

Homework 7

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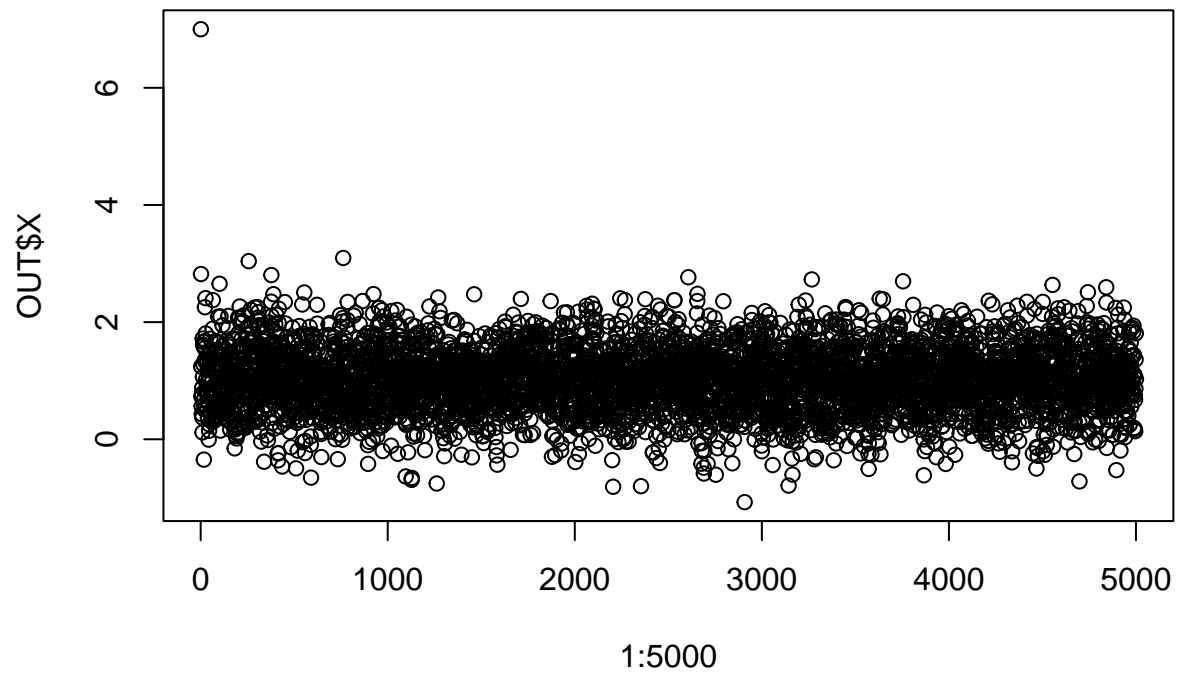
Problem 1

part (a)

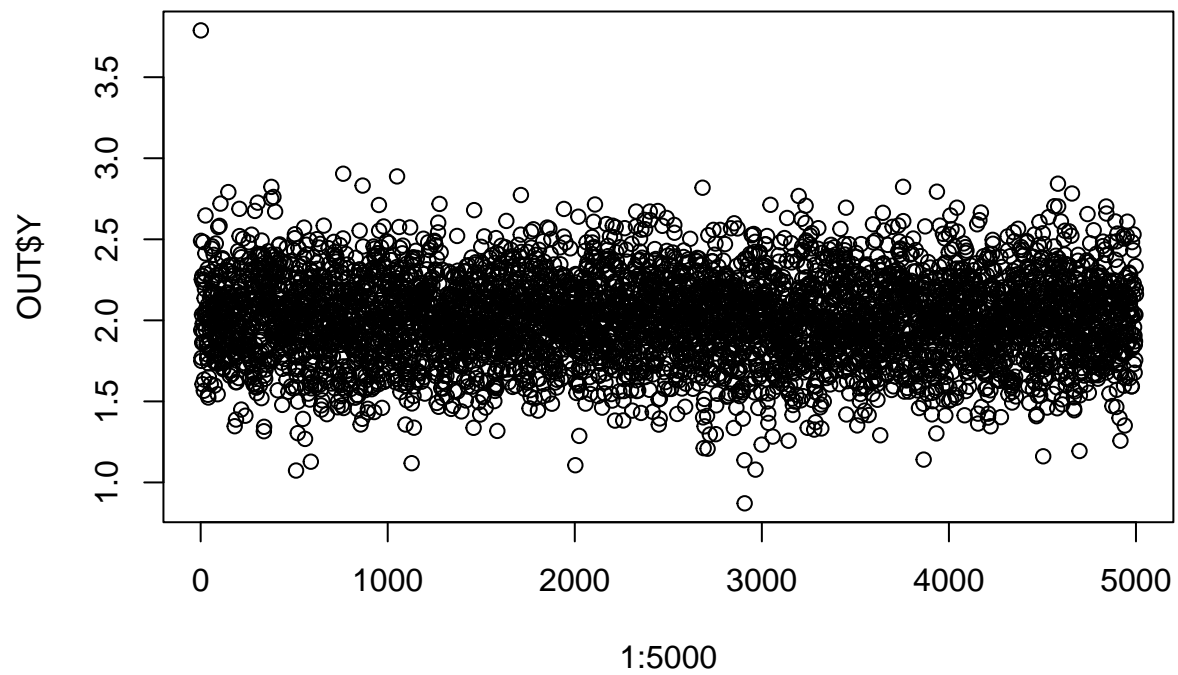
```
Gibbs <- function(N,mu,Sigma,x0,nburn,see.d){  
  # initialize X and Y  
  X <- rep(0,N)  
  Y <- X  
  X[1] = x0  
  # extract from sigma  
  mu1 = mu[1]  
  mu2 = mu[2]  
  s1 = sqrt(Sigma[1,1])  
  s2 = sqrt(Sigma[2,2])  
  rho = Sigma[2,1]  
  
  #for loop to generate samples  
  set.seed(see.d)  
  for (i in 1:N){  
    # sample from conditional rnorm  
  
    # Sample X from conditional normal distribution  
    y.mu = mu2 + rho*s2/s1*(X[i]-mu1)  
    y.sd = s2^2*(1-rho)  
    Y[i] <- rnorm(1,y.mu,y.sd)  
  
    # Sample Y from conditional normal distribution  
    x.mu = mu1 + rho*s1/s2*(Y[i]-mu2)  
    x.sd = s1^2*(1-rho)  
    X[i+1] <- rnorm(1,x.mu,x.sd)  
  
  }  
  X = X[1:N]  
  # Discard burn-in samples  
  return(list(X=X,Y=Y,Xburned = X[(nburn + 1):N], Yburned = Y[(nburn + 1):N]))  
}  
mu = c(1,2)  
S = matrix(c(1,.5,.5,.4),nrow=2, byrow=T)  
Gibbs(5000,mu,S,7,1000,534) -> OUT
```

