

STAT 578 - Advanced Bayesian Modeling - Fall 2019

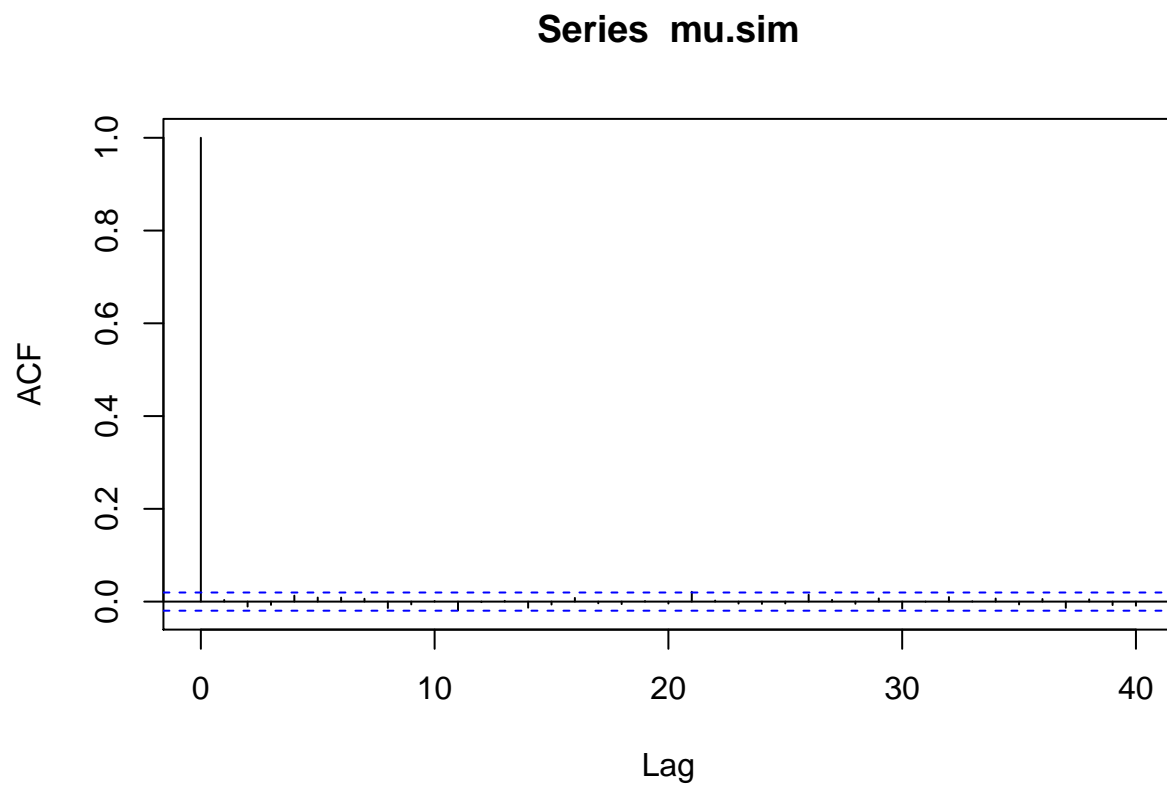
Assignment 3

Xiaoming Ji

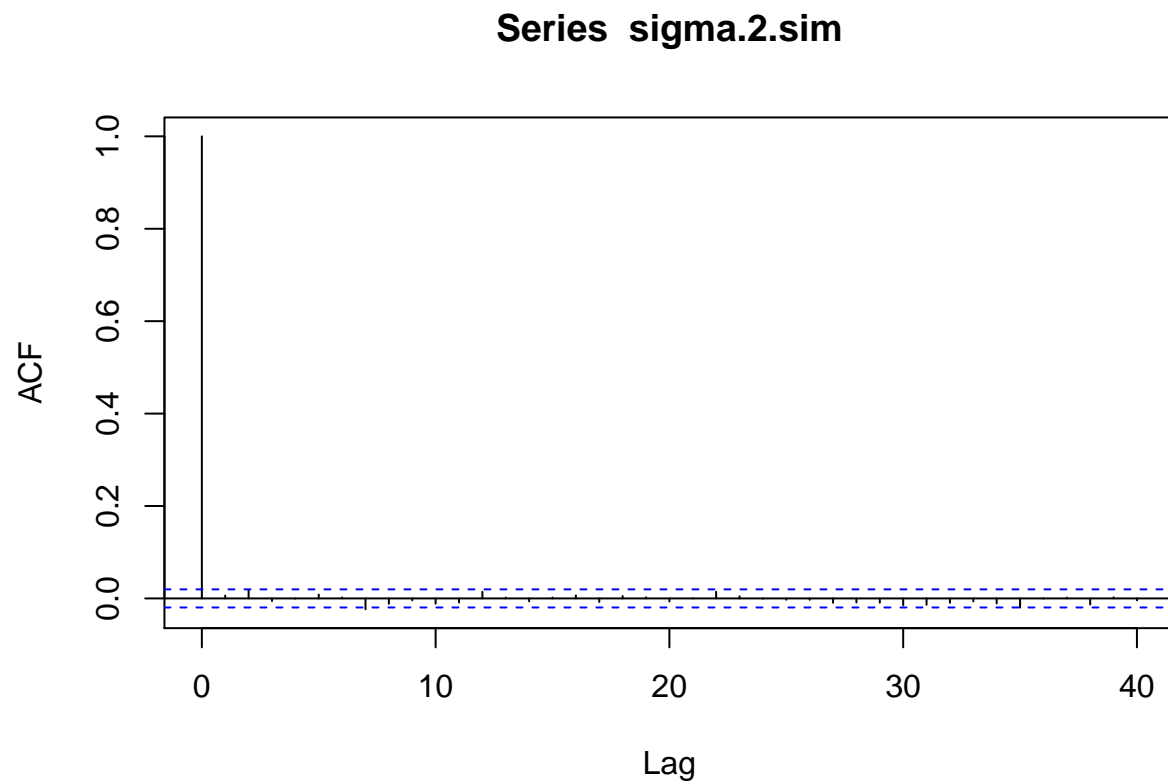
Solution for Problem 1

(a)

```
source("FlintGibbs.R")  
