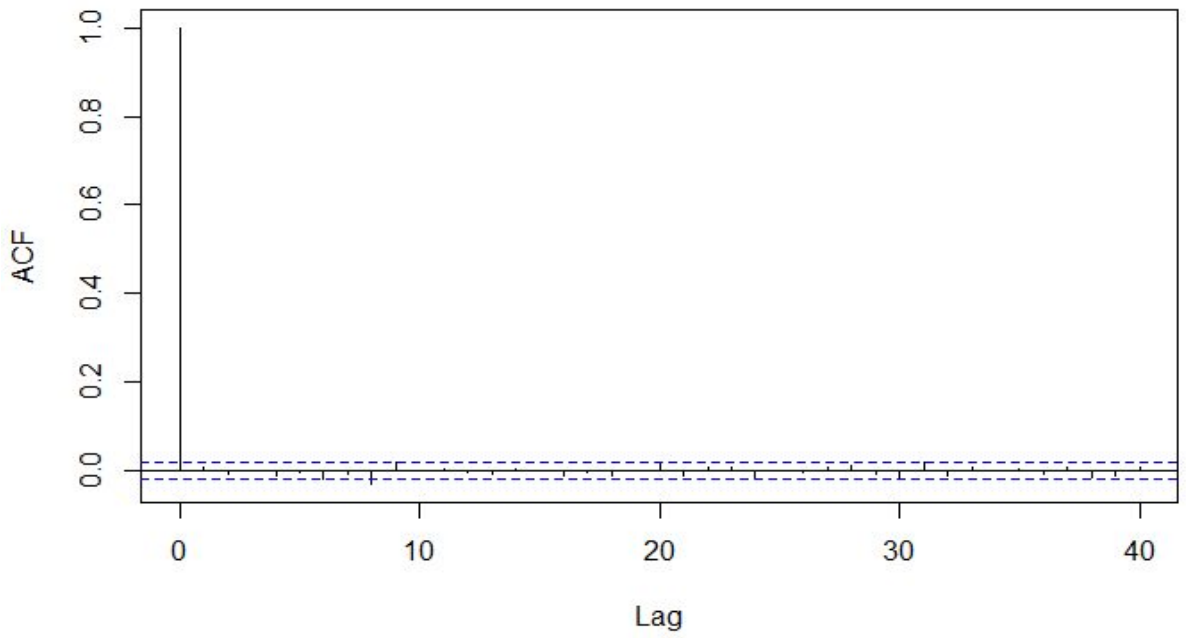
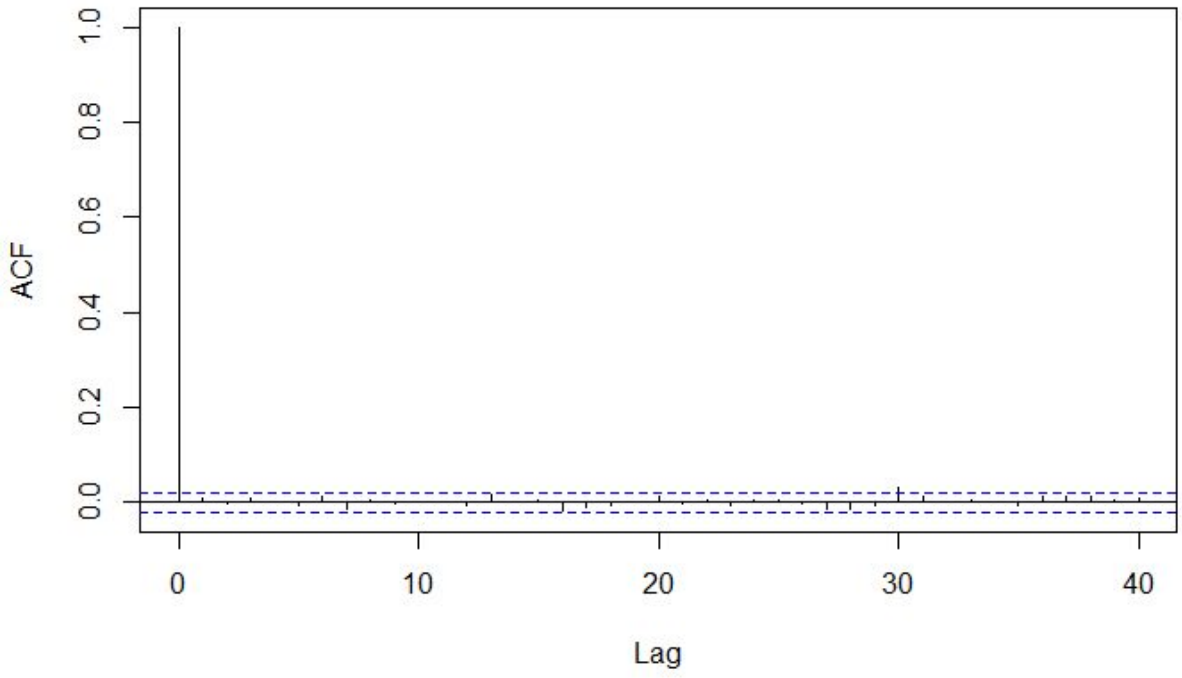
Aman Arora (amana4@illinois.edu)