part (b)

```
plot(1:5000,OUT$X)
```

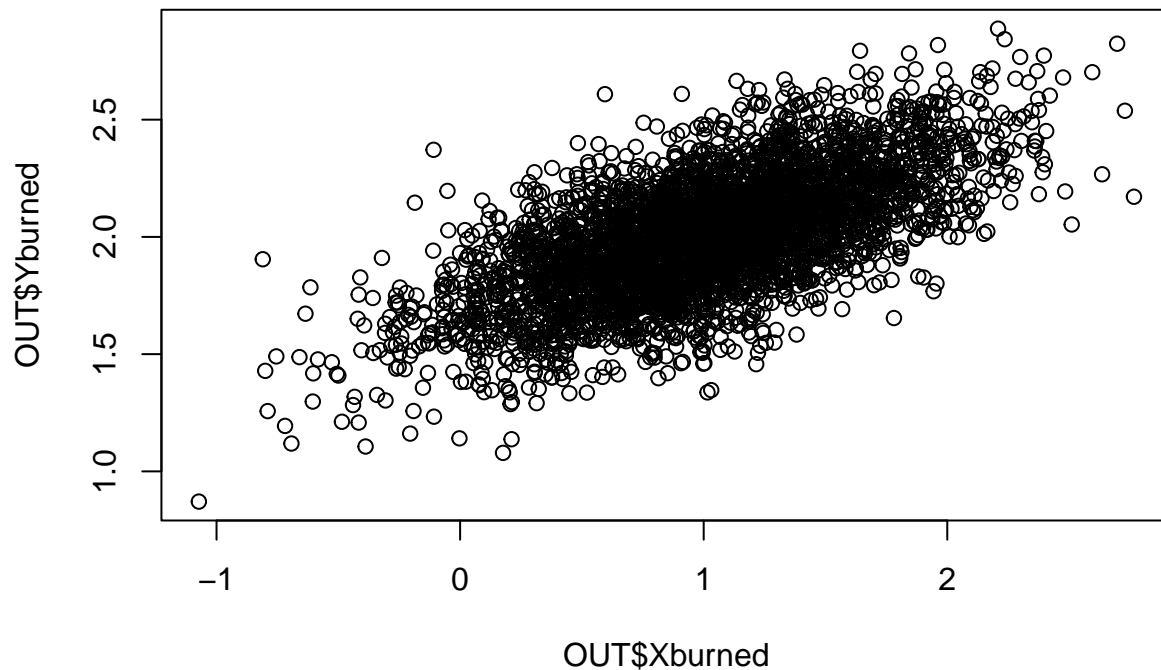


```
plot(1:5000,OUT$Y)
```



part (c)

```
plot(OUT$Xburned,OUT$Yburned)
```



You could say this resembles an ellipses that is centered at (1,2); the shadow of a bivariate Normal Distribution. The variance of the X variables are more spread than that of the Y variables as $\text{var}(Y) < \text{var}(X)$.

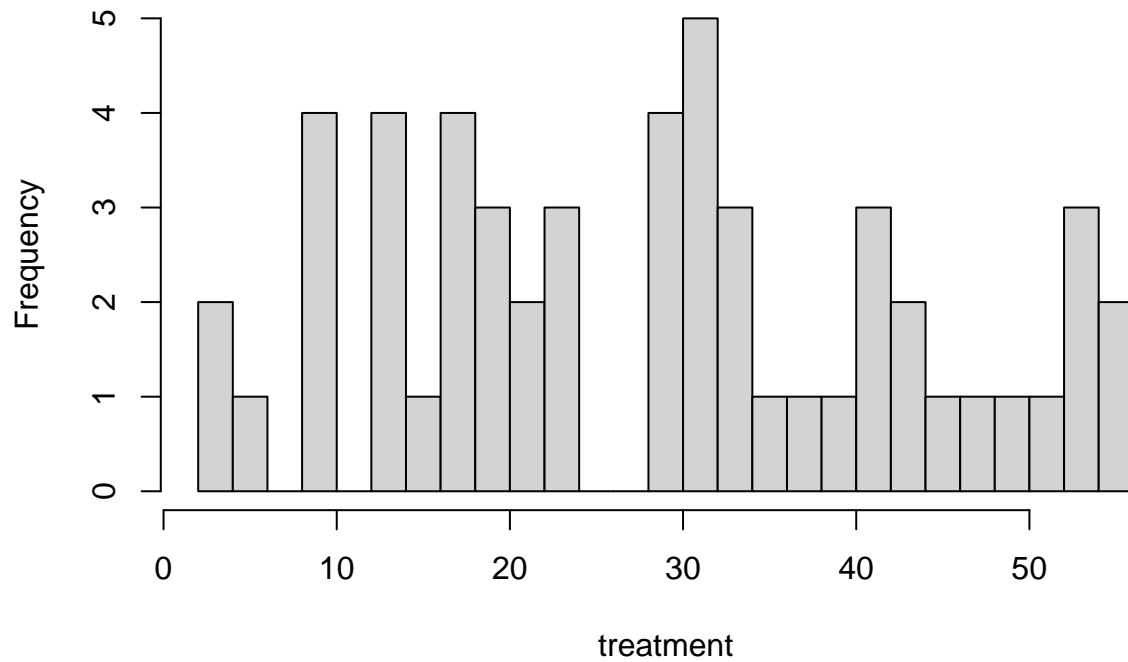
Problem 2

```
# load data
data <- read.table("breastcancer.dat", head = T)
```

part (a)

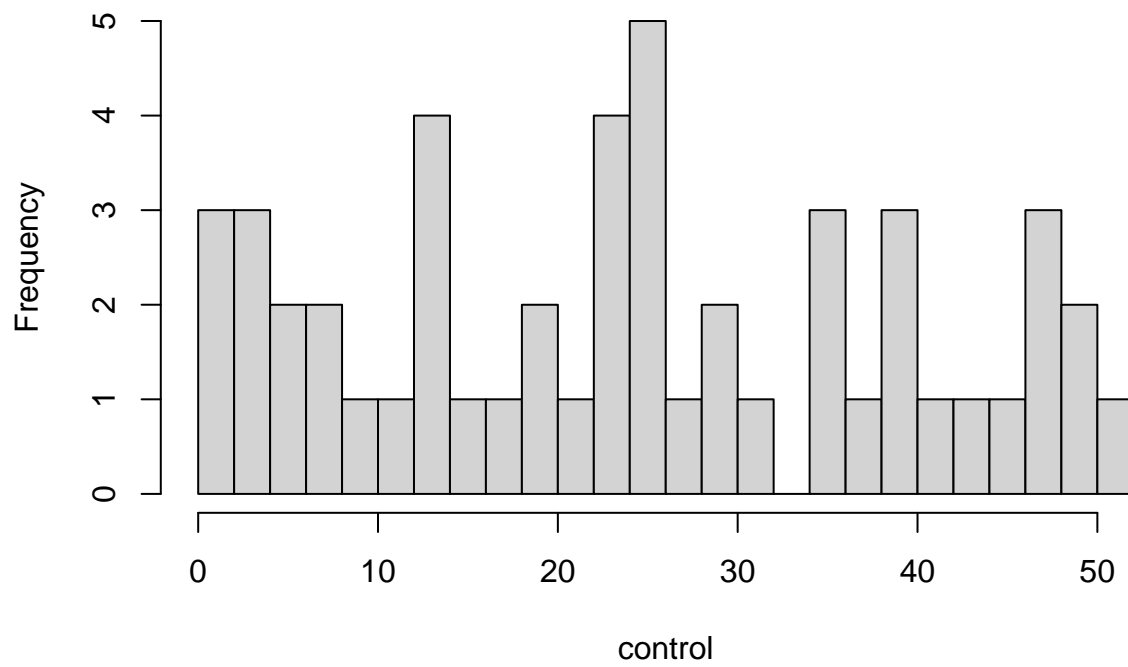
```
# make boxplots
treatment = data$recurtime[data$treatment == 1]
control = data$recurtime[data$treatment == 0]
hist(treatment, breaks=20)
```

