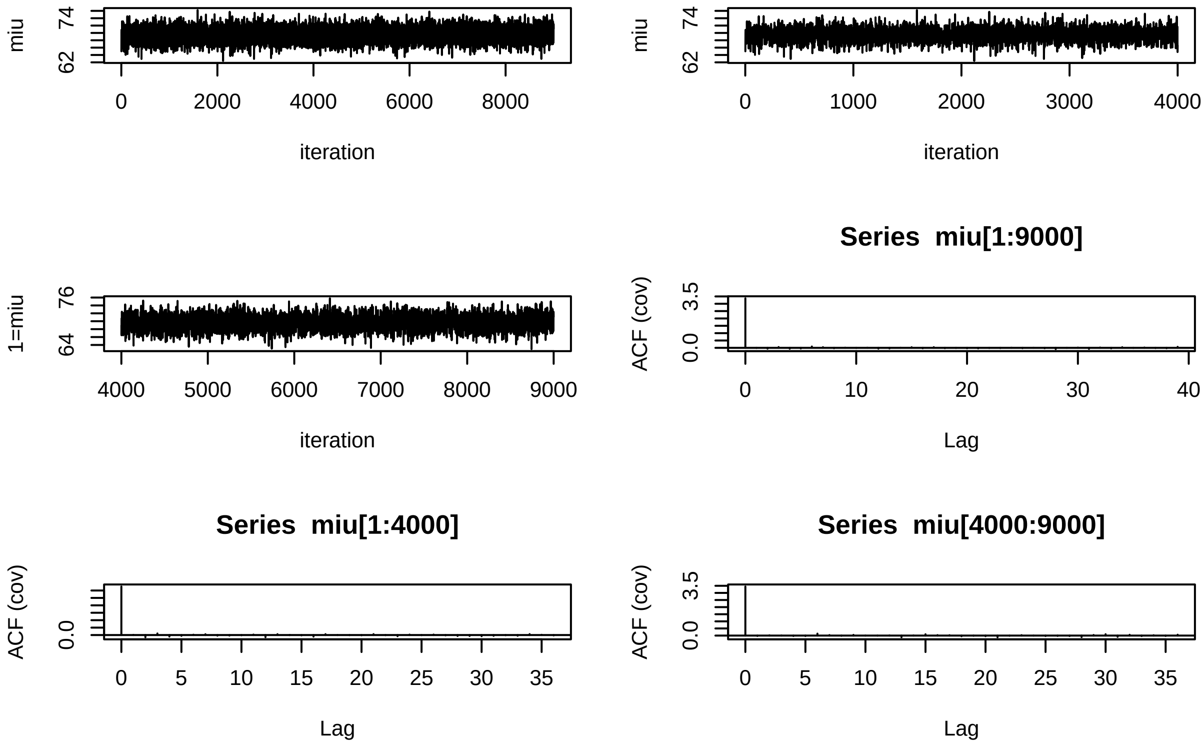
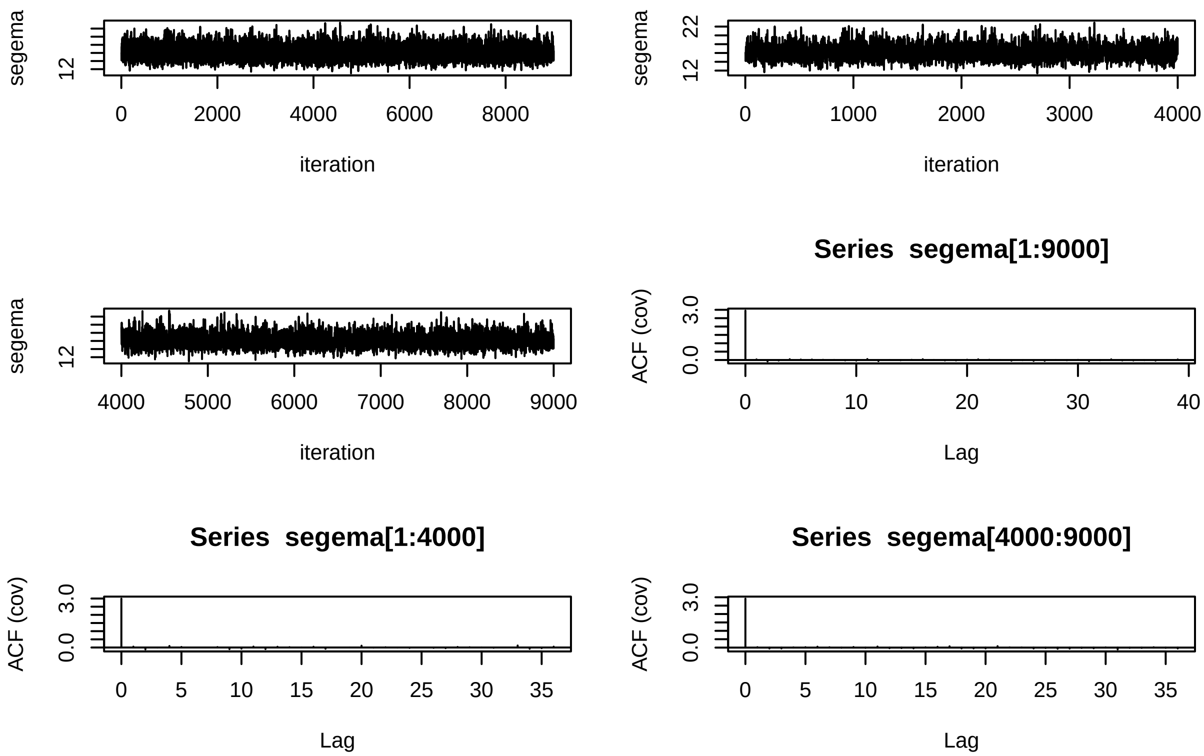
Assignment5

```r
##Q3

##(1) At iteration t, the Gibbs sampler draws Thetaj^t~p(thetaj|theta-j^(t-1),y),
##    for j=1,...,d, where theta-j^(t-1) represents all the components of theta,
##    expect for thetaj, at their current value:
##    Theta-j^(t-1)=(theta1^(t),..., thetaj-1^(t),thetaj+1^(t-1),...,thetad^(t-1))

## Based on the lecture note, we know that miu|,y ~
## N(((miu0/Tao^2)+(n*y-bar/segema^2))/ (1/Tao^2)+(n/segema^2)), 1/(1/tao^2+n/segema^2)))

##  segema^2| miu,y ~ Inv-X^2 (v+n, ((v*segema^2+nv)/(v+n))), v=1/n sum(yi-miu^t)^2

##  Initializing (miu^(0),segema^2(0))=(65,16)

##  For each iteration/update,
##  miu^(t) ~ miu| segema^(t-1),y
##  segema^2(t) ~segema^2| miu^t, y

## and we have data y1 = 70, y2=75 and y3=72.

## Code for sampling
library("invgamma") ## I will use rinvchisq in this package to sample
##                     from inverse chi-square distribution
y1<-70
y2<-75
y3<-72
ybar<-mean(c(70,75,72))
ysum<-sum(c(70,75,72))
rho<-0.8
N_iter<-9000


miu<-rep(0,N_iter)
segema<-rep(0,N_iter)
X<-rep(0,N_iter)
miu[1]<-65