Answer 1a)



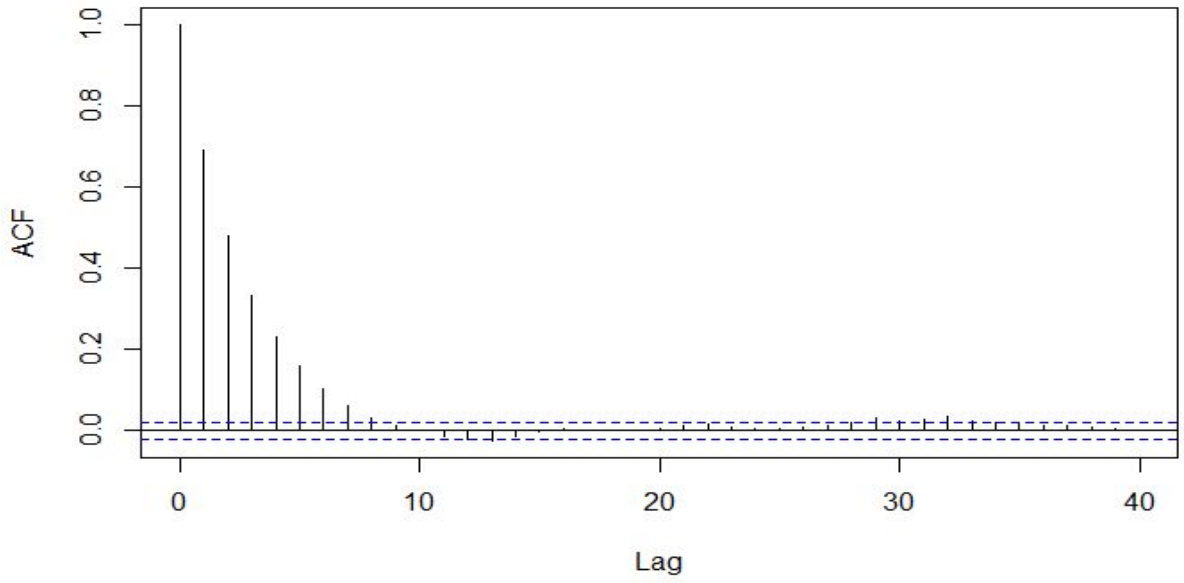
ACF plot for mu variates



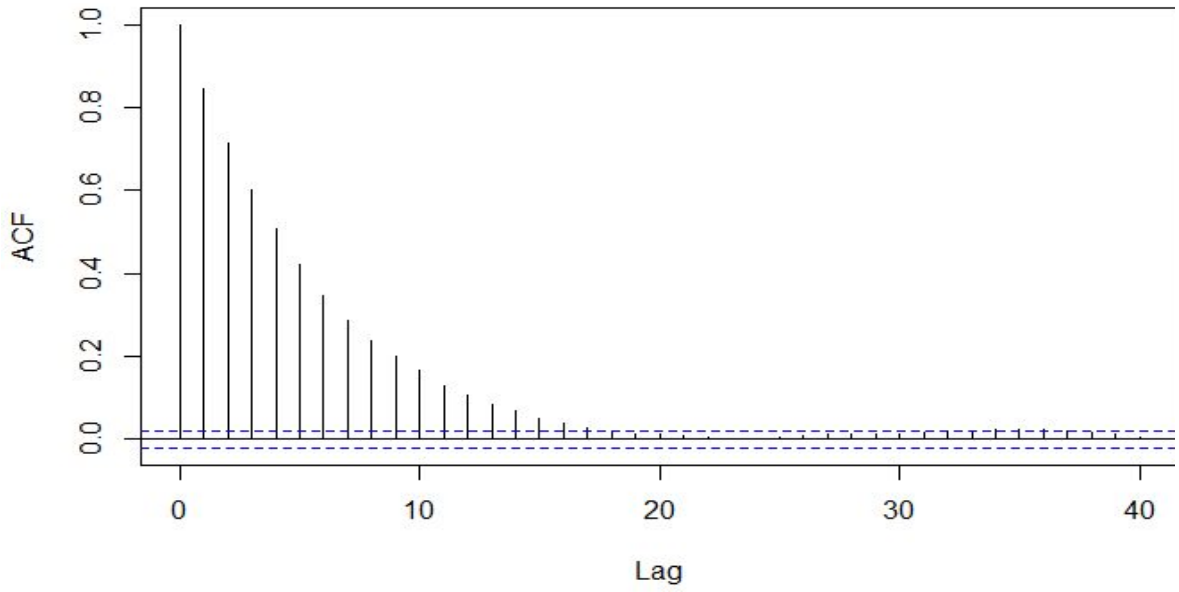
ACF plot for sigma^2 variates

b)
I) rho = .03 gives an acceptance rate of 0.3505522

II)



ACF plot for mu variates



ACF plot for sigma^2 variates

c) The Gibbs sampler displays higher mixing due to faster rate of decay of autocorrelation with lag.

Answer 2 a)

i) library(rjags)
d <- read.csv("polls2016.txt",sep = "",header = TRUE)