Histogram of treatment



```
hist(control,breaks = 20)
```

Histogram of control



part (b)

we know that

$$L(\theta, \tau | y) * f(\theta, \tau) \propto \theta^{(\sum \delta_i^C + \sum \delta_i^H)} \tau^{(\sum \delta_i^H)} \exp(-\theta \sum x_i^C - \tau \theta \sum x_i^H) \cdot \theta^a \tau^b \exp(-\theta(c + d\tau))$$

which simplifies to

$$\theta^{(a + \sum \delta_i^C + \sum \delta_i^H)} \tau^{(b + \sum \delta_i^H)} \exp(-\theta(c + d\tau + \tau \sum x_i^H + \sum x_i^C))$$

so when we look for everything depending on θ we get

$$f(\theta | \tau, y) = \theta^{(a + \sum \delta_i^C + \sum \delta_i^H)} \exp(-\theta(c + d\tau + \tau \sum x_i^H + \sum x_i^C))$$

which is a gamma distribution $X \sim \Gamma(a + \sum \delta_i^C + \sum \delta_i^H + 1, c + d\tau + \tau \sum x_i^H + \sum x_i^C)$

Likewise, doing the same for τ we get

$$f(\tau | \theta, y) = \tau^{(b + \sum \delta_i^H)} \exp(-\theta(d\tau + \tau \sum x_i^H))$$

which is also gamma distribution $X \sim \Gamma(b + \sum \delta_i^H + 1, \theta(d + \sum x_i^H))$

part (c)

```
GS <- function(N,data,theta,see.d){

  # set seed
  set.seed(see.d)

  # initialize sample vec
  gsvec = matrix(0,N,2)
  # hyperparams
  a = 3
  b = 1
  c = 60
  d = 120
  # get delts
  delta.c = sum(data$treatment == 0 & data$censored == 0)
  delta.h = sum(data$treatment == 1 & data$censored == 0)

  # control group
  x.c = sum(data$recurtime[data$treatment==0])
  x.h = sum(data$recurtime[data$treatment==1])

  # run loop
  for(i in 1:N){
    # tau / theta
    tau.theta = rgamma(1,shape = delta.h+b+1,rate = theta * (x.h + d))
    # theta / tau
    theta.tau = rgamma(1,shape = delta.c+delta.h+a+1,rate = (tau.theta * (x.h + d) + c + x.c))
    gsvec[i,] = c(tau.theta,theta.tau)
    theta = theta.tau
  }
  return(gsvec)
}
```

```

vec = GS(10000,data,1,534)
summary(mcmc(vec))

##
## Iterations = 1:10000
## Thinning interval = 1
## Number of chains = 1
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##           Mean          SD Naive SE Time-series SE
## [1,] 1.206764 0.48278 0.0048278      9.668e-03
## [2,] 0.009297 0.00266 0.0000266      5.274e-05
##
## 2. Quantiles for each variable:
##
##           2.5%       25%       50%       75%      97.5%
## var1 0.538415 0.865593 1.113011 1.44551 2.39937
## var2 0.004822 0.007404 0.009033 0.01095 0.01505

```

problem (d)

```

# render letters
tau <- vec[,1]
theta <- vec[,2]

# summary
sprintf("theta mean is %f while tau mean is %f",mean(theta),mean(tau))

## [1] "theta mean is 0.009297 while tau mean is 1.206764"

sprintf("theta CI is ( %f , %f )",quantile(theta, 0.025),quantile(theta, 0.975))

## [1] "theta CI is ( 0.004822 , 0.015055 )"

sprintf("tau CI is ( %f , %f )",quantile(tau, 0.025),quantile(tau, 0.975))

## [1] "tau CI is ( 0.538415 , 2.399374 )"

sprintf("Standard Dev. of theta : %f",sd(theta))

## [1] "Standard Dev. of theta : 0.002660"

sprintf("Standard Dev. of tau : %f",sd(tau))

## [1] "Standard Dev. of tau : 0.482782"

```

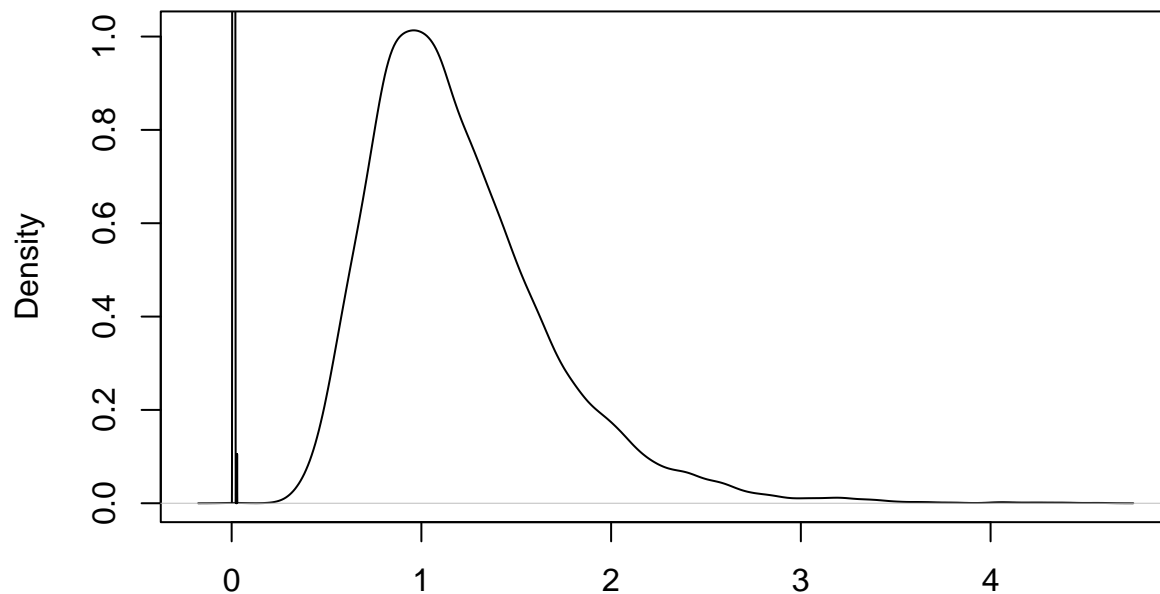
problem (e)

```

# render graphics
plot(density(tau))
lines(density(theta))

