

MCMC:HW3

Qi Chen(qc586)

March 1, 2017

Problem 1

Suppose

$$\pi(a, b) \propto a^4 b^6 e^{-a-b-3ab} \quad (1)$$

for $a, b > 0$ is required to be sampled. Find

$$\pi(a | b) \text{ and } \pi(b | a) \quad (2)$$

and hence find a transition density $p(a_{n+1}, b_{n+1} | a_n, b_n)$ which has π as the stationary density. Implement the chain and use the output to evaluate the integral

$$I = \int \int a b \pi(a, b) da db \quad (3)$$

Solution: According to the definition of the marginal density,

$$\begin{aligned} \pi(a | b) &= \frac{\pi(a, b)}{\pi(b)} \\ &= \frac{a^4 b^6 e^{-a-b-3ab}}{\int_0^\infty a^4 b^6 e^{-a-b-3ab} da} \\ &= \frac{a^4 b^6 e^{-a-b-3ab}}{e^{-b} b^6 \int_0^\infty a^4 e^{-(1+3b)a} da} \\ &= \frac{a^4 b^6 e^{-a-b-3ab}}{e^{-b} b^6 \frac{24}{(1+3b)^5}} \\ &= \frac{a^4 e^{-(1+3b)a} (1+3b)^5}{24} \end{aligned} \quad (4)$$

We can check that

$$\int_0^\infty \pi(a | b) da = 1 \quad (5)$$

$$\text{Integrate}[a^4 e^{-(1+3b)a}, \{a, 0, \infty\}, \text{Assumptions} \rightarrow \{b > 0\}]$$

$$\begin{aligned} &\frac{24}{(1+3b)^5} \\ \pi(b | a) &= \frac{\pi(a, b)}{\pi(a)} \\ &= \frac{a^4 b^6 e^{-a-b-3ab}}{\int_0^\infty a^4 b^6 e^{-a-b-3ab} db} \\ &= \frac{b^6 e^{-b-3ab}}{\int_0^\infty b^6 e^{-(1+3a)b} db} \\ &= \frac{b^6 e^{-b-3ab}}{\frac{720}{(1+3a)^7}} \\ &= \frac{b^6 e^{-b(1+3a)} (1+3a)^7}{720} \end{aligned} \quad (6)$$

We can check that

$$\int_0^\infty \pi(b | a) db = 1 \quad (7)$$

$$\text{Integrate}[b^6 e^{-(1+3a)b}, \{b, 0, \infty\}, \text{Assumptions} \rightarrow \{a > 0\}]$$

$$\frac{720}{(1+3a)^7}$$

We want to find the transition density $p(a_{n+1}, b_{n+1} | a_n, b_n)$ such that

$$\pi(a_{n+1}, b_{n+1}) = \int p(a_{n+1}, b_{n+1} | a_n, b_n) \pi(a_n, b_n) da_n db_n \quad (8)$$

Consider the marginal density

$$\pi(a_{n+1}) = \int p(a_{n+1} | a_n) \pi(a_n) da_n \quad (9)$$

Obviously,

$$p(a_{n+1} | a_n) = \int \pi(a_{n+1} | u) \pi(u | a_n) du$$

$$= \int \frac{a_{n+1}^4 e^{-(1+3u)a_{n+1}} (1+3u)^5}{24} \frac{u^6 e^{-u(1+3a_n)} (1+3a_n)^7}{720} du \quad (10)$$

satisfies the stationary condition. Similarly,

$$\pi(b_{n+1}) = \int p(b_{n+1} | b_n) \pi(b_n) db_n \quad (11)$$

$$p(b_{n+1} | b_n) = \int \pi(b_{n+1} | u) \pi(u | b_n) du$$

$$= \int \frac{b_{n+1}^6 e^{-b_{n+1}(1+3u)} (1+3u)^7}{720} \frac{u^4 e^{-(1+3b_n)u} (1+3b_n)^5}{24} du \quad (12)$$

So in principle we can sample from the marginal transition density, but the integrals are not easy to evaluate.

