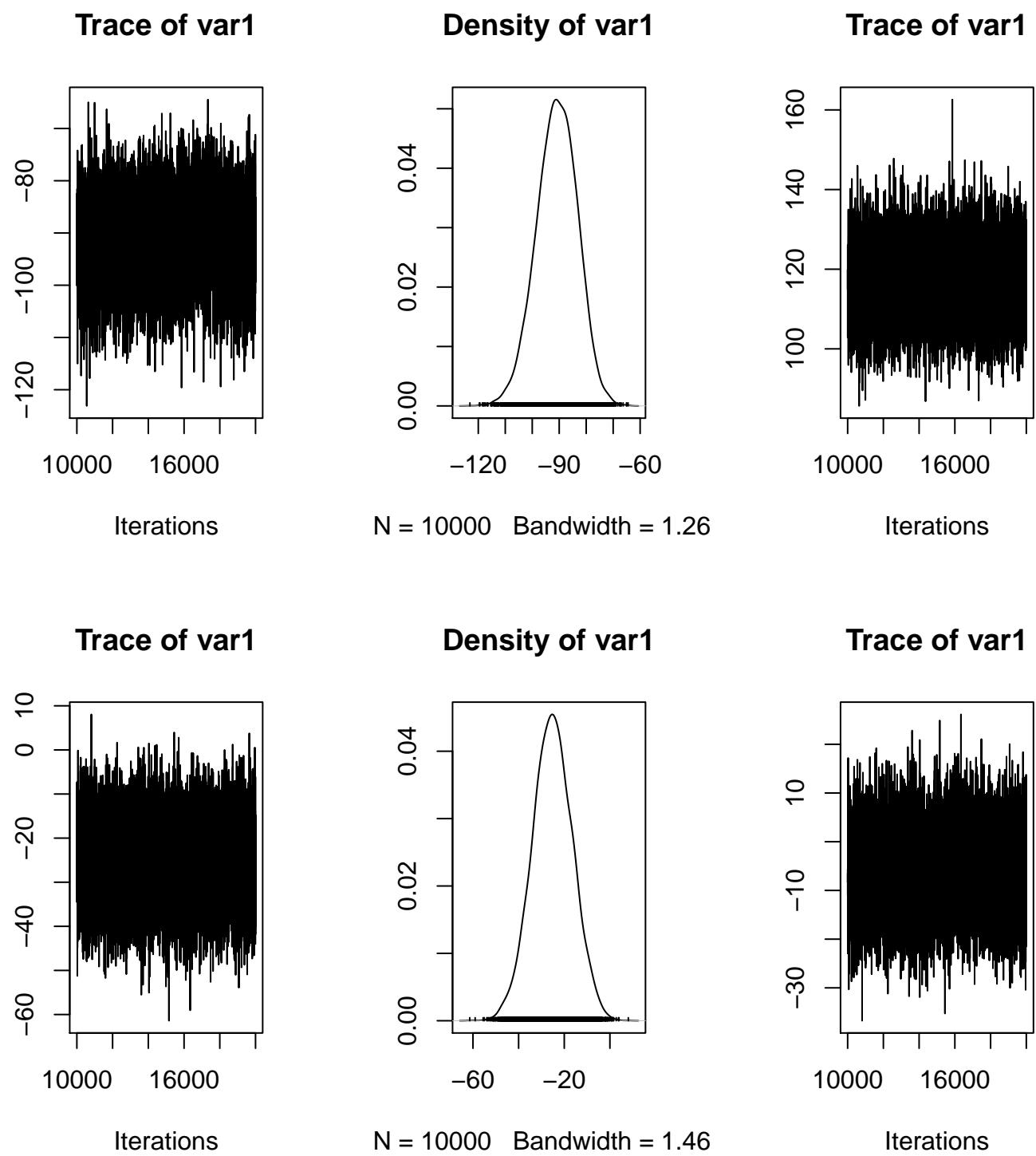


$N = 10000$ Bandwidth = 1.46

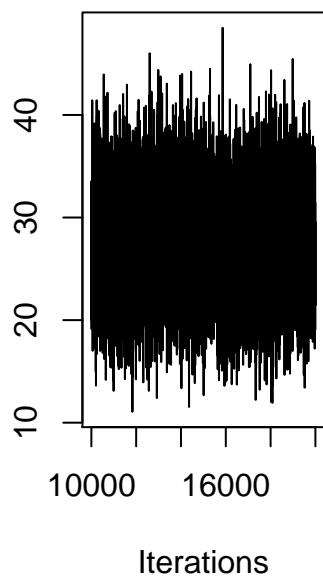
Trace of var1



Iterations

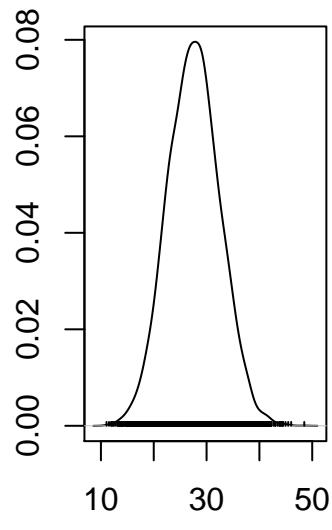


Trace of var1



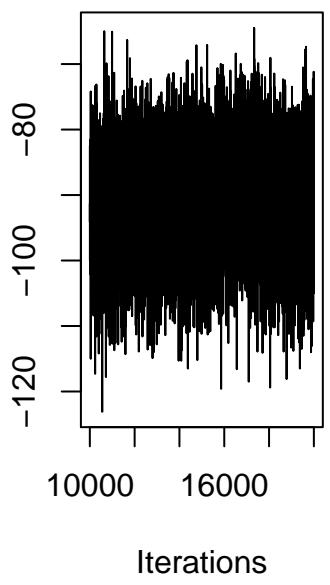
Iterations

Density of var1



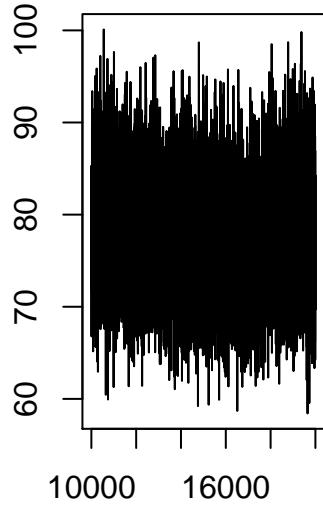
$N = 10000$ Bandwidth = 0.82

Trace of var1



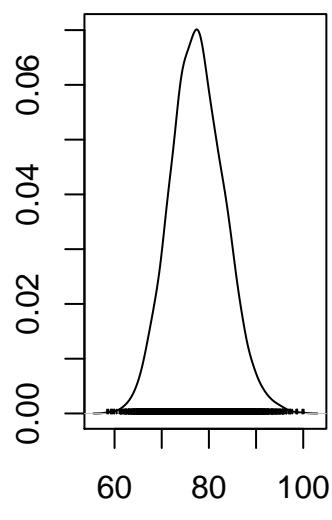