```

density(x = tau)



N = 10000 Bandwidth = 0.06173

From

our findings we can conclude that there is a 1.206764 factor difference in recurrence time between the hormone treated group and control group.

problem (g)

```
GS.2 <- function(f,N,data,theta,see.d){

  # set seed
  set.seed(see.d)

  # initialize sample vec
  gsvec = matrix(0,N,2)
  # hyperparams
  a = 3*f
  b = 1*f
  c = 60*f
  d = 120*f
  # get delts
  delta.c = sum(data$treatment == 0 & data$censored == 0)
  delta.h = sum(data$treatment == 1 & data$censored == 0)

  # control group
  x.c = sum(data$recurtime[data$treatment==0])
  x.h = sum(data$recurtime[data$treatment==1])

  # run loop
  for(i in 1:N){
    # tau | theta
    tau.theta = rgamma(1,shape = delta.h+b+1,rate = theta * (x.h + d))
    # theta | tau
```

```

theta.tau = rgamma(1,shape = delta.c+delta.h+a+1,rate = (tau.theta * ( x.h + d) + c + x.c))
gsvec[i,] = c(tau.theta,theta.tau)
theta = theta.tau
}
return(gsvec)
}

```

```

vec.half = GS.2(1/2,10000,data,1,534)
summary(mcmc(vec.half))

```

```

##
## Iterations = 1:10000
## Thinning interval = 1
## Number of chains = 1
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##           Mean          SD Naive SE Time-series SE
## [1,] 1.308366 0.544328 5.443e-03      1.127e-02
## [2,] 0.008713 0.002608 2.608e-05      5.246e-05
##
## 2. Quantiles for each variable:
##
##           2.5%       25%       50%       75%      97.5%
## var1 0.570576 0.924121 1.197060 1.5776 2.64827
## var2 0.004354 0.006865 0.008448 0.0103 0.01441

```

```

GS.2 <- function(f,N,data,theta,see.d){

  # set seed
  set.seed(see.d)

  # initialize sample vec
  gsvec = matrix(0,N,2)
  # hyperparams
  a = 3*f
  b = 1*f
  c = 60*f
  d = 120*f
  # get delts
  delta.c = sum(data$treatment == 0 & data$censored == 0)
  delta.h = sum(data$treatment == 1 & data$censored == 0)

  # control group
  x.c = sum(data$recurtime[data$treatment==0])
  x.h = sum(data$recurtime[data$treatment==1])

  # run loop
  for(i in 1:N){
    # tau / theta
    tau.theta = rgamma(1,shape = delta.h+b+1,rate = theta * (x.h + d))
    # theta / tau

```



```

theta.tau = rgamma(1,shape = delta.c+delta.h+a+1,rate = (tau.theta *( x.h + d) + c + x.c))
gsvec[i,] = c(tau.theta,theta.tau)
theta = theta.tau
}
return(gsvec)
}

vec.double = GS.2(2,10000,data,1,534)
summary(mcmc(vec.double))

##
## Iterations = 1:10000
## Thinning interval = 1
## Number of chains = 1
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##           Mean          SD Naive SE Time-series SE
## [1,] 1.06297 0.404979 4.050e-03      7.869e-03
## [2,] 0.01032 0.002733 2.733e-05      5.304e-05
##
## 2. Quantiles for each variable:
##
##           2.5%       25%       50%       75%      97.5%
## var1 0.497220 0.778352 0.98547 1.26821 2.05331
## var2 0.005601 0.008386 0.01009 0.01205 0.01613

```

The Tau mean value seemed to not change as much as when the hyperparameters to doubled.

Problem 3

```

set.seed(534)
# render pmf
P <- function(X){0.5*exp(-abs(X))}
# make looping algorithm
MH <- function(N,var){
  # make a sample vector
  vec <- rep(0,N)
  vec_bar = vec
  s <- sqrt(var)
  vec[1] <- rnorm(1,0,s)
  accept = 0
  # loop
  for(i in 2:N){
    # sample from norm
    rnorm(1,vec[i-1],s) -> x1
    runif(1) -> u
    P(x1)/P(vec[i-1]) -> alpha
    if(u < alpha){
      vec[i] = x1
      accept = accept+1
    }
  }
}

```

```

    #x1 -> x0
  } else {
    vec[i] = vec[i-1]
  }
  vec_bar[i] <- mean(vec[1:i])
}
# return sample vector
list(vec = vec, means = vec_bar, ratio = accept/N)
}

```

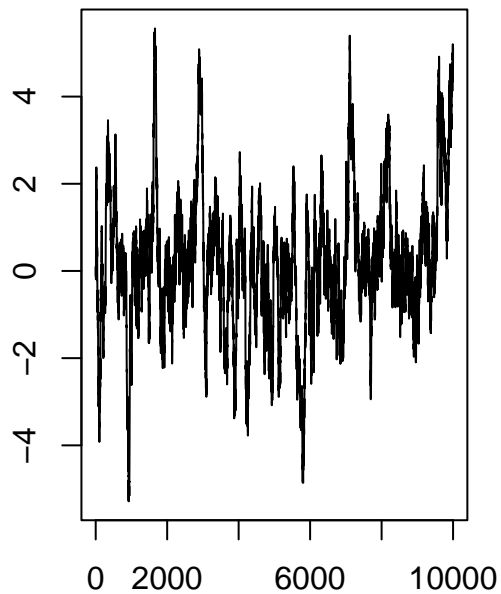
```

VARvec <- c(.05,.5,1,3,100)
n = 10000
for(i in 1:5){
  chain = MH(n,VARvec[i])
  print(chain$ratio)
  summary(mcmc(chain$vec))
  plot(mcmc(chain$vec))
}