acf(mu.sim)
```



```
acf(sigma.2.sim)
```



(b)

(i)

```
rho <- 0.03  
source("FlintMetropolis.R")
```

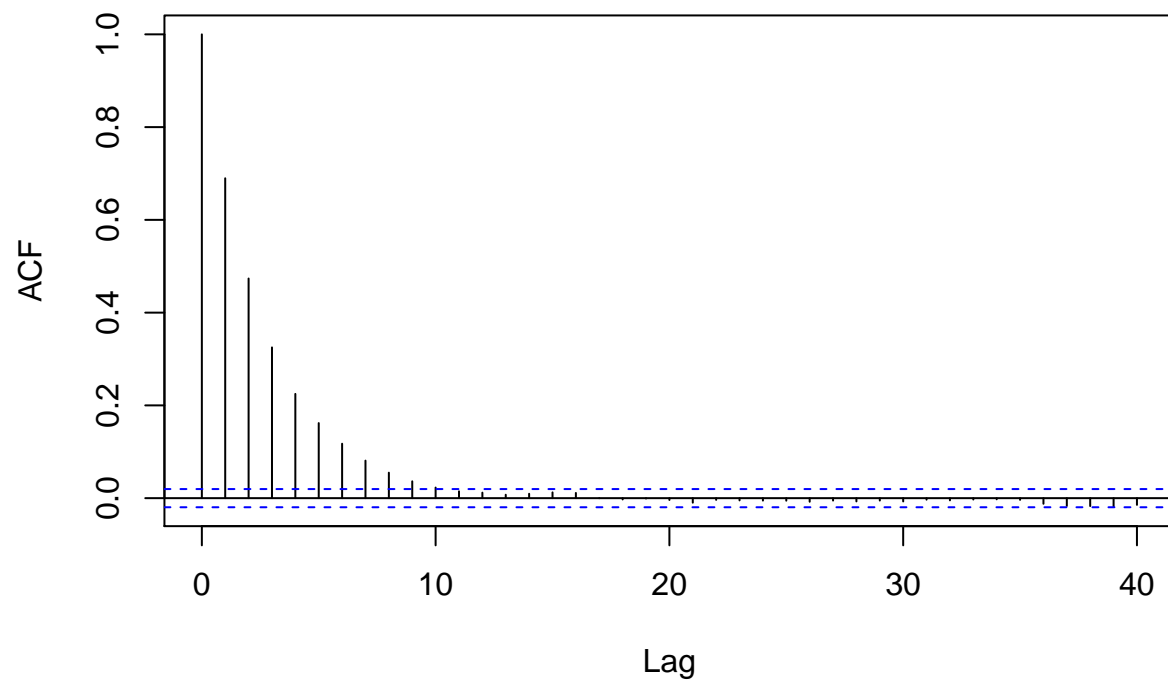
```
## [1] 0.3522545
```

ρ takes 0.03 will give acceptance rate of about 0.35.