Iterations

Trace of var1



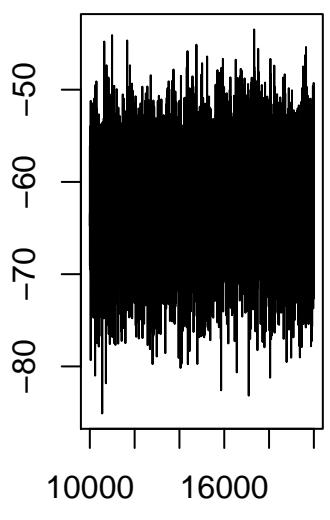
Iterations

Density of var1



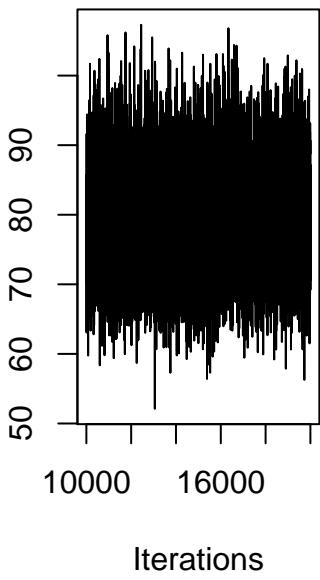
$N = 10000$ Bandwidth = 0.967

Trace of var1



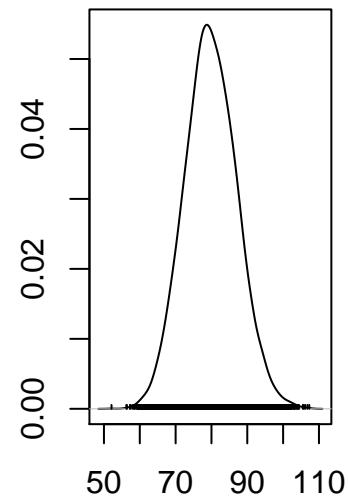
Iterations

Trace of var1



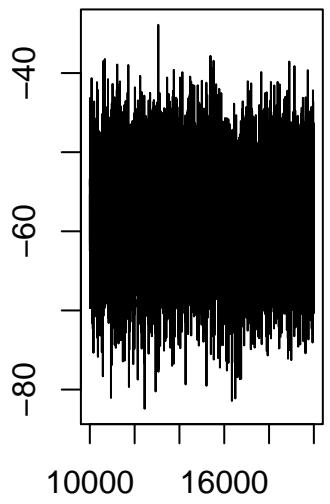
Iterations

Density of var1



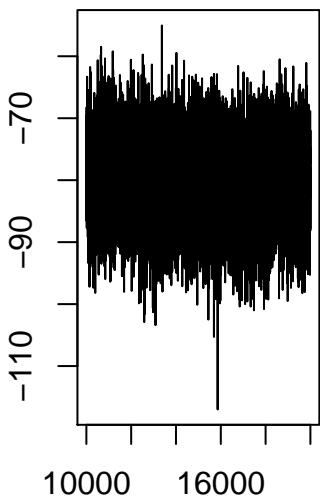