#initialize values for mu and tau
initial.values <- list(list(mu =100, tau = 100),
list(mu =100, tau = .01),
list(mu =-100, tau = 100),
list(mu =-100, tau = .01)
)
d$sigma <- d$ME/2

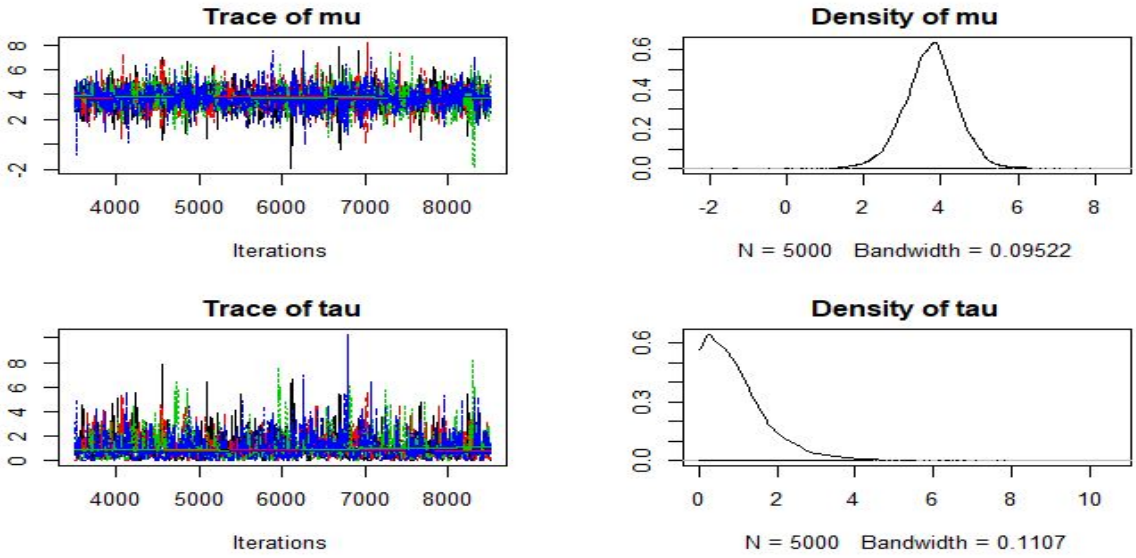
#setup the model
m1<-jags.model("polls20161.bug",d,initial.values, n.chains =4)

ii)
#Burn in 2500 iteration
update(m1,2500)

#Run for 5000 iterations and monitor mu and tau
x1<- coda.samples(m1,c("mu","tau"), n.iter = 5000)

iii) plot(x1)