(ii)

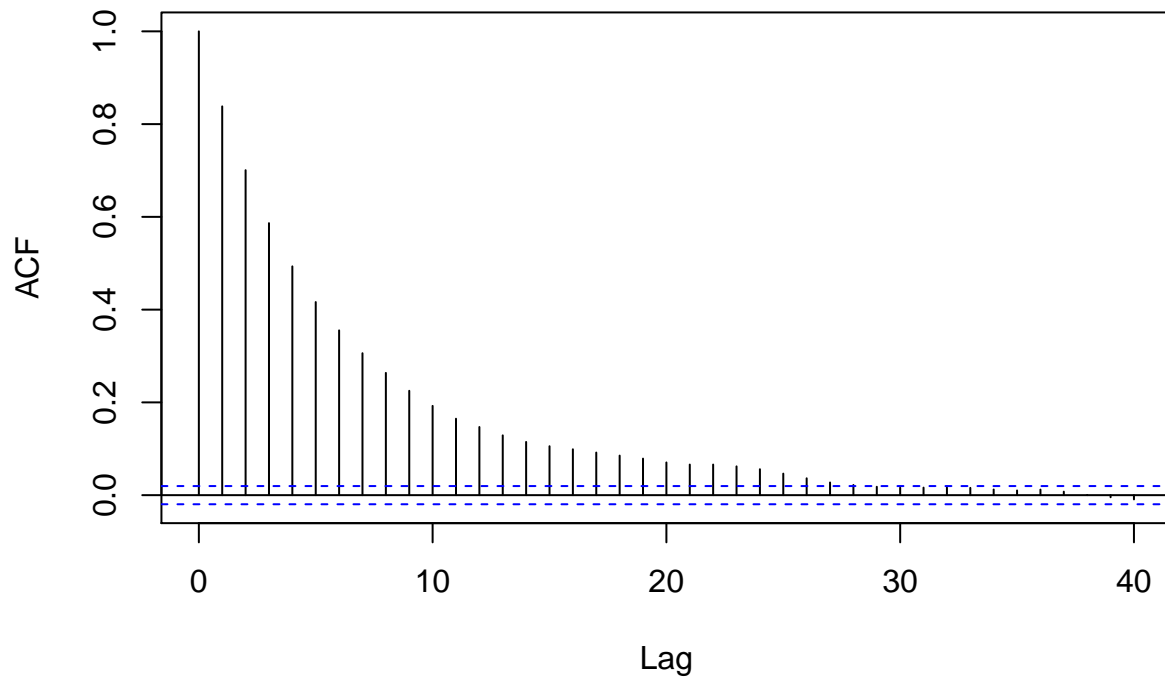
```
acf(mu.sim)
```

Series mu.sim



```
acf(sigma.2.sim)
```

Series sigma.2.sim



(c)

The autocorrelation plot for Gibbs sampler decays much faster than Metropolis sampler's. Thus, Gibbs sampler exhibited faster mixing.

Solution for Problem 1

(a)

```
library(rjags)

## Loading required package: coda
## Linked to JAGS 4.3.0
## Loaded modules: basemod,bugs
polls2016_df <- read.table("polls2016.txt", header=TRUE)
polls2016_df$sigma <- polls2016_df$ME/2
polls2016_df <- subset(polls2016_df, select = -c(poll, ME) )
```

(i)

```
initial_vals <- list(list(mu = 100, tau = 100),
                     list(mu = 100, tau = 0.01),
```

```

list(mu = -100, tau = 100),
list(mu = -100, tau = 0.01))

poll_model <- jags.model("polls20161.bug", polls2016_df, initial_vals, n.chains = 4)

## Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 7
##   Unobserved stochastic nodes: 9
##   Total graph size: 42
##
## Initializing model