Alternatively, We can verify that

$$p(a_{n+1}, b_{n+1} | a_n, b_n)$$

$$= \pi(a_{n+1} | b_{n+1}) \pi(b_{n+1} | a_n)$$

$$= \frac{a_{n+1}^4 e^{-(1+3b_{n+1})a_{n+1}} (1+3b_{n+1})^5}{24} \frac{b_{n+1}^6 e^{-b_{n+1}(1+3a_n)} (1+3a_n)^7}{720} \quad (13)$$

satisfies Eq. (8) as

$$\int p(a_{n+1}, b_{n+1} | a_n, b_n) \pi(a_n, b_n) da_n db_n$$

$$= \int \pi(a_{n+1} | b_{n+1}) \pi(b_{n+1} | a_n) \pi(a_n, b_n) da_n db_n$$

$$= \int \pi(a_{n+1} | b_{n+1}) \pi(b_{n+1} | a_n) \pi(a_n) da_n \quad (14)$$

$$= \pi(a_{n+1} | b_{n+1}) \pi(b_{n+1})$$

$$= \pi(a_{n+1}, b_{n+1})$$

In evaluating the integral, notice that

$$I = \iint a b \pi(a, b) da db$$

$$= \frac{\iint a b \text{kernel}(a, b) da db}{\iint \text{kernel}(a, b) da db} \quad (15)$$

where

$$\text{kernel}(a, b) = a^4 b^6 e^{-a-b-3ab} \quad (16)$$

The exact value is given by

$$I \approx 1.43461 \quad (17)$$

$$\text{I2} = \text{Integrate}[a^4 b^6 e^{-a-b-3ab}, \{a, 0, \infty\}, \{b, 0, \infty\}]$$

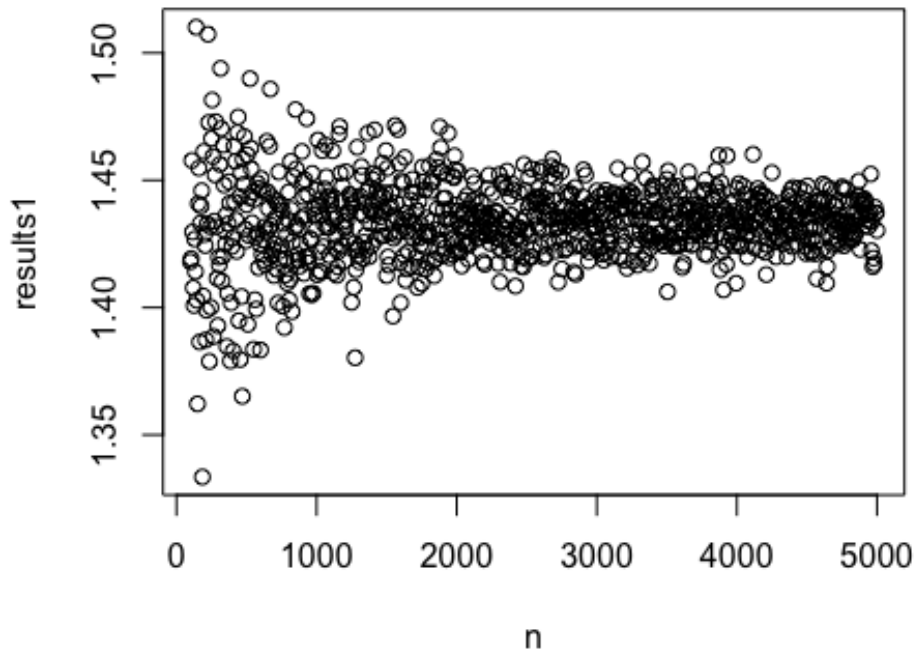
$$\frac{-43842 - 43813 e^{1/3} \text{ExpIntegralEi}[-\frac{1}{3}]}{177147}$$

$$\begin{aligned}
 & \mathbf{i1} = \text{Integrate}\left[\mathbf{a b a^4 b^6 e^{-a-b-3 a b}}, \{\mathbf{a}, \mathbf{0}, \infty\}, \{\mathbf{b}, \mathbf{0}, \infty\}\right] \\
 & \frac{2 \left(541842 + 506573 e^{1/3} \text{ExpIntegralEi}\left[-\frac{1}{3}\right]\right)}{1594323} \\
 & \mathbf{N}\left[\frac{\mathbf{i1}}{\mathbf{i2}}\right] \\
 & 1.43461
 \end{aligned}$$