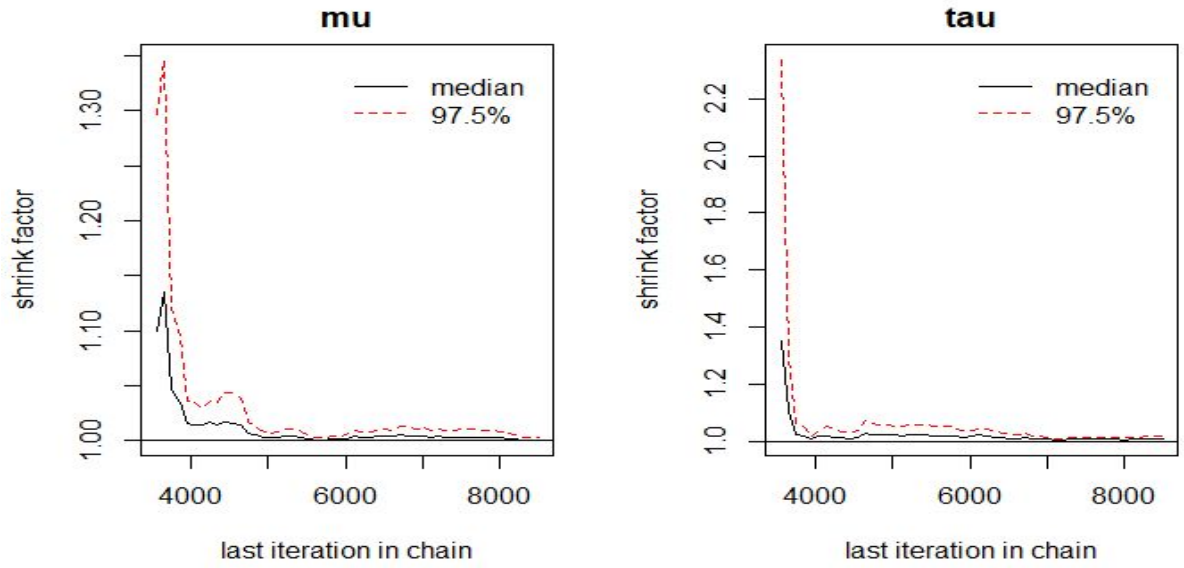
The chains are sampling from the same regions and the density plots looks to have a single mode, from visual inspection there does not seem to be a problem with convergence.



iv) gelman.diag(x1,autoburnin = FALSE)
gelman.plot(x1,autoburnin = FALSE)

	Point est.	Upper C.I.
mu	1.00	1.00
tau	1.01	1.02

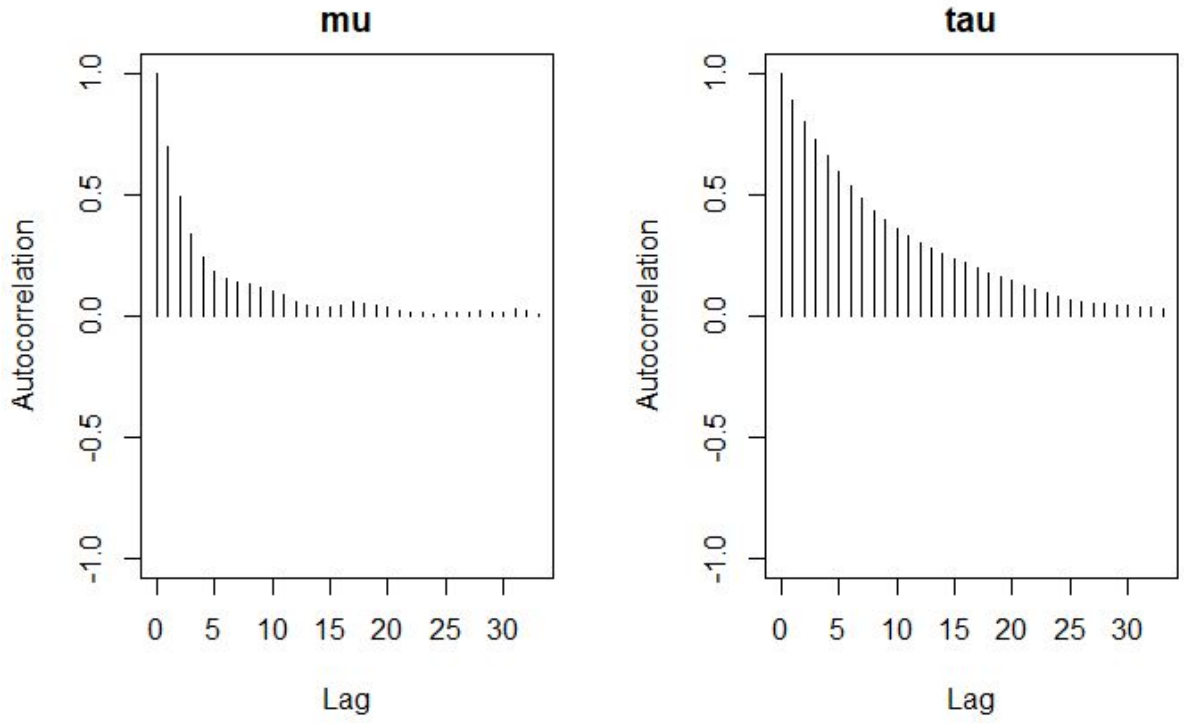
As we can see from the trend the gelam-Rubin statistic is converging to 1 indicating no convergence problem.