$N = 10000$ Bandwidth = 1.22

Trace of var1



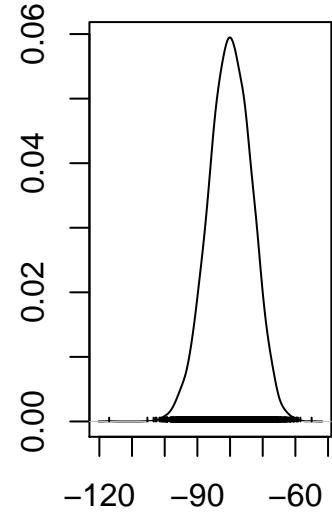
Iterations

Trace of var1



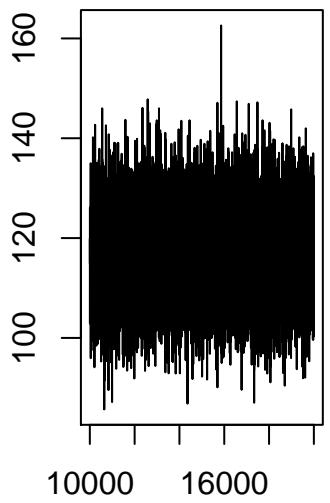
Iterations

Density of var1



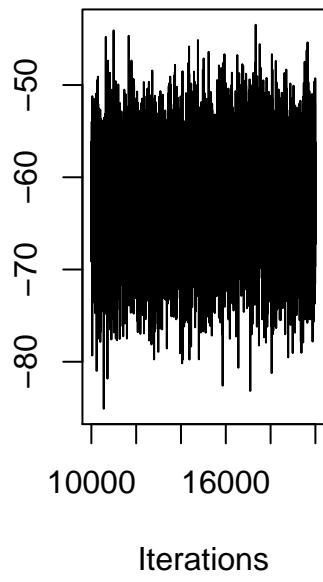
$N = 10000$ Bandwidth = 1.09

Trace of var1



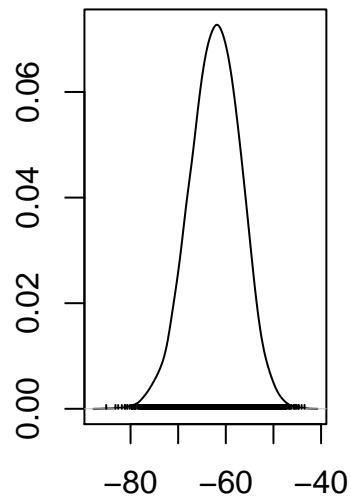
Iterations

Trace of var1



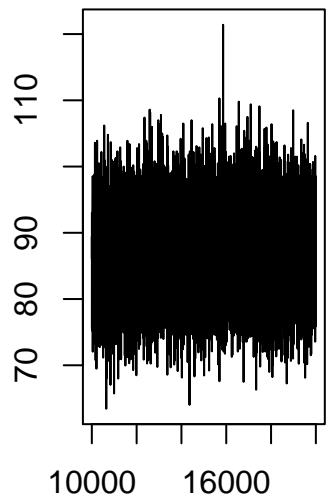
Iterations