By use of the transition density Eq. (13), the MCMC simulation results for $n = 1000$ gives

$$I \approx 1.435733 \quad (18)$$

The convergence is monitored as follows:



Problem 2

Suppose we wish to sample from

$$\pi(x) \propto \frac{\exp\left(-\frac{1}{2}x^2\right)}{1+x^2} \quad (19)$$

using a Metropolis-Hastings algorithm with density $q(x' | x) = N(x' | x, \sigma^2)$ for some σ as the proposal density.

Describe what you think might be the problems encountered if (i) σ is too small and (ii) σ is too big. Run the algorithm with such σ to verify your conclusions.

Without using any theory, find what you think is a suitable σ and run the algorithm with this σ to evaluate

$$I = \int x \pi(x) dx \quad (20)$$

What happens if instead you use $q(x' | x) = N(x' | -x, \sigma^2)$.

Solution: The pdf of our choice of easy to sample density is

$$q(x' | x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x'-x)^2}{2\sigma^2}} \quad (21)$$

According to the Metropolis-Hastings algorithm,

$$p(x' | x) = \min \left\{ 1, \frac{\pi(x') q(x | x')}{\pi(x) q(x' | x)} \right\} q(x' | x) + (1 - r(x)) \mathbf{1}(x' = x) \quad (22)$$

$$= r(x) \tilde{q}(x' | x) + (1 - r(x)) \mathbf{1}(x' = x)$$

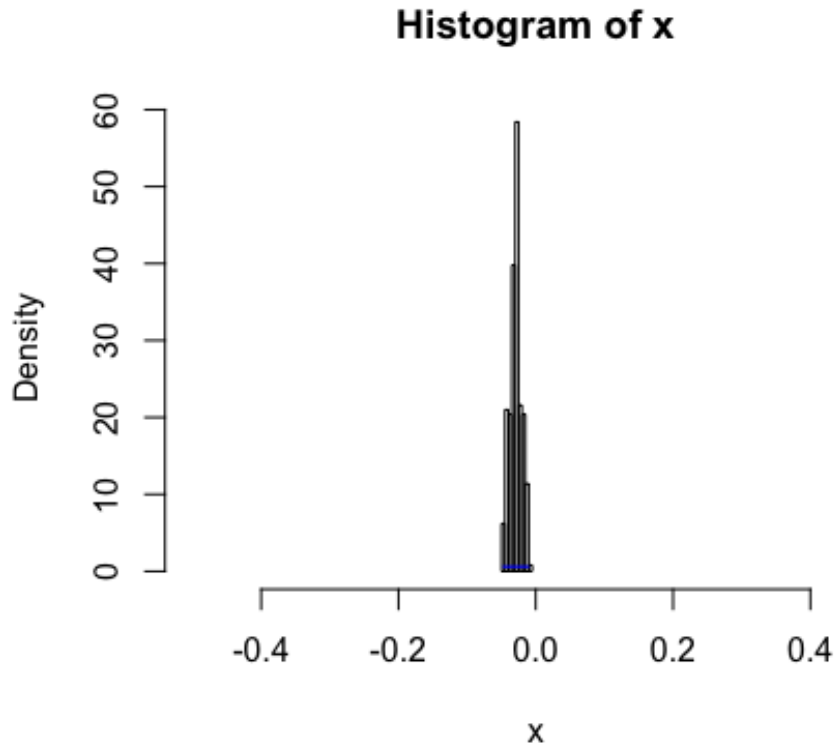
$$\tilde{q}(x' | x) = \frac{\alpha(x', x) q(x' | x)}{r(x)} \quad (23)$$