```

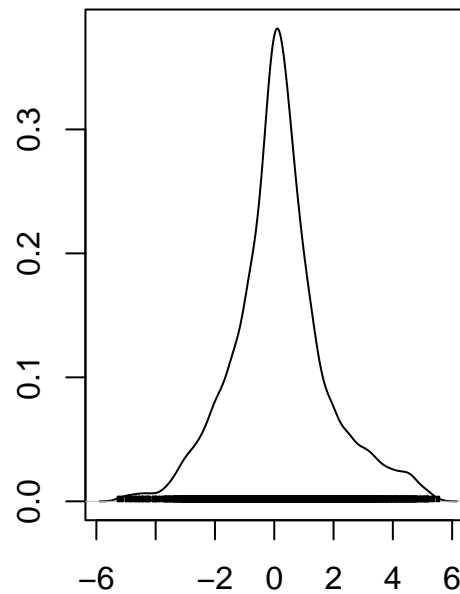
[1] 0.921

Trace of var1



Iterations

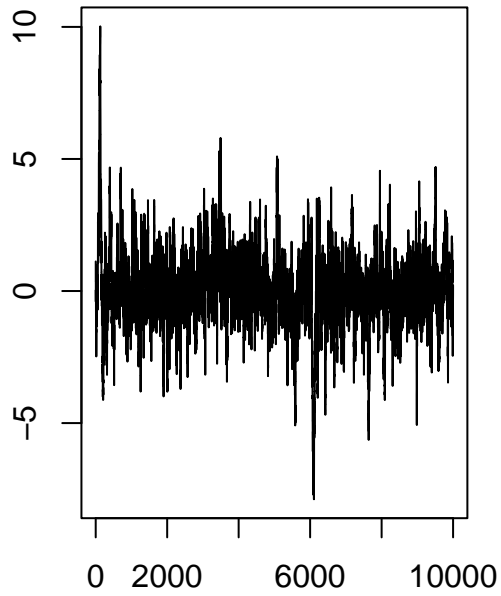
Density of var1



N = 10000 Bandwidth = 0.2008

[1] 0.7741

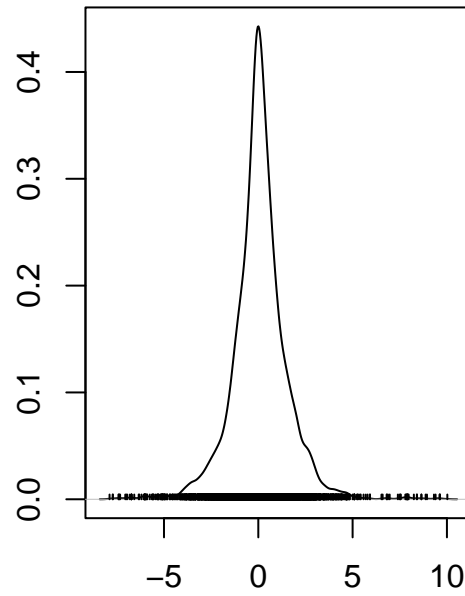
Trace of var1



Iterations

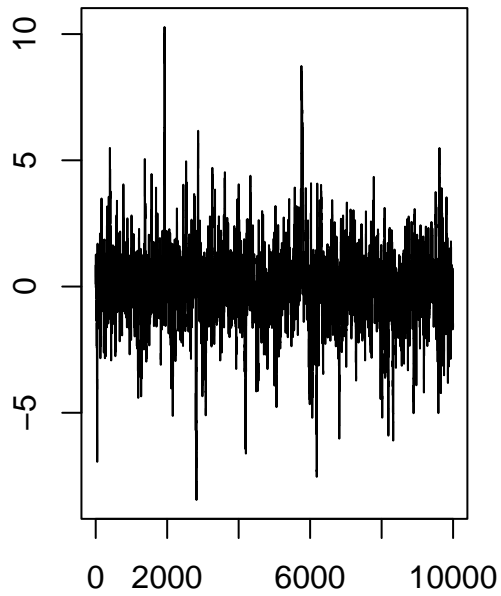
[1] 0.7

Density of var1



N = 10000 Bandwidth = 0.173

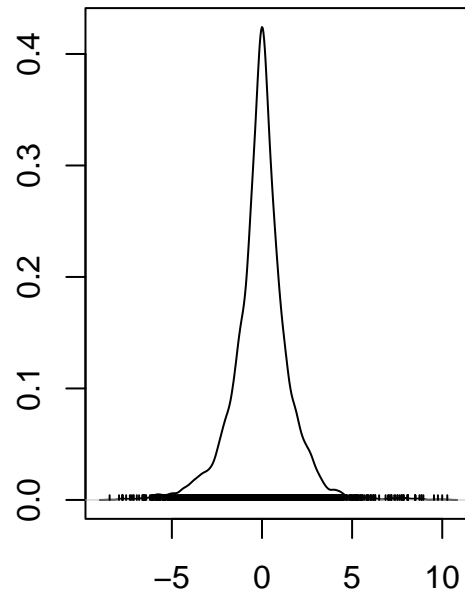
Trace of var1



Iterations

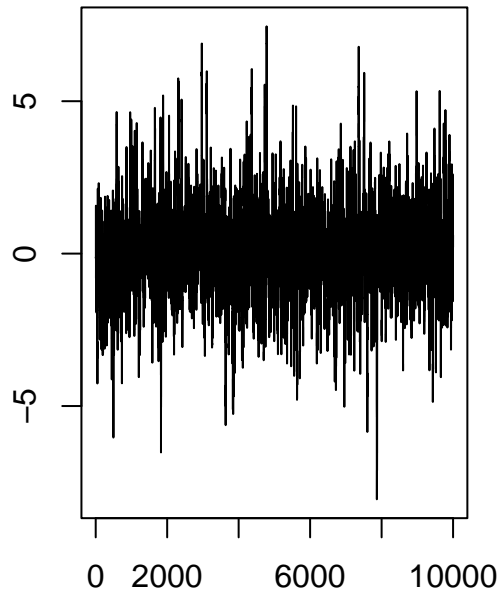
[1] 0.5632

Density of var1



N = 10000 Bandwidth = 0.1821

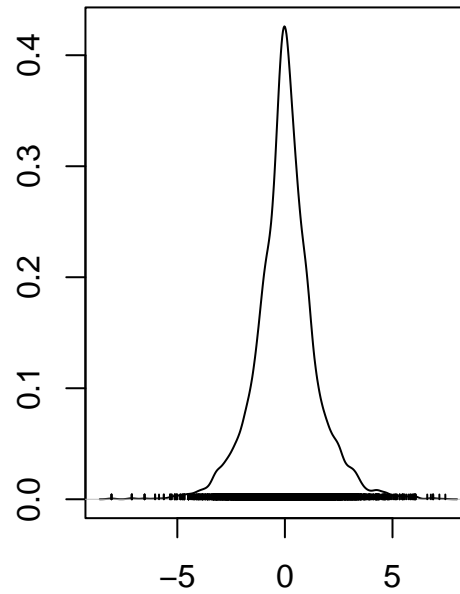
Trace of var1



Iterations

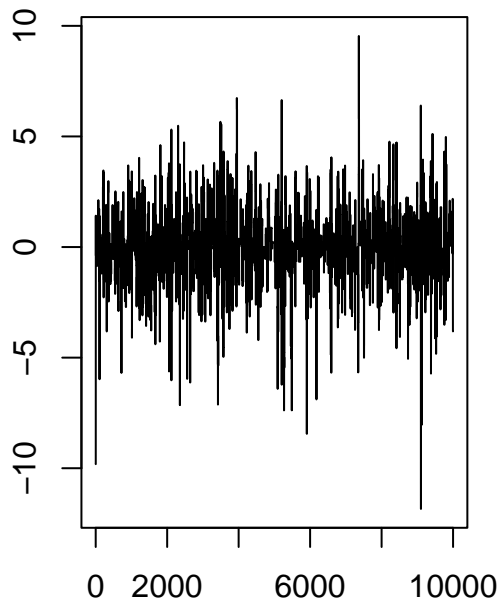
[1] 0.1563

Density of var1



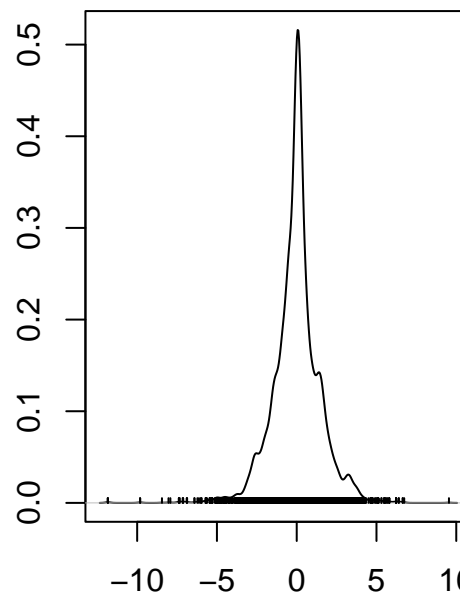
N = 10000 Bandwidth = 0.1824

Trace of var1



Iterations

Density of var1



N = 10000 Bandwidth = 0.1696

```
set.seed(534)
P <- function(X){
  if(X >= 0){exp(-X)}
  else{0}
```

```

    } # render pmf
# make looping algorithm
MHexp <- function(N,var){
  # make a sample vector
  vec <- rep(0,N)
  vec_bar = vec
  s <- sqrt(var)
  vec[1] <- rnorm(1,0,s)