Density of var1



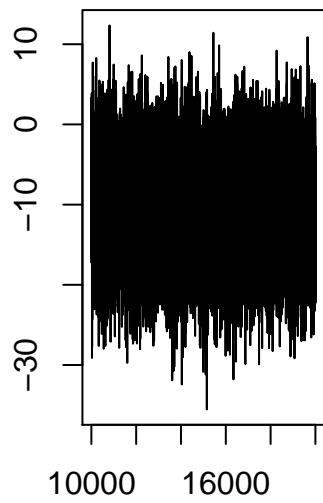
$N = 10000$ Bandwidth = 0.898

Trace of var1



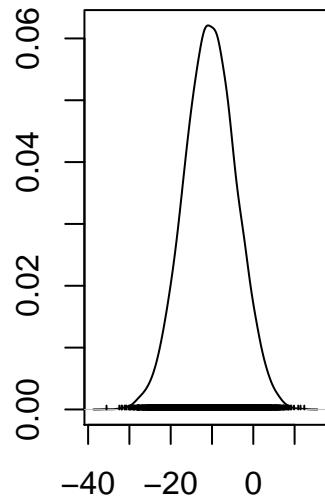
Iterations

Trace of var1



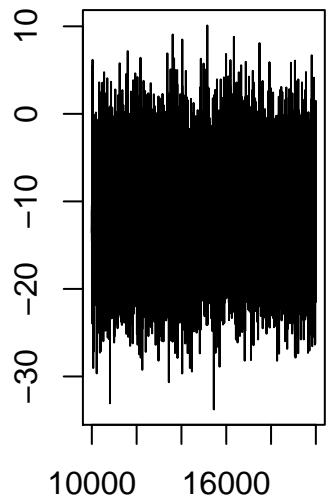
Iterations

Density of var1



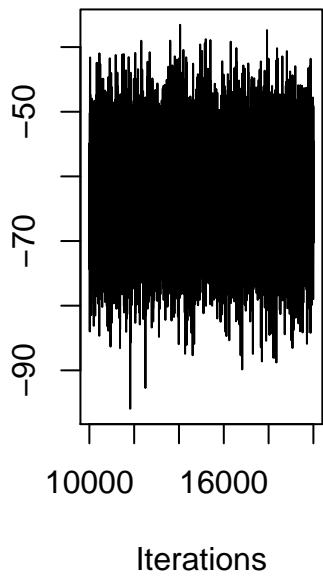
$N = 10000$ Bandwidth = 1.06

Trace of var1



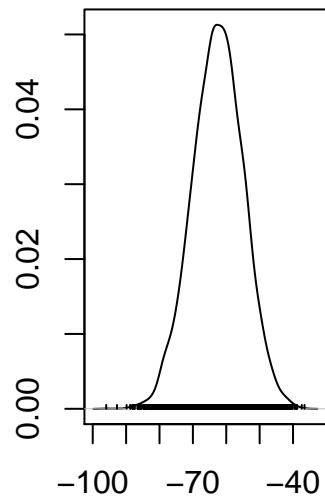
Iterations