v) autocorr.plot(x1[[1]])

The mixing seems to high for mu due to fast rate of decay of autocorrelation with lag. At lag 20 the samples become almost uncorrelated with autocorrelation close to 0.

The mixing for tau is lower than mu as we can see the autocorrelation remains high till lag 25. This is seen in effective sample size in next answer as well where tau has lower effective size than mu.



vi) effectiveSize(x1)

mu tau
2323.6259 933.3335

Since they are greater than suggested minimum size 400 - they are adequate

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b)

i)

```
model {

  for (j in 1:length(y)) {
    y[j] ~ dnorm(theta[j], 1/sigma[j]^2)
    theta[j] ~ dnorm(mu, 1/tau^2)
  }

  mu ~ dunif(-1000,1000)
  logtau ~ dunif(-100,100)
  tau<-exp(logtau)

}
```

ii)

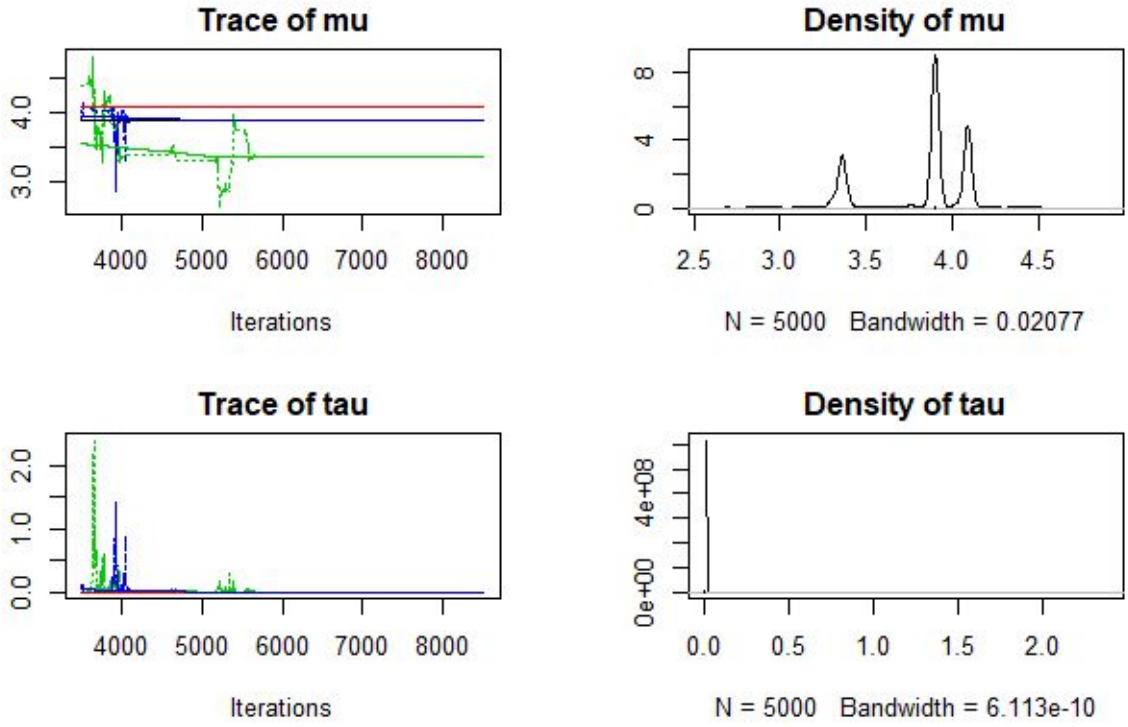
```
library(rjags)

d <- read.csv("polls2016.txt",sep = "",header = TRUE)
initial.values <- list( list(mu =100, logtau = log(100),
                        list(mu =100, logtau = log(.01),
                        list(mu =-100, logtau = log(100),
                        list(mu =-100, logtau = log(.01)
                        )
d$sigma <- d$ME/2
m1<-jags.model("polls20162.bug",d,initial.values, n.chains =4)
```

