STAT 578 - Advanced Bayesian Modeling - Fall 2019 Assignment 3

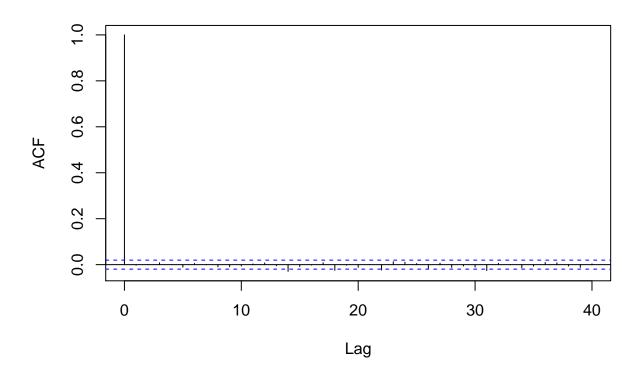
Xiaoming Ji

Solution for Problem 1

(a)

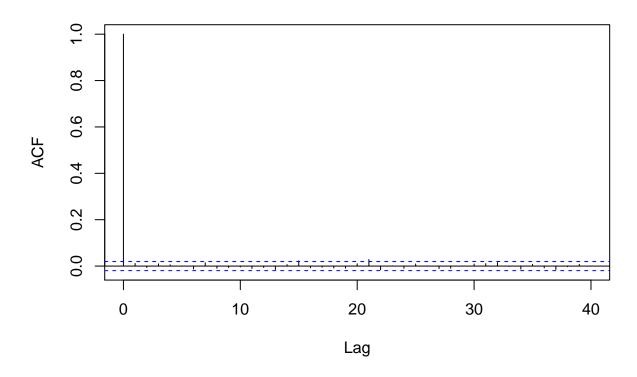
```
source("FlintGibbs.R")
acf(mu.sim)
```

Series mu.sim



acf(sigma.2.sim)

Series sigma.2.sim



(b)

(i)

rho <- 0.03
source("FlintMetropolis.R")</pre>

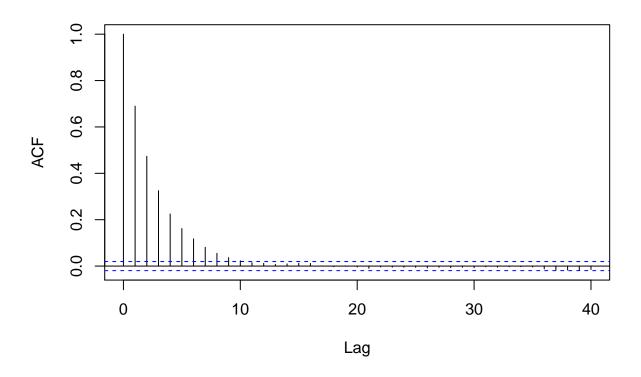
[1] 0.3522545

 ρ takes 0.03 will give acceptance rate of about 0.35.

(ii)

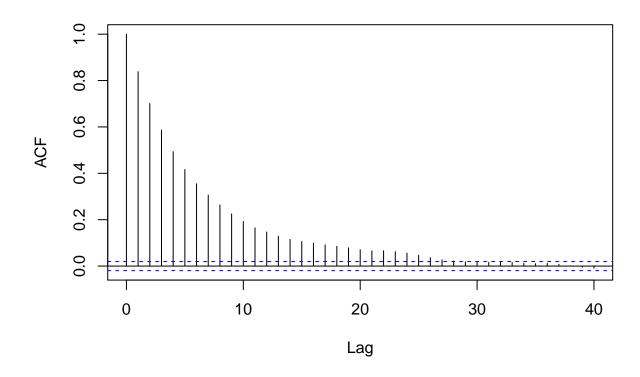
acf(mu.sim)

Series mu.sim



acf(sigma.2.sim)

Series sigma.2.sim



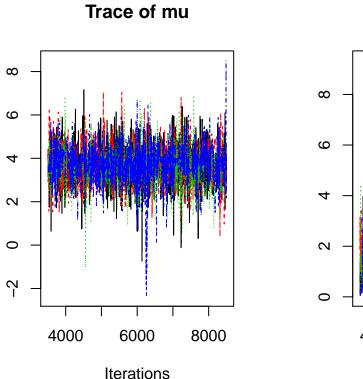
(c)