segema[1]<-16

for(t in 2:N_iter){
   miu1<-((65/9+ysum/segema[t-1])/(1/9+3/segema[t-1]))
   segema1<-(1/(1/9+3/segema[t-1]))
   miu[t]<-rnorm(1,miu1,sqrt(segema1))

   VV<-function(x,x0){
        return(sum((x-x0)^2))}
```

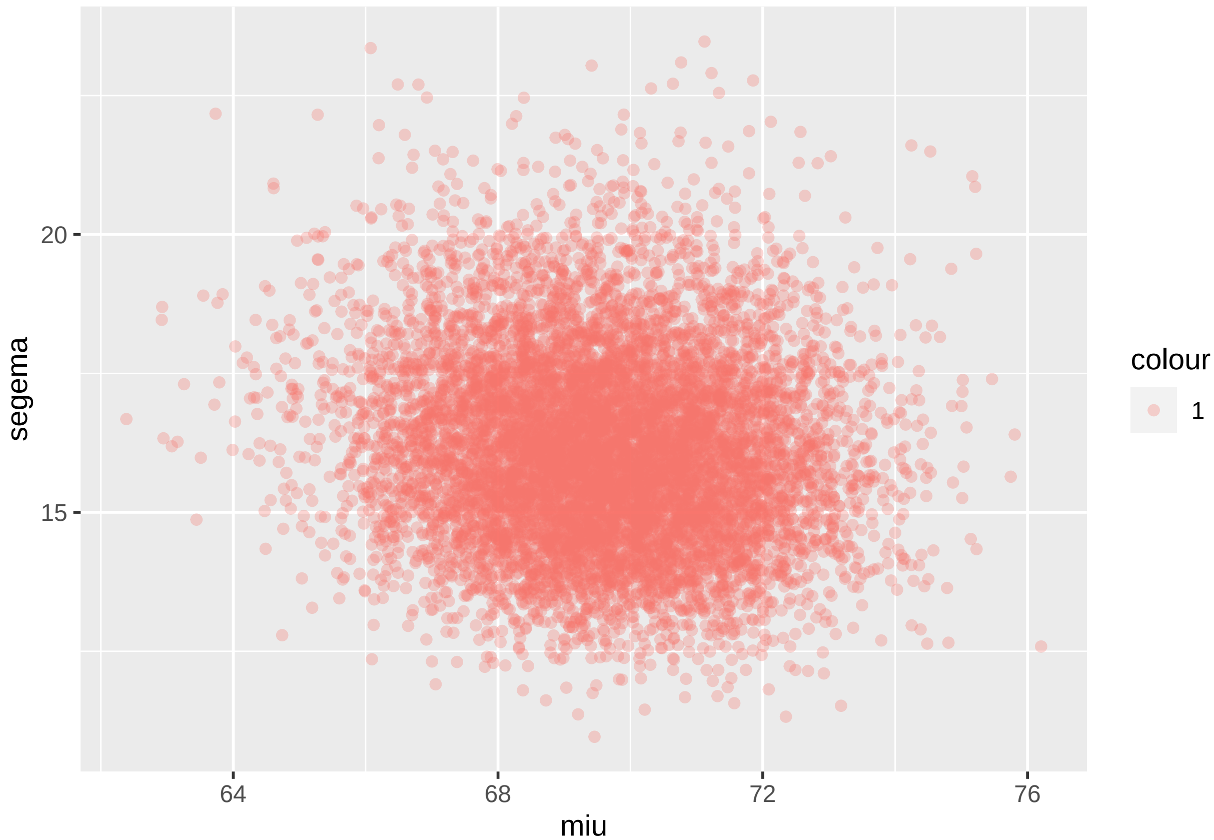
```r
    V<-VV(c(70,75,72),miu[t])

    X<-rchisq(1,178)
    segema2<-(175*16+V)/(178)
    segema[t]<-((178*segema2)/X)


}

### Yes, the chain mixing well, there is no visual evidence of high autocorrelation.
# make a "trace plot" of the draws of theta

## Yes,the Markov Chain appear to converged after 4000 burn-in samples.(because of the
## low correlation)
## I will used first 4000 as burn-in data.
## For the trace plot at 4000:9000 iterations, there is no clear upward/downward trend
## so we conclude the chain has converged.
## The convergence is better for segema than for miu.

## With the zoom in of both trace and afc plot of miu and segema

## We could see the correlation at 4000:9000 iterations and at 1:4000 iterations
## all have very low autocorrelation and less correlation at 4000:9000 iterations.


## There is no visual evidence of high autocorrelation.But somehow bit correlated
## The autocorrelation drop down with the iterations go on.

par(mfrow=c(3,2))