```

(ii)

```

update(poll_model, 2500)
x <- coda.samples(poll_model, c("mu", "tau"), n.iter = 5000)

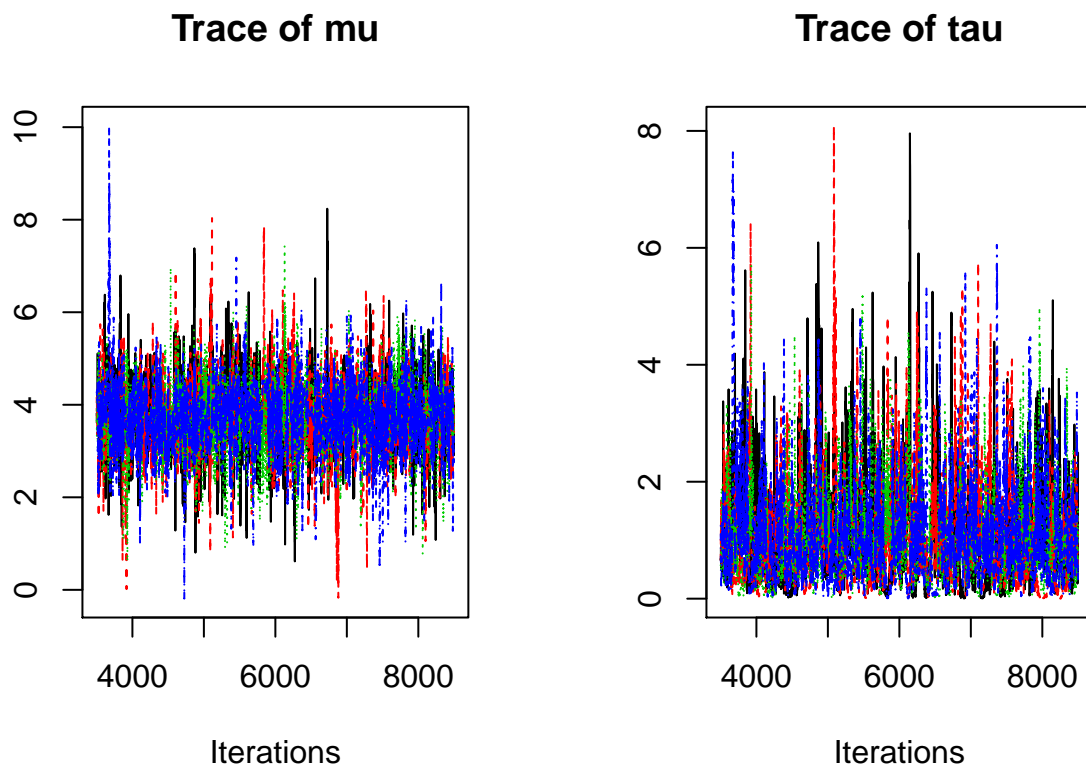
```

(iii)

```

plot(x, smooth=FALSE, density = FALSE)

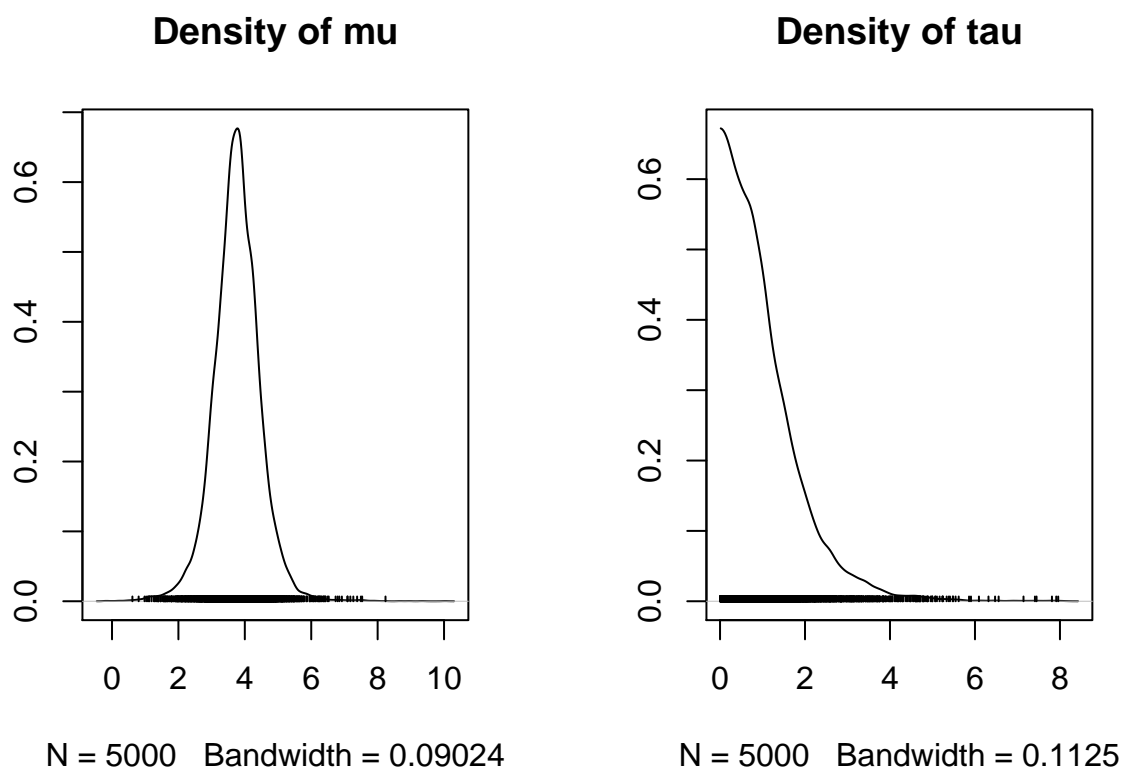
```



```

plot(x, smooth=FALSE, trace = FALSE)

```



The trace plot shows 4 chains for mu and tau span the similar range and we can't observe obvious convergence problem.