$$r(x) = \int \alpha(x', x) q(x' | x) dx' \quad (24)$$

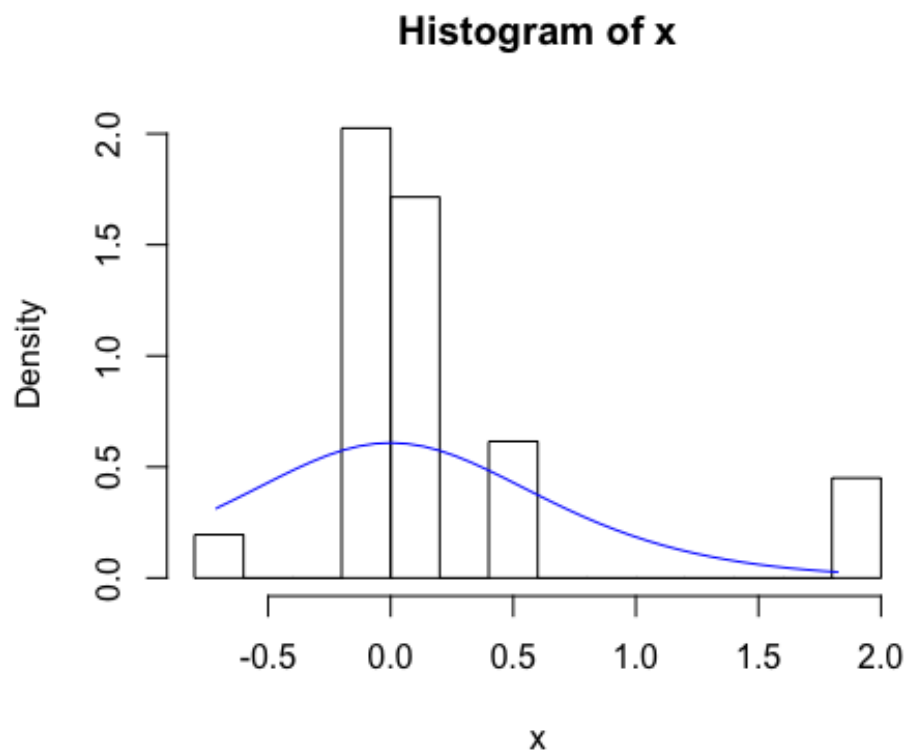
$$\alpha(x', x) = \min \left\{ 1, \frac{\pi(x') q(x | x')}{\pi(x) q(x' | x)} \right\} = \min \left\{ 1, \frac{\pi(x')}{\pi(x)} \right\} \quad (25)$$

Since $\tilde{q}(x' | x)$ and $\mathbf{1}(x' = x)$ are two densities, we sample x' from $\tilde{q}(x' | x)$ with density $r(x)$ else we sample x' from $\mathbf{1}(x' = x)$ with probability $1 - r(x)$. But we do not know $r(x)$ as it involves an integral. The trick is we sample x' from $q(x' | x)$, u from $U(0, 1)$. If $u < \alpha(x', x)$, x' automatically comes from $\tilde{q}(x' | x)$; otherwise we set $x' = x$.

In our problem, if σ is too small, then we can only generate x' too close to x from $q(x' | x)$, which will not be able to cover the whole support. As a result, the sampling is too close to the initial value. This is demonstrated in the following histogram for the choice of $\sigma = 100$



On the other hand, if σ is too big, then we will generate x' that has a sparse distribution in $(-\infty, \infty)$ from $q(x' | x)$. Among all the x' , only those $|x'| \lesssim |x|$ will be likely to succeed, for those not succeed, we set $x' = x$, so the histogram of x will be very sparse with high peaks around a few values, which means the chain does not move very well. This is demonstrated in the following histogram for the choice of $\sigma = 100$