iii)

```
update(m1,2500)
x1<- coda.samples(m1,c("mu","tau"), n.iter = 5000)
```

iv) The trace for mu and delta indicates the chains are sampling from different regions of distribution and likely not fully representative of actual distribution - indicating convergence has not happened



v)
gelman.diag(x1,autoburnin = FALSE)

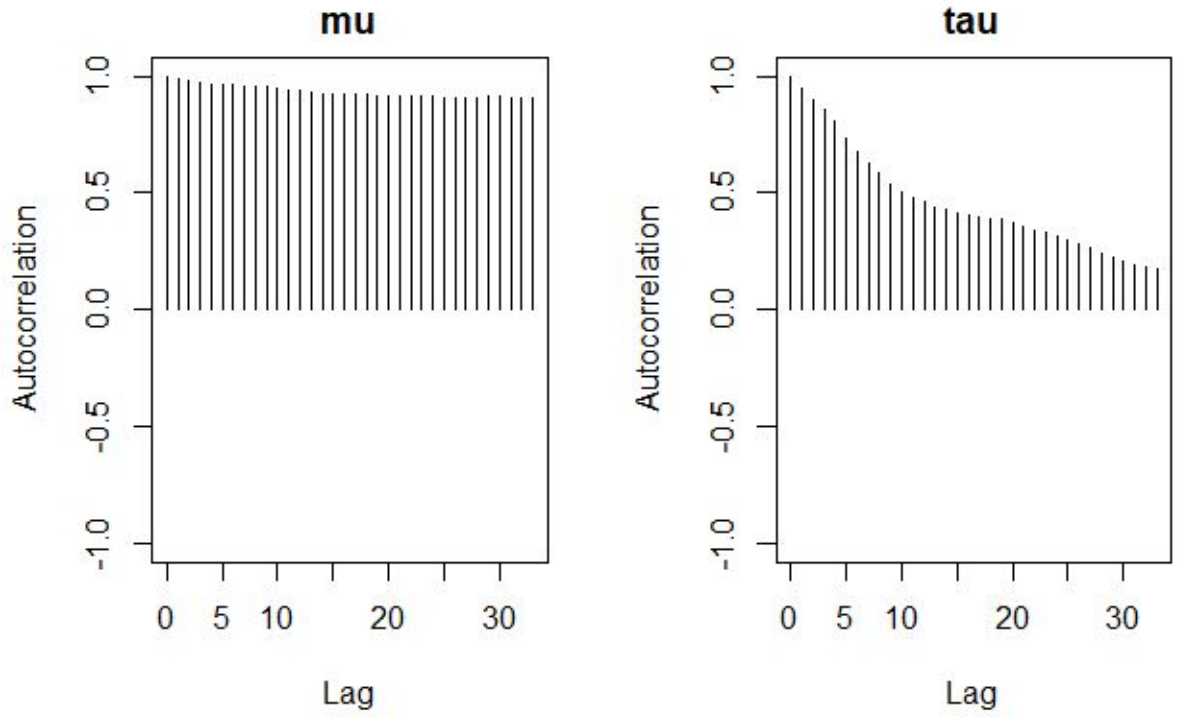
Potential scale reduction factors:

	Point est.	Upper C.I.
mu	3.20	14.99
tau	1.22	1.41

The gelman-rubin statistic is higher than 1, indicating the chains have not converged

vi) autocorr.plot(x1[[1]])

The autocorrelation plots show relatively high correlations at lags of even 30. The mixing is slow in this case.



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vii) The model is using an improper hyperprior p(log(τ)) that's resulting in improper posterior distribution of τ (BDA3 5.4). Improper posteriors do not define true distributions, sampling from improper posteriors will yield samples not representative of the required distribution.