(iv)

```
gelman.diag(x, autoburnin=FALSE)
```

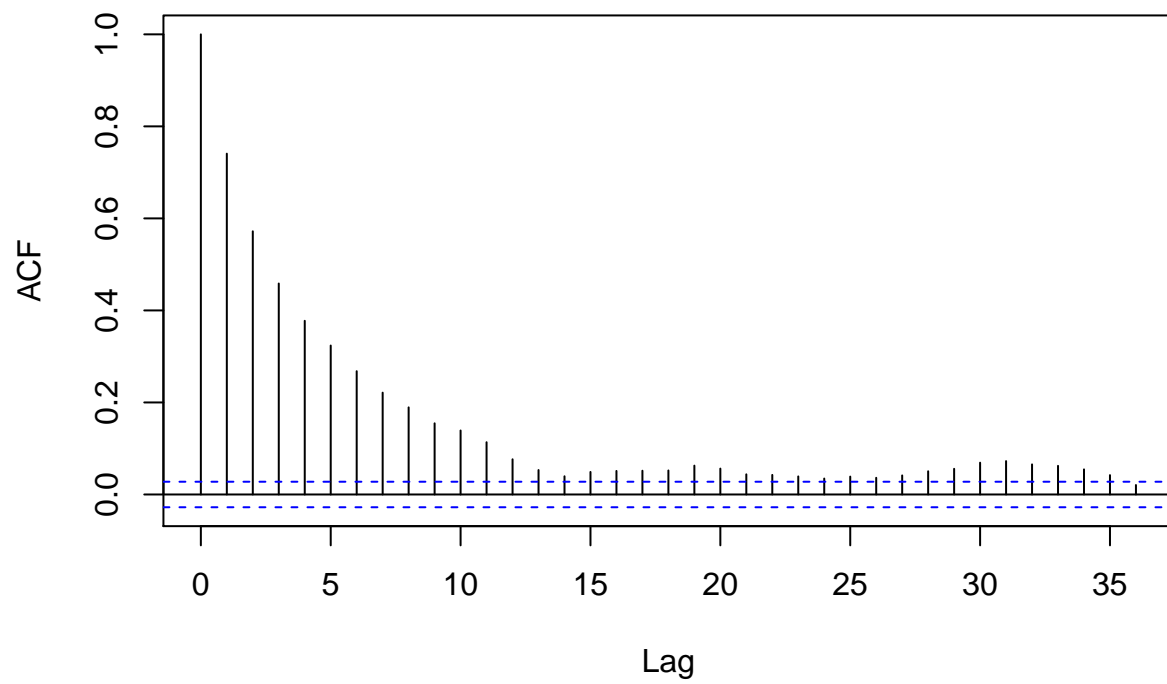
```
## Potential scale reduction factors:
##
##      Point est. Upper C.I.
## mu      1.00      1.00
## tau      1.01      1.02
##
## Multivariate psrf
##
## 1
```

Gelman-Rubin statistics (Potential scale reduction factor) for mu and tau are close to 1 with upper confidence limits close to 1, thus there don't appear to have any convergence problem.

(v)