Trace of var1



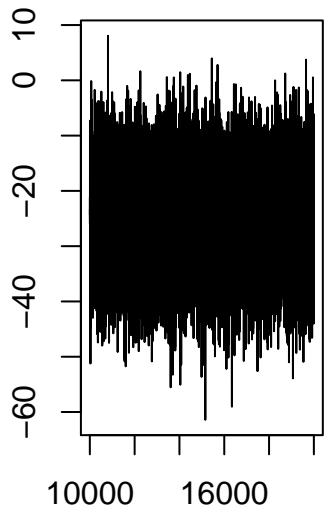
Iterations

Density of var1



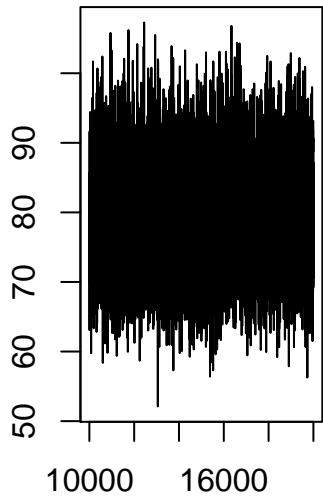
$N = 10000$ Bandwidth = 1.28

Trace of var1



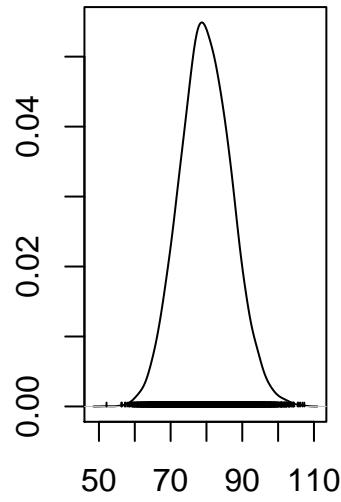
Iterations

Trace of var1



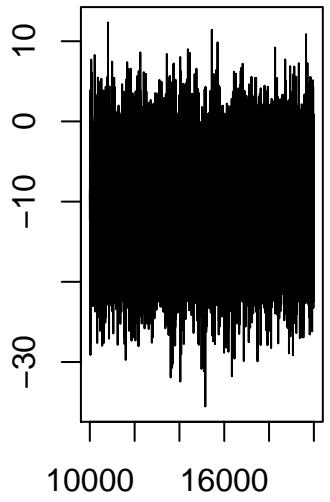
Iterations

Density of var1



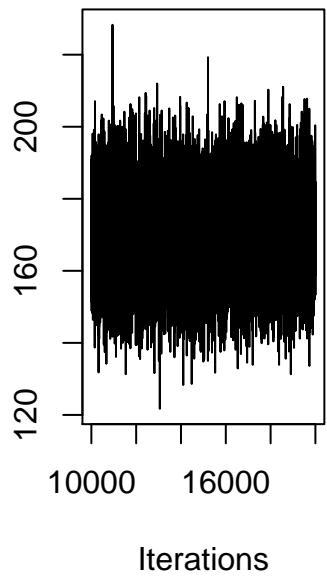
$N = 10000$ Bandwidth = 1.28