  accept = 0
  # loop
  for(i in 2:N){
    # sample from norm
    rnorm(1,vec[i-1],s) -> x1
    # while(x1 < 0){rnorm(1,vec[i-1],s) -> x1}
    runif(1) -> u
    P(x1)/P(vec[i-1]) -> alpha
    if(u < alpha){
      vec[i] = x1
      accept = accept+1
      #x1 -> x0
    } else {
      vec[i] = vec[i-1]
    }
    vec_bar[i] <- mean(vec[1:i])
  }
  # return sample vector
  list(vec = vec, means = vec_bar, ratio = accept/N)
}

```

```

chain = MHexp(10000,7)
sprintf("Acceptance rate is %f",chain$ratio)

```

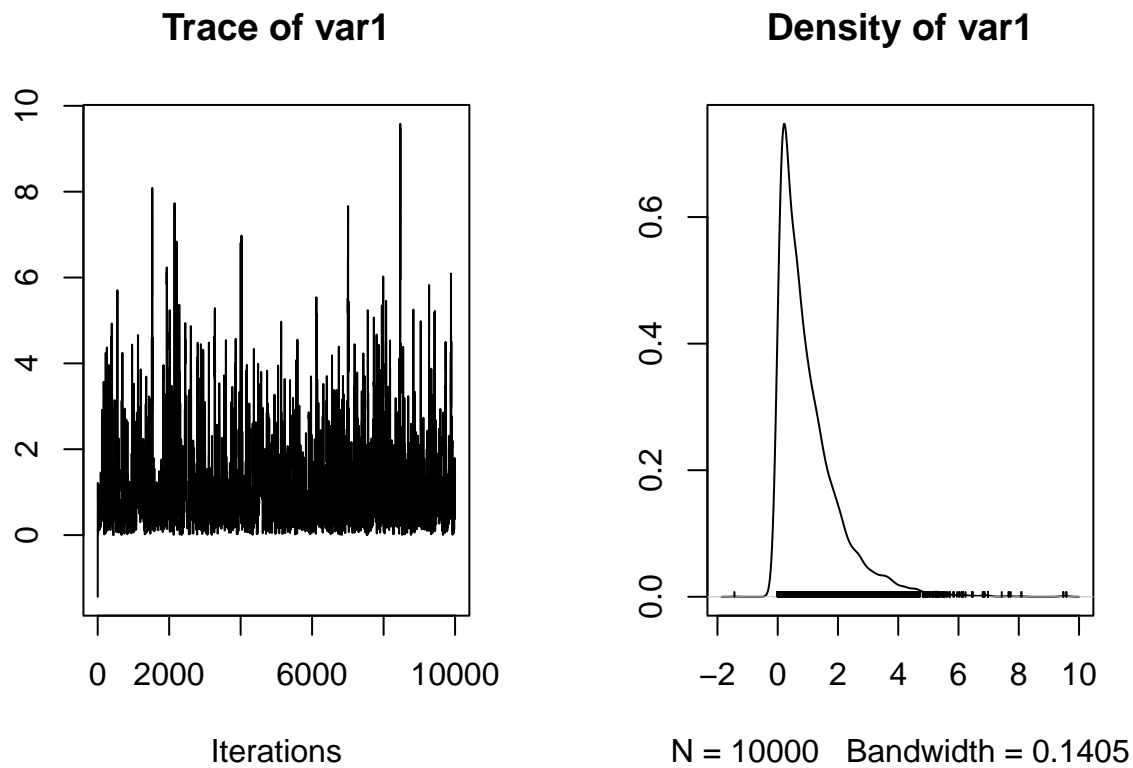
```
## [1] "Acceptance rate is 0.270900"
```

```
summary(mcmc(chain$vec))
```

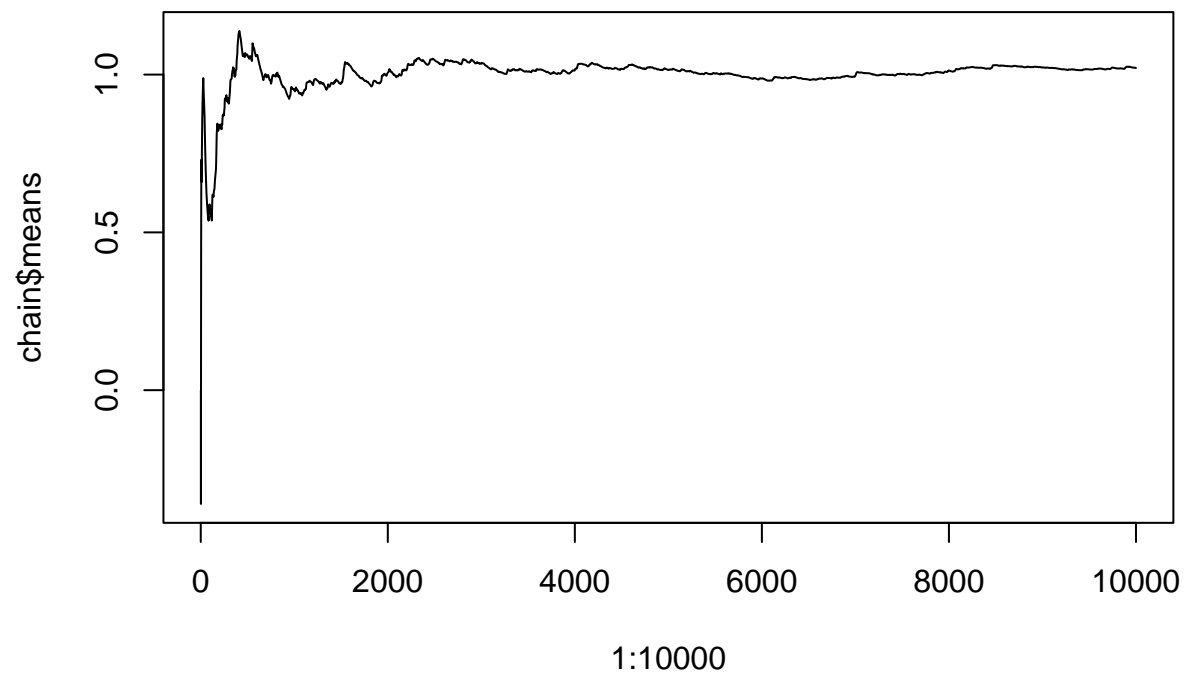
```
##
## Iterations = 1:10000
## Thinning interval = 1
## Number of chains = 1
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##           Mean           SD      Naive SE Time-series SE
##      1.02114      1.02972      0.01030      0.03533
##
## 2. Quantiles for each variable:
##
##      2.5%      25%      50%      75%      97.5%
## 0.03154 0.28735 0.70831 1.40771 3.80582