The exact value of the integral is 0 by symmetry

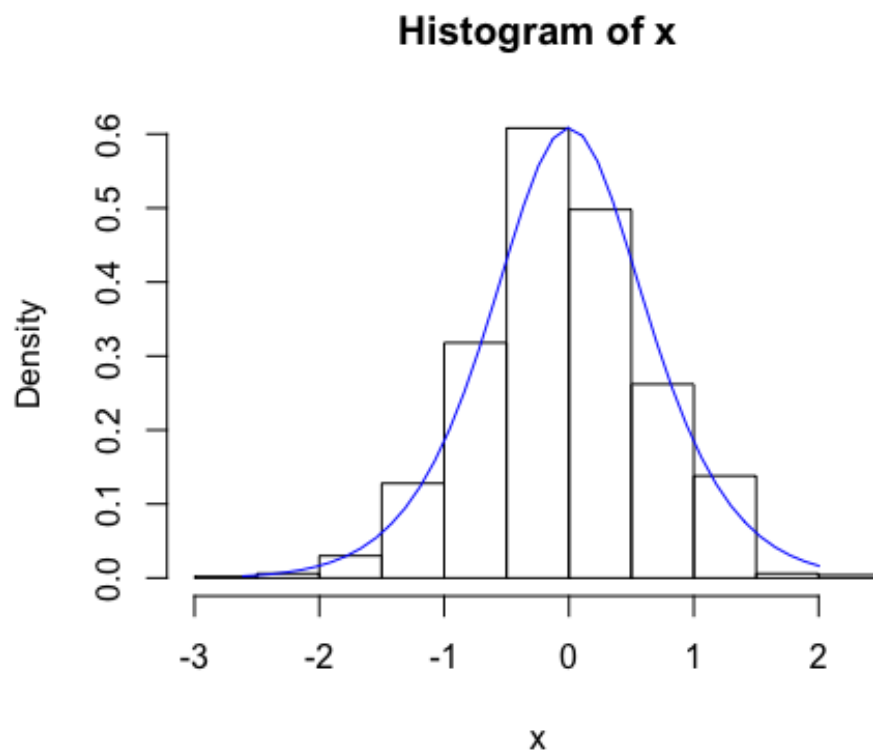
$$I = \int x \pi(x) dx \propto \int_{-\infty}^{\infty} x \frac{\exp(-\frac{1}{2}x^2)}{1+x^2} dx = 0 \quad (26)$$

`N[Integrate[x^2 Exp[-1/2 x^2]/(1+x^4), {x, -∞, ∞}]/`
`Integrate[Exp[-1/2 x^2]/(1+x^4), {x, -∞, ∞}]`
 0.396347

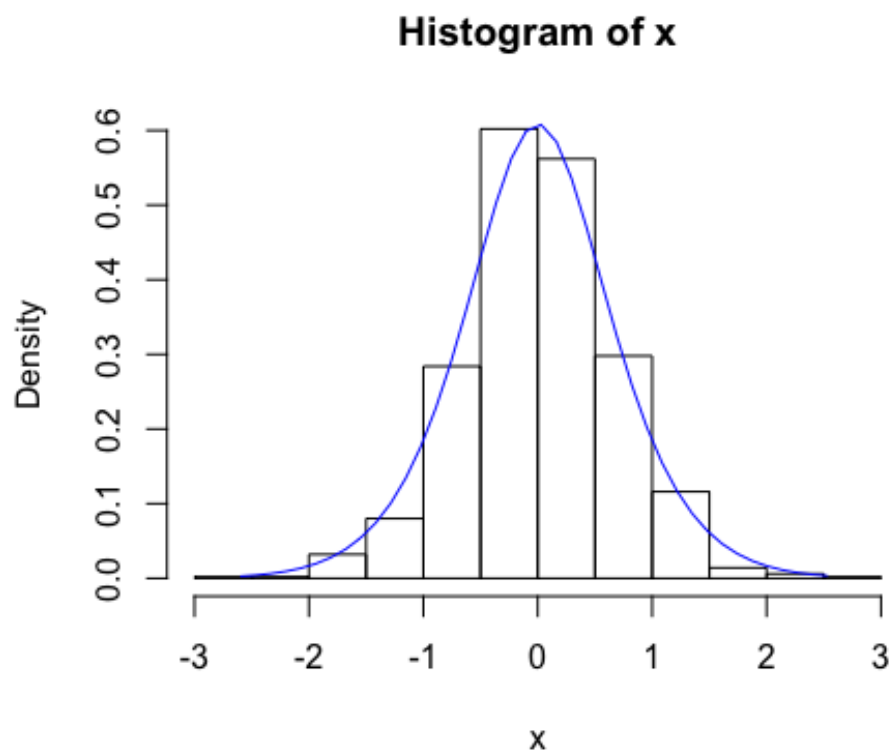
By choosing $\sigma = 1$, we find

$$I = -0.04562668 \quad (27)$$

The sampling histogram for $n = 1000$ compared with pdf is given as follows:



If we choose $q(x' | x) = N(x' | -x, \sigma^2)$, the sampling becomes more symmetric around $x=0$ according to the following histogram:



This is due to the even nature of $\pi(x)$, x and $-x$ should have equal probability of being accepted in the choice of

$$q(x' | x) = N(x' | -x, \sigma^2). \text{ The integral is evaluated to be } I \approx 0.004607338 \quad (28)$$

Problem 3

Suppose a posterior density is given by

$$f(\theta | \text{data}) \propto e^{\theta a} e^{-n e^\theta} e^{-\frac{1}{2} \theta^2} \quad (29)$$

for some $a > 0$ and n integer, and $-\infty < \theta < +\infty$. In fact this is a Poisson model with mean e^θ and standard normal prior for θ .

Find a Markov chain for sampling from f and implement it.

Solution: We want to find $p(\theta_{n+1} | \theta_n)$ such that

$$f(\theta_{n+1} | \text{data}) = \int p(\theta_{n+1} | \theta_n) f(\theta_n | \text{data}) d\theta_n \quad (30)$$

By Metropolis-Hastings algorithm, we can choose

$$q(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2} x^2} \quad (31)$$

$$p(x' | x) = \min \left\{ 1, \frac{\pi(x') q(x)}{\pi(x) q(x')} \right\} q(x') + (1 - r(x)) \mathbf{1}(x' = x) \quad (32)$$

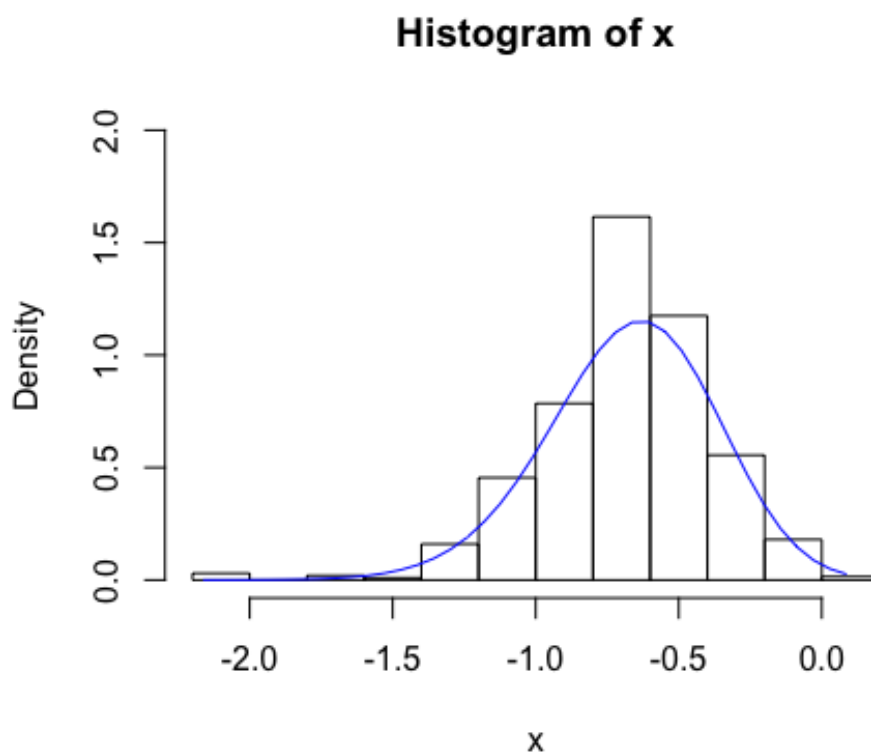
$$= r(x) \tilde{q}(x' | x) + (1 - r(x)) \mathbf{1}(x' = x) \quad (33)$$

$$\tilde{q}(x' | x) = \frac{\alpha(x', x) q(x')}{r(x)}$$

$$r(x) = \int \alpha(x', x) q(x') dx' \quad (34)$$

$$\alpha(x', x) = \min \left\{ 1, \frac{\pi(x') q(x)}{\pi(x) q(x')} \right\} \quad (35)$$