Trace of var1



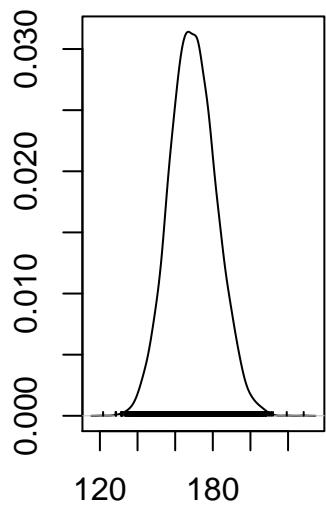
Iterations

Trace of var1



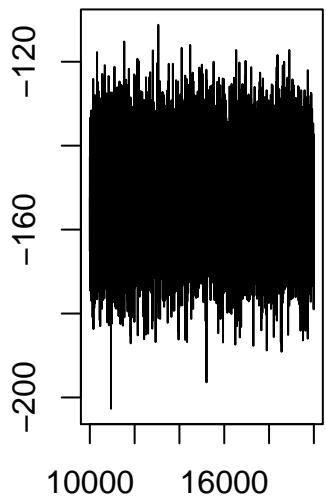
Iterations

Density of var1



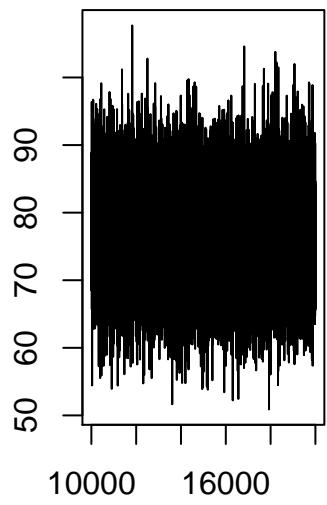
$N = 10000$ Bandwidth = 2.07

Trace of var1



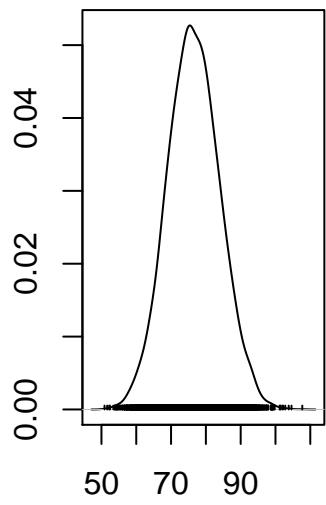
Iterations

Trace of var1



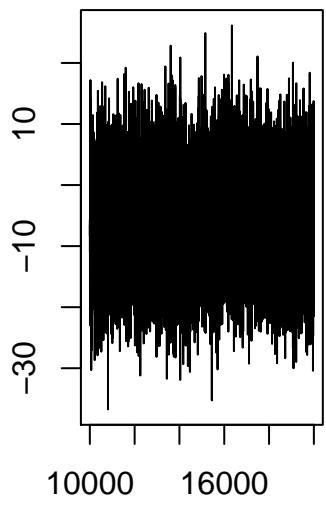
Iterations

Density of var1