```

```
plot(mcmc(chain$vec))
```

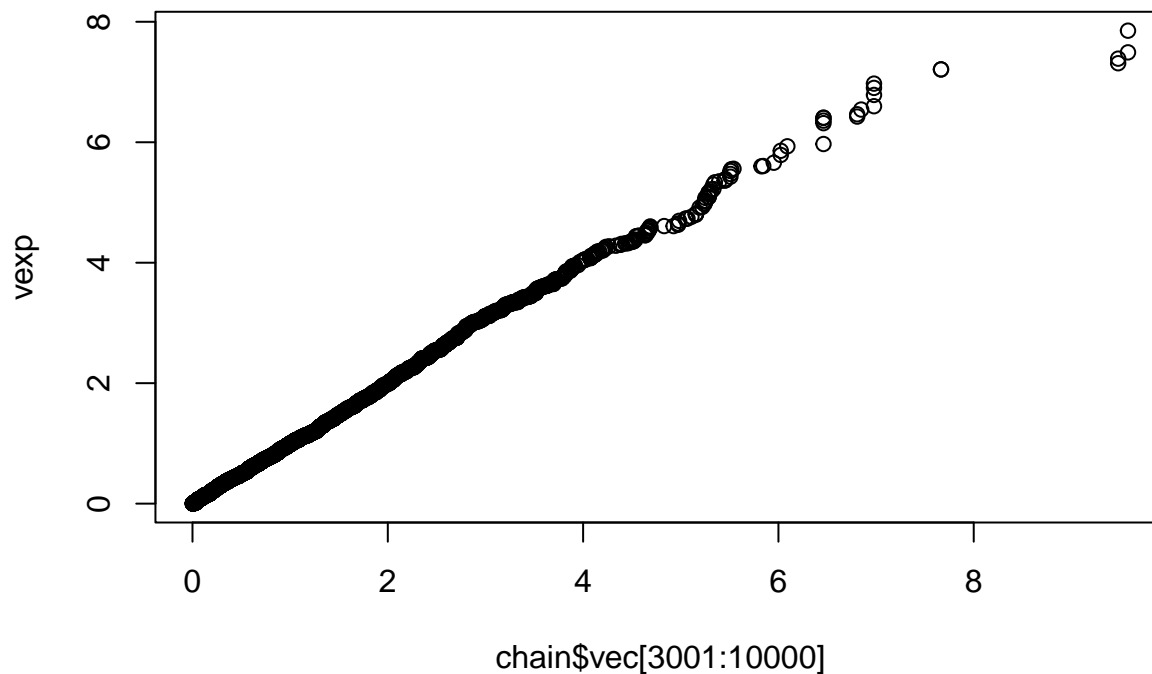


```
plot(1:10000,chain$means,type = 'l')
```



I decided to burn 3000.

```
vexp <- rexp(7000,1)
qqplot(chain$vec[3001:10000],vexp)
```



Problem (5).

system 1

```
# render bivariate normal function
P <- function(v){
  v[1] -> X
  v[2] -> Y
  x = matrix(c(X,Y),nrow=2)
  mu = matrix(c(1,2),nrow=2)
  S = matrix(c(1,.9,.9,1),nrow=2,byrow=T)
  1/(2*pi*sqrt(det(S)))*exp(-.5*t(x-mu)%*%solve(S)%*(x-mu))
}

# make looping algorithm
WALK.BVU <- function(N,nburn){
  # make a sample vector
  vec <- matrix(0,N,2)
  vec_bar = vec
  vec[1,1] <- runif(1,-.75,.75)
  vec[1,2] <- runif(1,-1,1)
  accept = 0
  # loop
  for(i in 2:N){
    # render z
    z = c(runif(1,-.75,.75),runif(1,-1,1))
    vecprime = z + vec[i-1,]
    # while(x1 < 0){rnorm(1,vec[i-1],s) -> x1}
    runif(1) -> u
    min(P(vecprime)/P(vec[i-1,]),1) -> alpha
    if(u < alpha){
      vec[i,] = vecprime
    }
  }
}
```

```

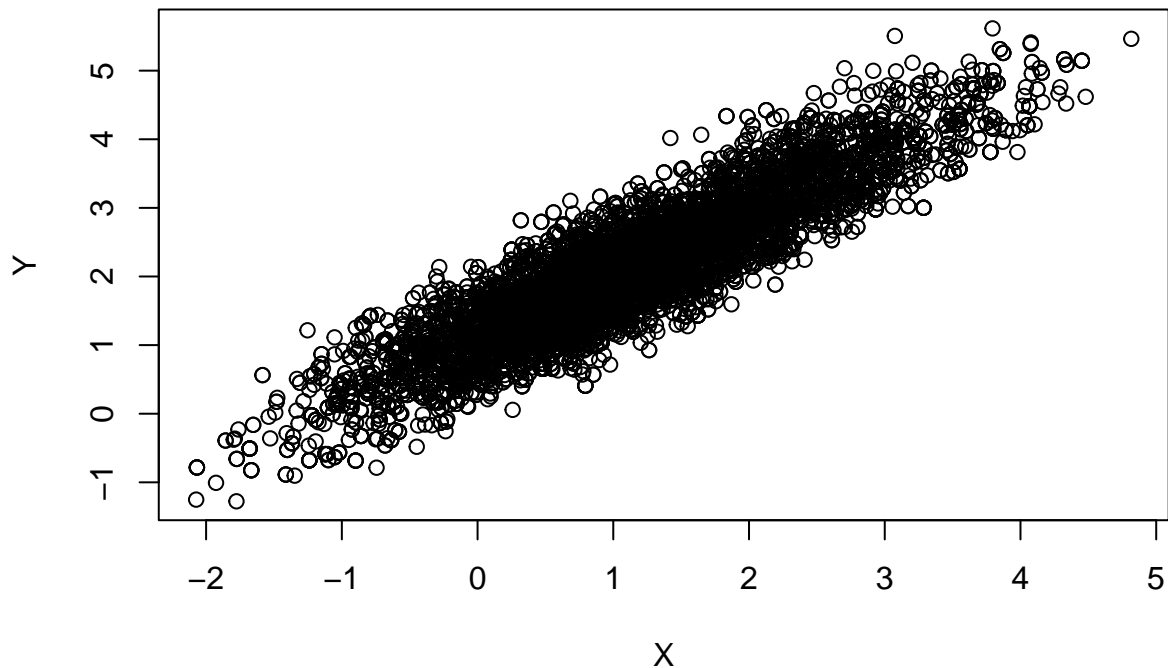
    accept = accept+1
    #x1 -> x0
  } else {
    vec[i,] = vec[i-1,]
  }
  vec_bar[i,] <- mean(vec[1:i,])
}
# burn
vec = vec[(nburn+1):N,]
vec_bar = vec_bar[(nburn+1):N]
# return sample vector
list(vec = vec, means = vec_bar, ratio = accept/N)
}