plot(x=c(1:9000),y=miu[1:9000],type="l",xlab="iteration",ylab="miu")
plot(x=c(1:4000),y=miu[1:4000],type="l",xlab="iteration",ylab="miu")
plot(x=c(4000:9000),y=miu[4000:9000],type="l",xlab="iteration",ylab="1=miu")
acf(miu[1:9000], type = "covariance")
acf(miu[1:4000], type = "covariance")
acf(miu[4000:9000], type = "covariance")
```




```r
par(mfrow=c(3,2))
plot(x=c(1:9000),y=segema[1:9000],type="l",xlab="iteration",ylab="segema")
plot(x=c(1:4000),y=segema[1:4000],type="l",xlab="iteration",ylab="segema")
plot(x=c(4000:9000),y=segema[4000:9000],type="l",xlab="iteration",ylab="segema")
acf(segema[1:9000], type = "covariance")
acf(segema[1:4000], type = "covariance")
acf(segema[4000:9000], type = "covariance")
```




```r
### (3) two-demensional plot for miu and segema.
dataa<-as.data.frame(cbind(miu,segema))
library("ggplot2")

colnames(dataa)[1] <- "miu"
colnames(dataa)[2] <- "segema"
ggplot()+geom_point(data =dataa ,aes(miu,segema, color = '1'), alpha = 0.3)
```


20
15
segema
64
68
72
76
miu
colour
1