Here we choose $a = 10$, $n = 20$ for MCMC sampling. The histogram $n = 1000$ compared with the pdf is given as follows:



Appendix: R-code

```
# problem 1
n<-1000
a<-array(dim=n)
b<-array(dim=n)
# initialize
a[1]<-1
b[1]<-1
# MCMC
for(i in 2:n){
  b[i]<-rgamma(1,shape=7,scale=1/(1+3*a[i-1]))
  a[i]<-rgamma(1,shape=5,scale=1/(1+3*b[i]))
}
I <- sum(a*b)/n
I
# integral vs n
I_N<- function(n){
  a<-array(dim=n)
  b<-array(dim=n)
  # initialize
  a[1]<-1
  b[1]<-1
  # MCMC
  for(i in 2:n){
    b[i]<-rgamma(1,shape=7,scale=1/(1+3*a[i-1]))
    a[i]<-rgamma(1,shape=5,scale=1/(1+3*b[i]))
  }
  return(sum(a*b)/n)
}
```



```

n = seq.int(100,5000,5)
results1 <- lapply(n,I_N)
plot(n, results1)

# problem 2
n<-1000
# pi(x)
pi <- function(x){
  return(exp(-1/2*x**2)/(1+x**2))
}
# normalized density
f <- function(x){
  result=integrate(pi,-Inf,Inf)$val
  return(pi(x)/result)
}
# q(x1|x2)
q <- function(x1,x2,sigma){
  return(dnorm(x1,x2,sigma))
}
# alpha(x1,x2)
alpha <- function(x1,x2,sigma){
  return(min(1,pi(x1)*q(x2,x1,sigma)/(pi(x2)*q(x1,x2,sigma))))
}

x<-array(dim=n)
u<-array(dim=n)
x[1]=-0.01
u[1]=0.1
sigma=1
for(i in 2:n){
  x[i]<-rnorm(1,x[i-1],sigma)
  u[i]<-runif(1,0,1)
  if(u[i]>=alpha(x[i],x[i-1],sigma)){
    x[i]=x[i-1]
  }
}
I <- sum(x)/n
I
hist(x,freq=FALSE)
xfit<-seq(min(x),max(x),length=40)
yfit<-lapply(xfit,f)
lines(xfit, yfit, col="blue")

# problem 3
n<-1000
# pi(x)
pi <- function(x){
  a<-10
  m<-20
  return(exp(a*x)*exp(-m*exp(x))*exp(-1/2*x**2))
}
# normalized density
library(cubature)
f <- function(x){
  result=integrate(pi,-50,50)$val
  return(pi(x)/result)
}
# q(x1,x2)
q <- function(x1,x2){
  #return(dnorm(x1,x2,1))
  return(dnorm(x1,0,1))
}
# alpha(x1,x2)
alpha <- function(x1,x2){
  return(min(1,pi(x1)*q(x2,x1)/(pi(x2)*q(x1,x2))))
}

```

```
x<-array(dim=n)
u<-array(dim=n)
x[1]=0
u[1]=0.1
for(i in 2:n){
  x[i]<-rnorm(1,0,1)
  u[i]<-runif(1,0,1)
  if(u[i]>=alpha(x[i],x[i-1])){
    x[i]=x[i-1]
  }
}
I <- sum(x)/n
I
hist(x,freq=FALSE,ylim=c(0,2))
xfit<-seq(min(x),max(x),length=40)
yfit<-sapply(xfit,f)
lines(xfit, yfit, col="blue")
```
