hw07

Chunlei Liu 10/30/2018

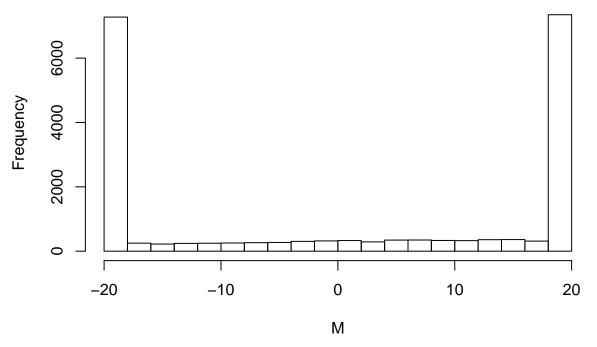
```
Q1:
The target distribution is \pi(x) \propto \exp(\mu \sum_{i=1}^{d-1} x_i x_{i+1}) = g(x),
at time step t, x^{(t)} = (x_1^{(1)}, ..., x_d^{(d)}),
at each direction i, draw x_i^{(t+1)} from the conditional distribution g(x_i^{(t+1)}|x_1^{(t+1)},...x_{i-1}^{(t+1)},x_{i+1}^{(t)},...,x_d^{(t)}) = 0
\frac{g(x_i^{(t+1)}, x_1^{(t+1)}, \dots, x_{i-1}^{(t+1)}, x_{i+1}^{(t)}, \dots, x_d^{(t)})}{g(x_1^{(t+1)}, \dots, x_{i-1}^{(t+1)}, x_{i+1}^{(t)}, \dots, x_d^{(t)})} = C_i * exp(\mu x_{i-1}^{(t+1)} x_i + \mu x_i x_{i+1}^{(t)}), C_i \text{ is a constant.}
Becasue x_i only equals 1 or -1, C_i * exp(\mu(x_{i-1}^{(t+1)} * 1 + 1 * x_{i+1}^{(t)})) + C_i * exp(\mu(x_{i-1}^{(t+1)} * -1 + -1 * x_{i+1}^{(t)})) = 1

C_i = \frac{1}{exp(\mu(x_{i-1}^{(t+1)} + x_{i+1}^{(t)})) + exp(\mu(-x_{i-1}^{(t+1)} - x_{i+1}^{(t)}))}
There are two special cases.
if i = 1, g(x_1^{(t+1)}|x_{\lceil -1 \rceil}^{(t)}) = C_1 * exp(\mu x_1 x_2^{(t)}), same rule as before C_1 = \frac{1}{exp(\mu x_2^{(t)}) + exp(-\mu x_2^{(t)})}
if i = d, g(x_d^{(t+1)}|x_{\lceil -d \rceil}^{(t+1)}) = C_d * exp(\mu x_{d-1}^{(t+1)}x_d), same rule as before C_d = \frac{1}{exp(\mu x_{d-1}^{(t+1)}) + exp(-\mu x_{d-1}^{(t+1)})}
rm(list = ls())
set.seed(1)
d = 20
mu = 2
t = 50000
x_0 = sample(c(-1,1), d, replace = T)
x_matrix = matrix(0, t+1, d)
x_matrix[1, ] = x_0
gibbs = function(x, mu) {
   x_{new} = x
   for (i in 1:d) {
      if (i == 1) {
          c = 1/(exp(mu * x_new[i+1]) + exp(-mu * x_new[i+1]))
         prob = exp(mu * x_new[i+1])*c
         x_new[i] = rbinom(1,1,prob)*2-1
      }
      else if (i == d) {
          c = 1/(exp(mu * x_new[i-1]) + exp(-mu * x_new[i-1]))
         prob = exp(mu * x_new[i-1])*c
          x_{new}[i] = rbinom(1,1,prob)*2-1
      }
      else {
          c = \frac{1}{\exp(mu * (x_new[i-1] + x_new[i+1]))} + \exp(-mu * (x_new[i-1] + x_new[i+1])))
          prob = exp(mu * (x_new[i-1] + x_new[i+1]))*c
          x_{new}[i] = rbinom(1,1,prob)*2-1
      }
   }
   return(x_new)
}
```

```
for (j in 1:t) {
  x_matrix[j+1,] = gibbs(x_matrix[j,], mu)
}

trunc_sample = tail(x_matrix, 20000)
  M = apply(trunc_sample, 1, sum)
  hist(M)
```

Histogram of M



Q2:

 $\omega = 0.04, \alpha = 2, \beta = 0.5, n = 5, \text{ The target distribution is } p(\mu, \tau | y_1, ..., y_n) \propto (2\pi)^{-\frac{n+1}{2}} \tau^{\frac{n}{2}} e^{-\frac{\tau}{2} \sum_{i=1}^n (y_i - \mu)^2} \omega^{\frac{1}{2}} e^{-\frac{\omega}{2} \mu^2} \frac{\tau^{\alpha - 1}}{\Gamma(\alpha)\beta^{\alpha}} e^{-\frac{\tau}{\beta}}$ at time step t, we draw

$$\mu^{(t+1)} \text{ from } p(\mu|\tau^{(t)}, y_1...y_n) \propto e^{-\frac{\tau}{2} \sum_{i=1}^n (y_i - \mu)^2} e^{-\frac{\omega}{2} \mu^2} \propto e^{-\frac{n\tau + \omega}{2} (\mu - \frac{n\tau \bar{y}}{n\tau + \omega})^2} \sim N(\frac{n\tau \bar{y}}{n\tau + \omega}, \frac{1}{n\tau + \omega}),$$

$$\tau^{(t+1)} \text{ from } p(\tau|\mu^{(t+1)}, y_1...y_n) \propto \tau^{\frac{n}{2} + \alpha - 1} e^{-(\frac{\sum (y_i - \mu)^2}{2} + \frac{1}{\beta})\tau} \sim \Gamma(\frac{n}{2} + \alpha, \frac{\sum (y_i - \mu)^2}{2} + \frac{1}{\beta})$$

The mean is (2.1130266, 0.8561928)

```
rm(list = ls())
set.seed(1)
y = c(1.9, 3.4, 0.3, 2.5, 2.6)
n = 5
omega = 0.04
alpha = 2
beta = 0.5
y_mean = mean(y)
t = 20000
x_0 = c(0, 1)
x_matrix = matrix(0, t+1, 2)
```

```
x_matrix[1, ] = x_0
gibbs = function(x){
    x_new = x
    x_new[1] = rnorm(1, (n*x_new[2]*y_mean)/(n*x_new[2]+omega), sqrt(1/(n*x_new[2]+omega)))
    x_new[2] = rgamma(1, shape = n/2+alpha, rate = (sum((y-x_new[1])^2)/2+1/beta))
    return(x_new)
}
for (i in 1:t) {
    x_matrix[i+1, ] = gibbs(x_matrix[i, ])
}
trunc_sample = tail(x_matrix, 10000)
M = apply(trunc_sample, 2, mean)
M
```

[1] 2.1130266 0.8561928