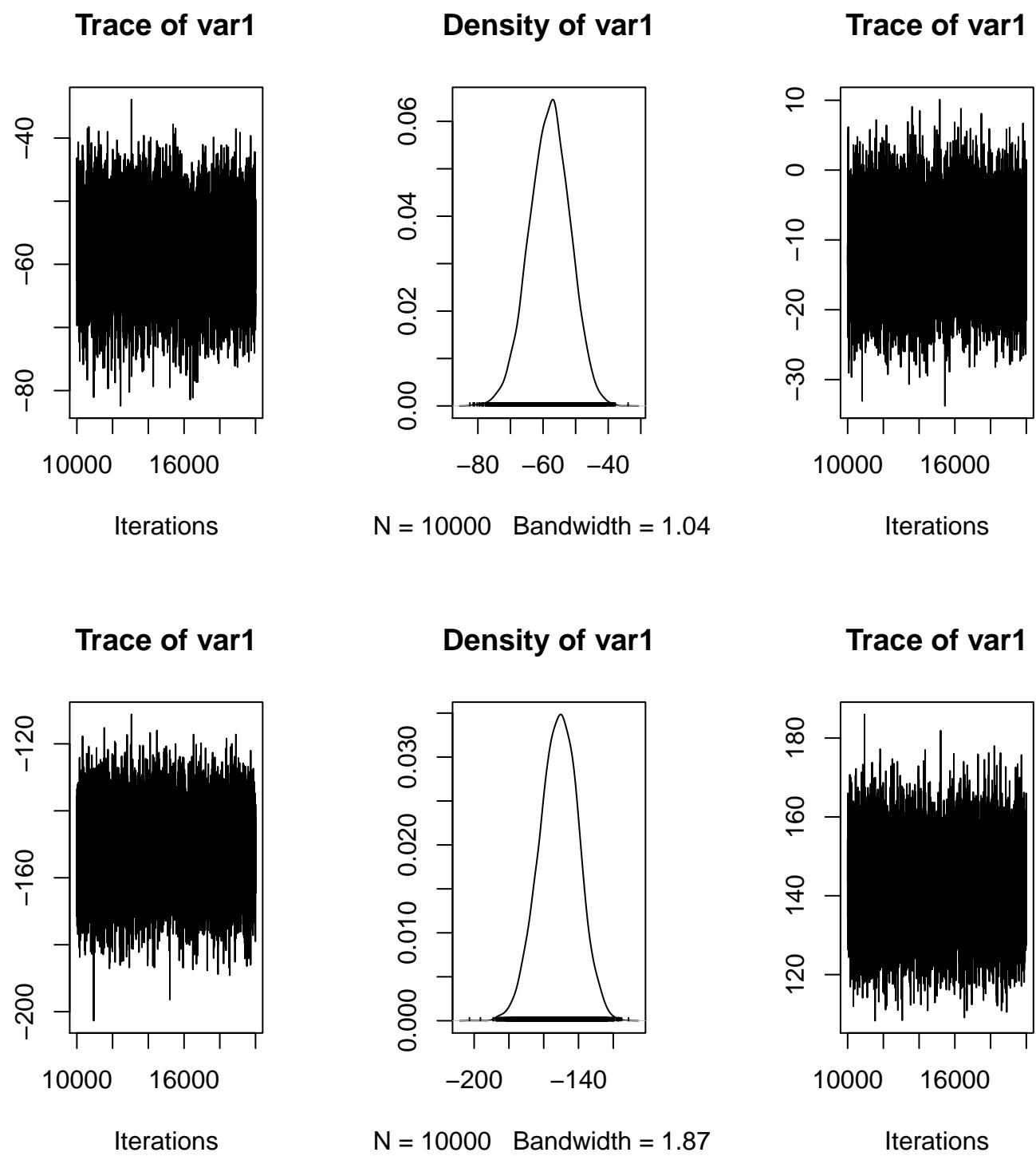


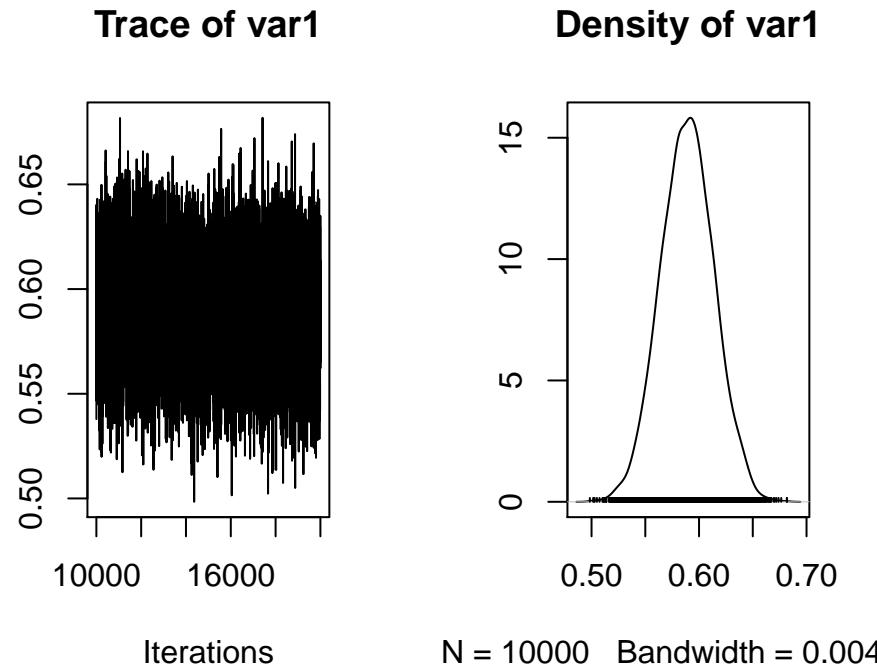
$N = 10000$ Bandwidth = 1.25

Trace of var1



Iterations

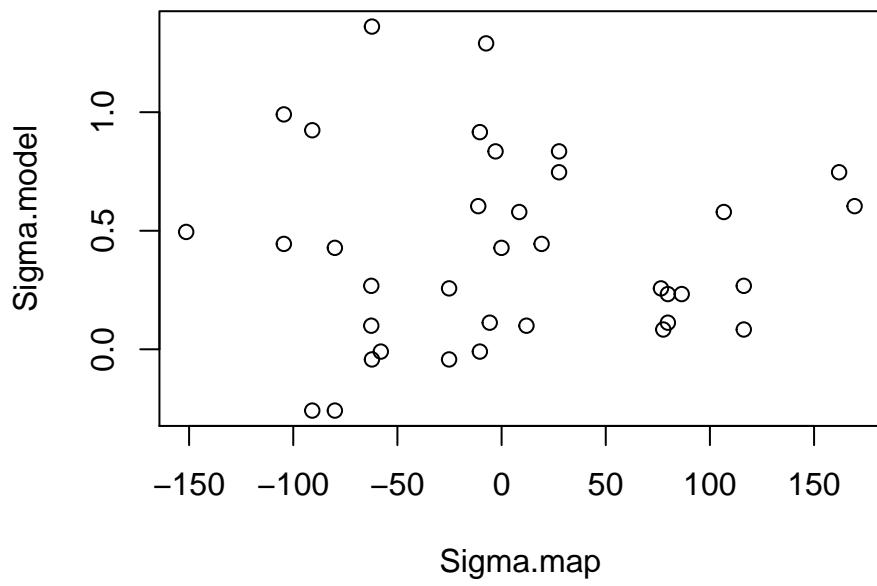




```

Sigma.map <- unlist(posterior.means)[1:36]
Sigma.model <- unlist(sig$mat)
plot(Sigma.map, Sigma.model)

```



```
rho.map <- unlist(posterior.means)[43]  
nu.map <- unlist(posterior.means)[37:42]
```