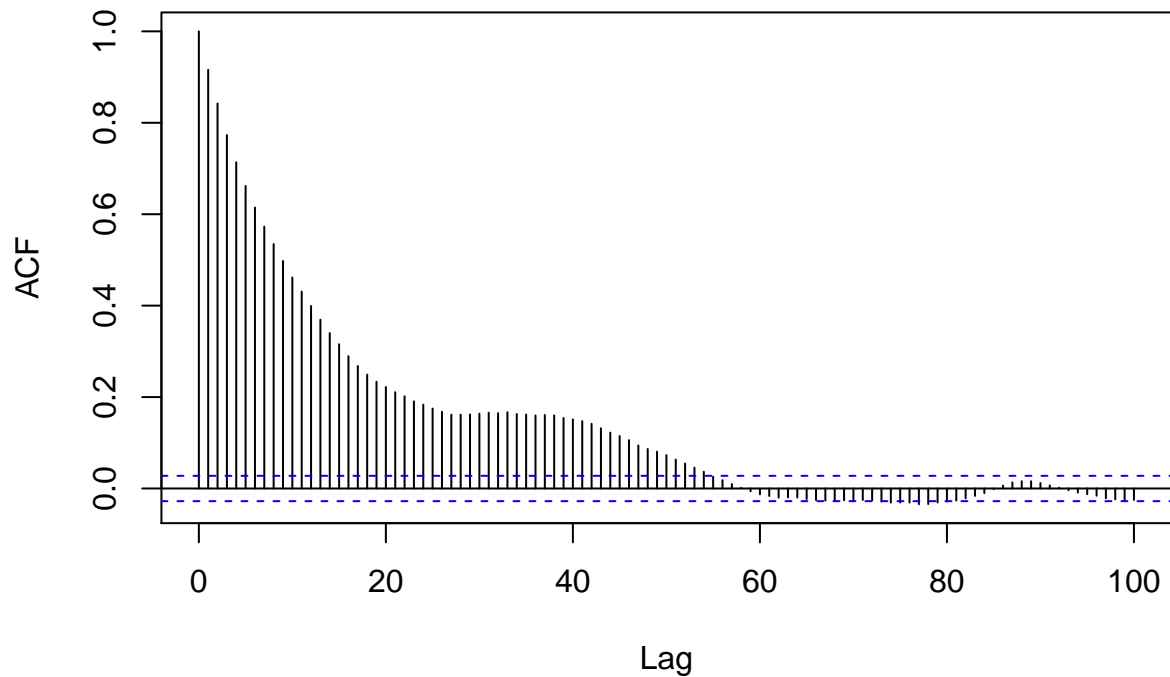
```
mu_chain_1 = x[[1]][,1]
tau_chain_1 = x[[1]][,2]
acf(mu_chain_1)
```

Series mu_chain_1



```
acf(tau_chain_1, lag.max = 100)
```

Series tau_chain_1



We see autocorrelation (of Chain 1) goes zero for μ by lag around 15 and for τ by lag around 80. Thus mixing of μ is faster than τ 's.

(vi)

```
effectiveSize(x)
```

```
##      mu      tau
## 2319.6440 928.5312
```

The effective sample size for μ and τ is less than 2000, thus our sample size of 5000 is adequate.

(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)

```
initial_vals_new <- list(list(mu = 100, logtau = 100),
                          list(mu = 100, logtau = 0.01),
                          list(mu = -100, logtau = 100),
                          list(mu = -100, logtau = 0.01))

poll_model_new <- jags.model("polls20161_new.bug", polls2016_df, initial_vals_new, n.chains = 4)

## Compiling model graph
##   Resolving undeclared variables
##   Allocating nodes
## Graph information:
##   Observed stochastic nodes: 7
##   Unobserved stochastic nodes: 9
##   Total graph size: 44
##
## Initializing model
```

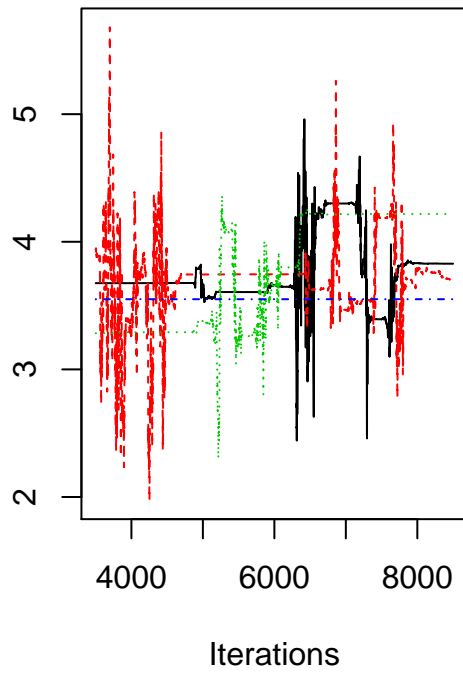
(iii)

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

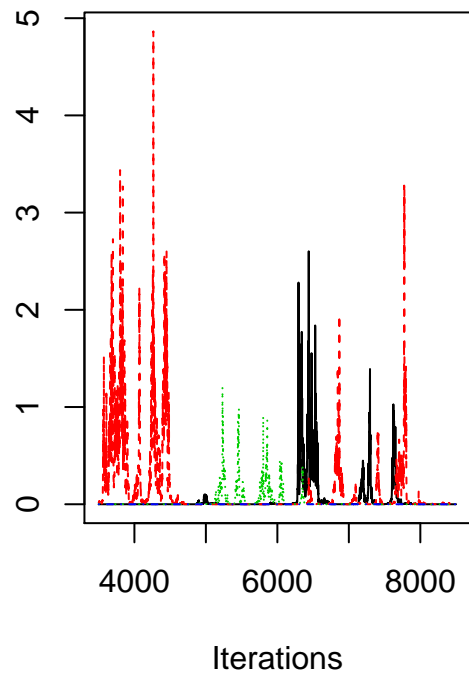
(iv)

```
plot(x_new, smooth=FALSE, density = FALSE)
```

