(b) Load "data.RData" which includes Y (I x J matrix) where I=5 and J=20 and run the Gibbs sampler on the parameters of the model. Monitor cumulative averages. What do you find from this monitoring?

Step 1. Load the data.

```
setwd("C:/Bayesian")
load("data.RData")
```

Step 2. Set the starting values.

```
I <- nrow(Y)
J <- ncol(Y)

al <- NULL
be <- array(NA, dim=c(I, 50000))
var_b <- NULL
var_e <- NULL

# starting values
al[1] <- 0
be[,1] <- rep(1:5)
var_b <- 1
var_e <- 1
```

Step 3. Sampling with 50000 iteratively.

```
library(invgamma)

for(j in 2:50000){
  for(i in 1:5){
    be[i,j] <- rnorm(1, var_b[j-1]*(sum(Y[i,])-J*al[j-1])/(J*var_b[j-1]+var_e[j-1]),
                     sqrt(1/((J/var_e[j-1])+(1/var_b[j-1]))))
  }
  al[j] <- rnorm(1, sum(Y-be[,j])/(I*J), sqrt(var_e[j-1]/(I*J)))
  var_b[j] <- rinvgamma(1, shape=I/2, rate=1/(sum(be[,j]^2)/2))
  var_e[j] <- rinvgamma(1, shape=(I+J)/2, rate=1/(sum((Y-al[j]-be[,j])^2)/2))
}
```

Step 4. Burn-in (first 40000 values).

```
al <- al[-c(1:40000)]
be <- be[,-c(1:40000)]
var_b <- var_b[-c(1:40000)]
var_e <- var_e[-c(1:40000)]
```

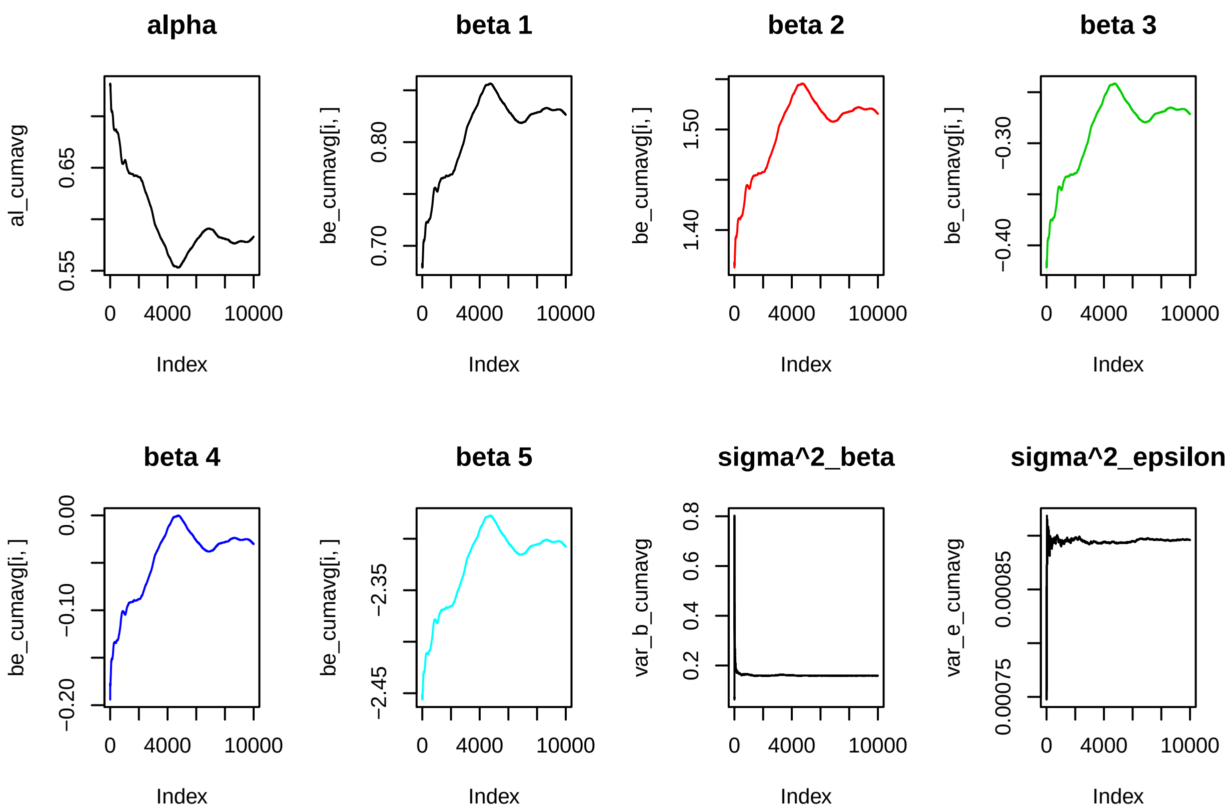
Step 5. Calculate cumulative averages.

```
al_cumavg <- NULL
be_cumavg <- array(NA, dim=c(I, 10000)); be_cumavg[,1] <- rep(1:5);
var_b_cumavg <- NULL
var_e_cumavg <- NULL
```

```r
for(k in 1:10000){
  al_cumavg[k] <- mean(al[1:k])
  var_b_cumavg[k] <- mean(var_b[1:k])
  var_e_cumavg[k] <- mean(var_e[1:k])
}
for(k in 2:10000){
  be_cumavg[,1] <- be[,1]
  be_cumavg[,k] <- rowMeans(be[,1:k])
}
```

Step 6. Plotting.

```r
par(mfrow=c(2,4))
plot(al_cumavg, type="l", main="alpha")
for(i in 1:5){plot(be_cumavg[i,], col=i, type="l", main=paste("beta",i))}
plot(var_b_cumavg, type="l", main="sigma^2_beta")
plot(var_e_cumavg, type="l", main="sigma^2_epsilon")
```



The cumulative average of α and β have exactly opposite shapes. If α's decreases, then β_i's increases. In contrast, if α's increases, then β_i's decreases.

The cumulative average of σ^2_β and σ^2_β converges.