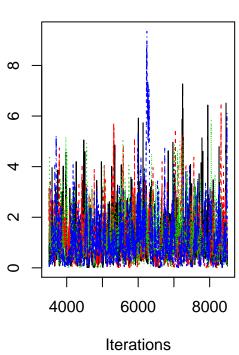
The autocorrelation plot for Gibbs sampler decays much faster than Metropolis sampler's. Thus, Gibbs sampler exhibited faster mixing.

Solution for Problem 1

(a)

```
list(mu = -100, tau = 100),
                     list(mu = -100, tau = 0.01))
poll_model <- jags.model("polls20161.bug", polls2016_df, initial_vals, n.chains = 4)</pre>
## 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)
```



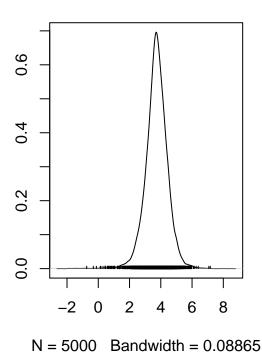


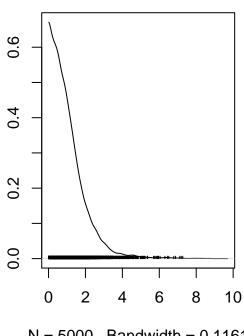
Trace of tau

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

Density of mu

Density of tau





N = 5000 Bandwidth = 0.1161

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)
```

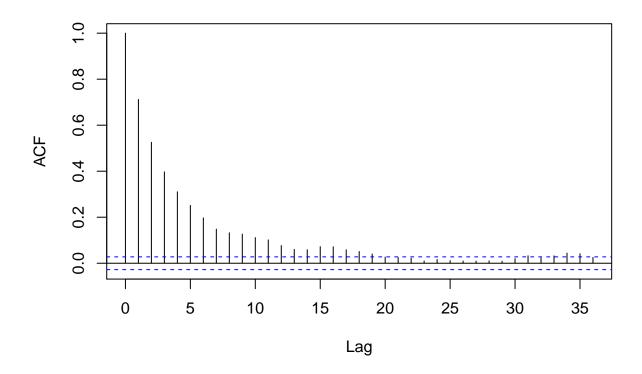
```
## Potential scale reduction factors:
##
##
       Point est. Upper C.I.
## mu
             1.00
                         1.01
             1.01
##
   tau
                         1.01
##
## Multivariate psrf
##
## 1
```

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)
```

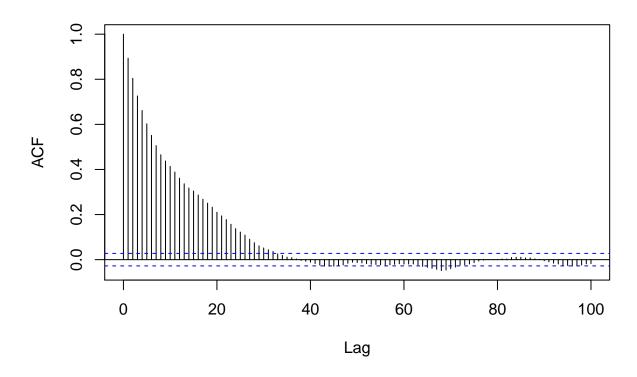
```
mu_chain_1 = x[[1]][,1]
tau_chain_1 = x[[1]][,2]
acf(mu_chain_1)
```

Series mu_chain_1



acf(tau_chain_1, lag.max = 100)

Series tau_chain_1



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

(vi)

effectiveSize(x)

```
## mu tau
## 1818.649 729.951
```

The effective sample size for mu and tau 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)
}</pre>
```

```
(ii)
initial_vals_new <- list(list(mu = 100, logtau = 100),</pre>
                      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)</pre>
## 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)
(iv)
(v)
(vi)
(vii)
```