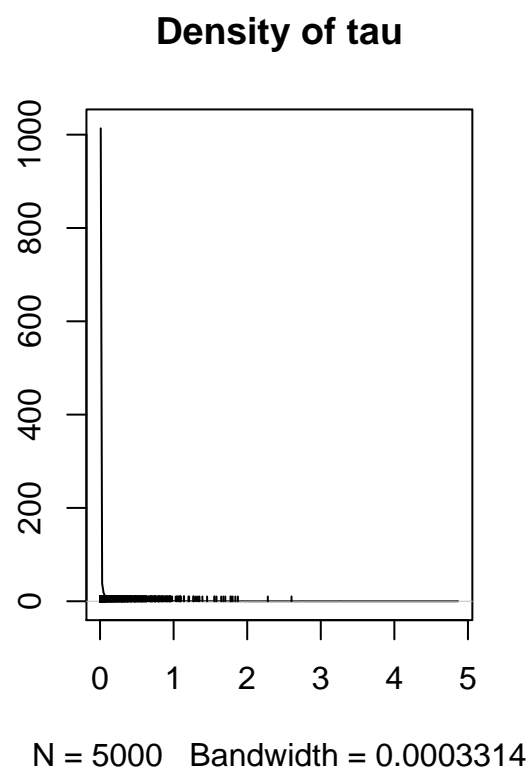
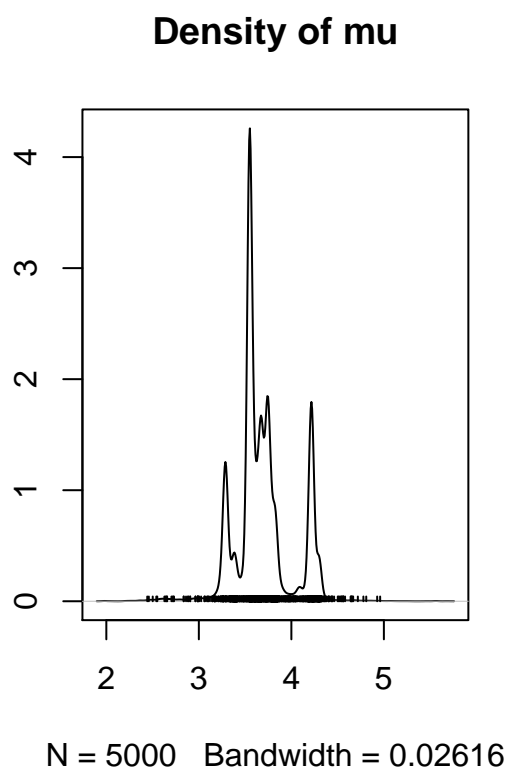
Trace of mu



Trace of tau



```
plot(x_new, smooth=FALSE, trace = FALSE)
```



(v)

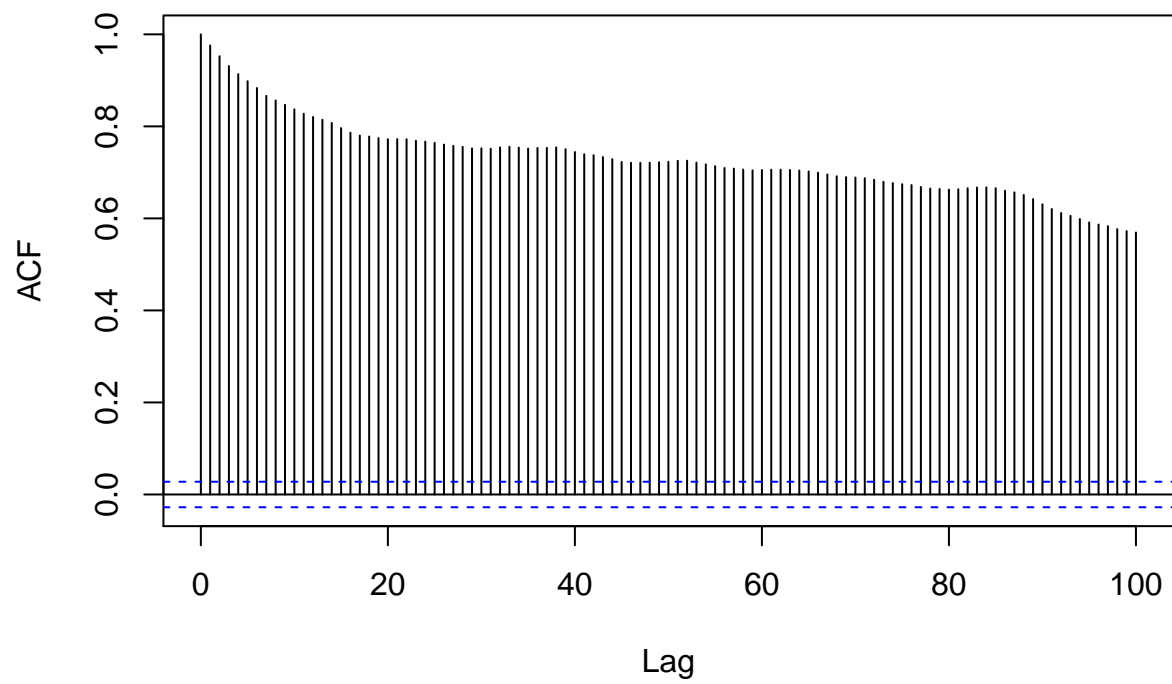
```
gelman.diag(x_new, autoburnin=FALSE)
```

```
## Potential scale reduction factors:
##
##      Point est. Upper C.I.
## mu      1.13      1.36
## tau     1.24      1.70
##
## Multivariate psrf
##
## 1.1
```

(vi)

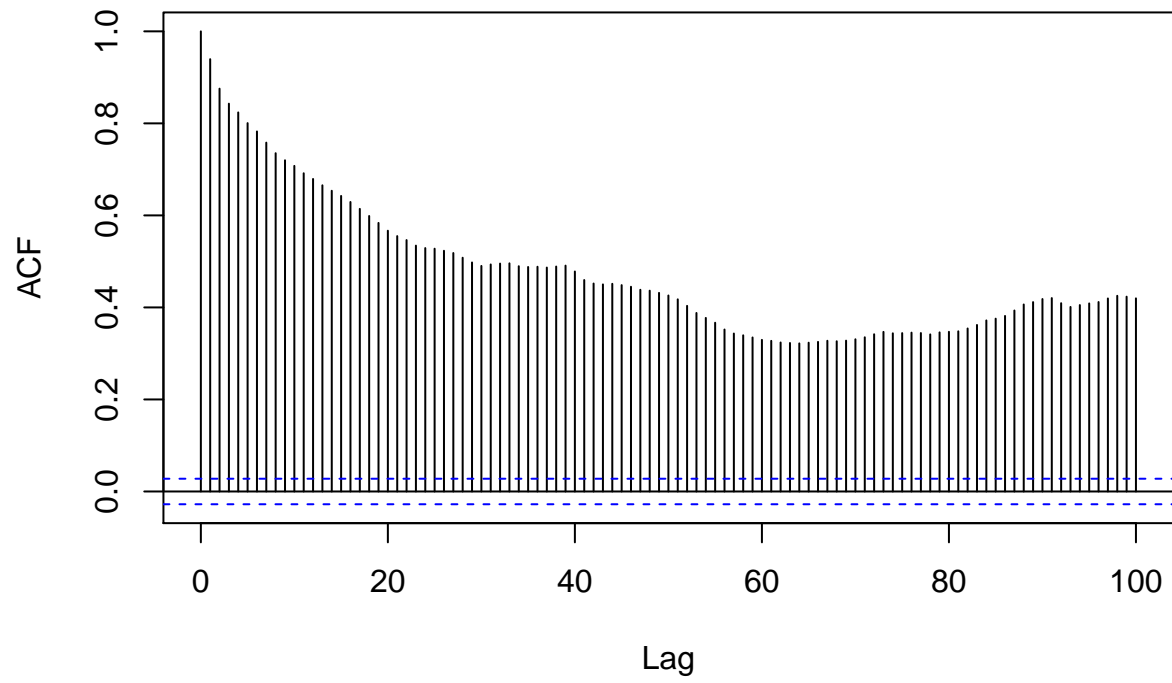
```
mu_chain_1_new = x_new[[1]][,1]
tau_chain_1_new = x_new[[1]][,2]
acf(mu_chain_1_new, lag.max = 100)
```

Series mu_chain_1_new



```
acf(tau_chain_1_new, lag.max = 100)
```

Series tau_chain_1_new



(vii)