```

```

WALK.BVU(10000,2000) -> chain
X = chain$vec[,1]
Y = chain$vec[,2]
plot(X,Y)

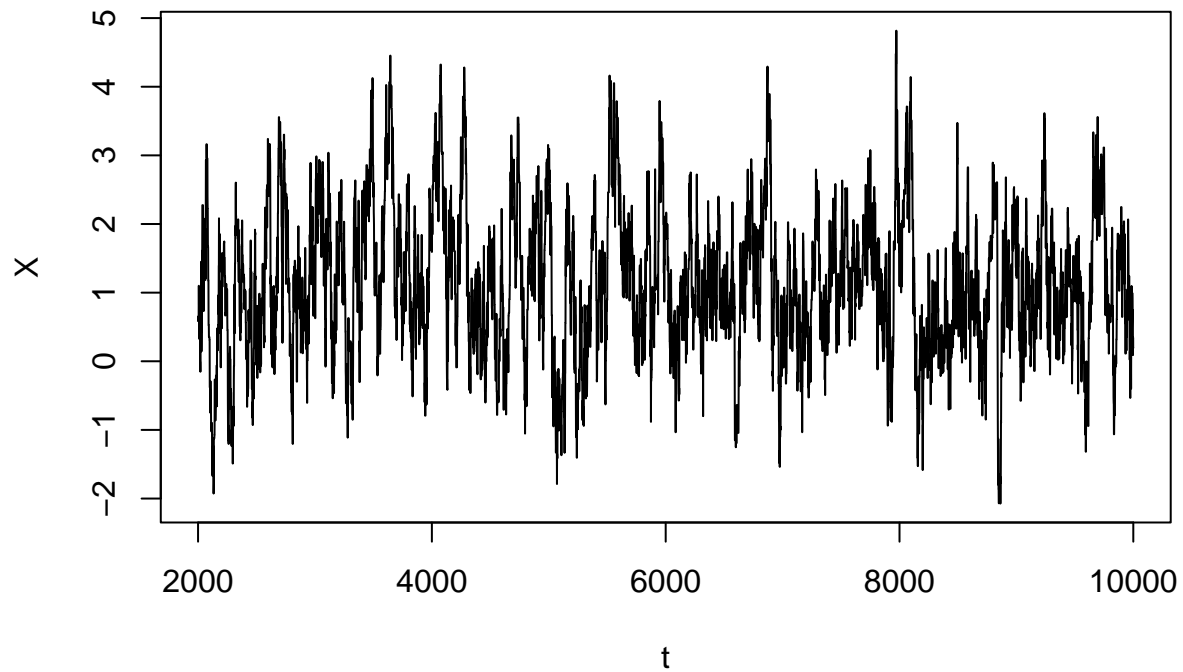
```



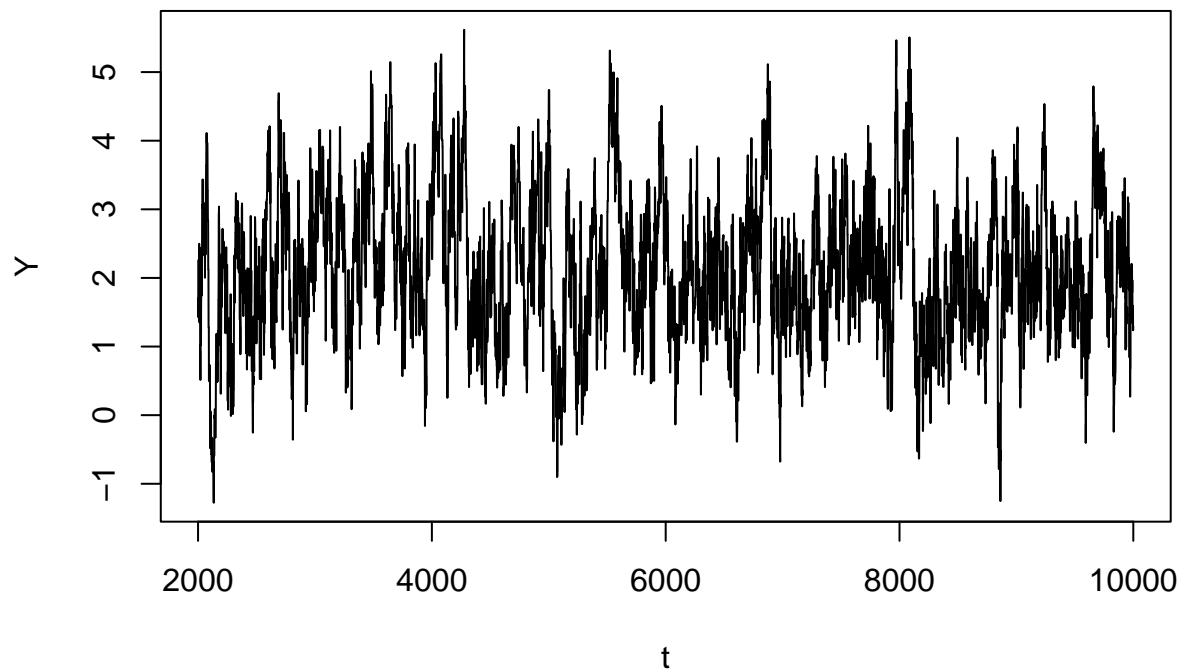
```

t = 2001:10000
plot(t,X,type = 'l')

```

```
plot(t,Y,type = "l")
```



```
sprintf("Acceptance rate is for system 1 is %f",chain$ratio)
```

```
## [1] "Acceptance rate is for system 1 is 0.515000"
```

This is not an acceptable acceptance rate because it is just above the 40-50% range in the article.

system 2

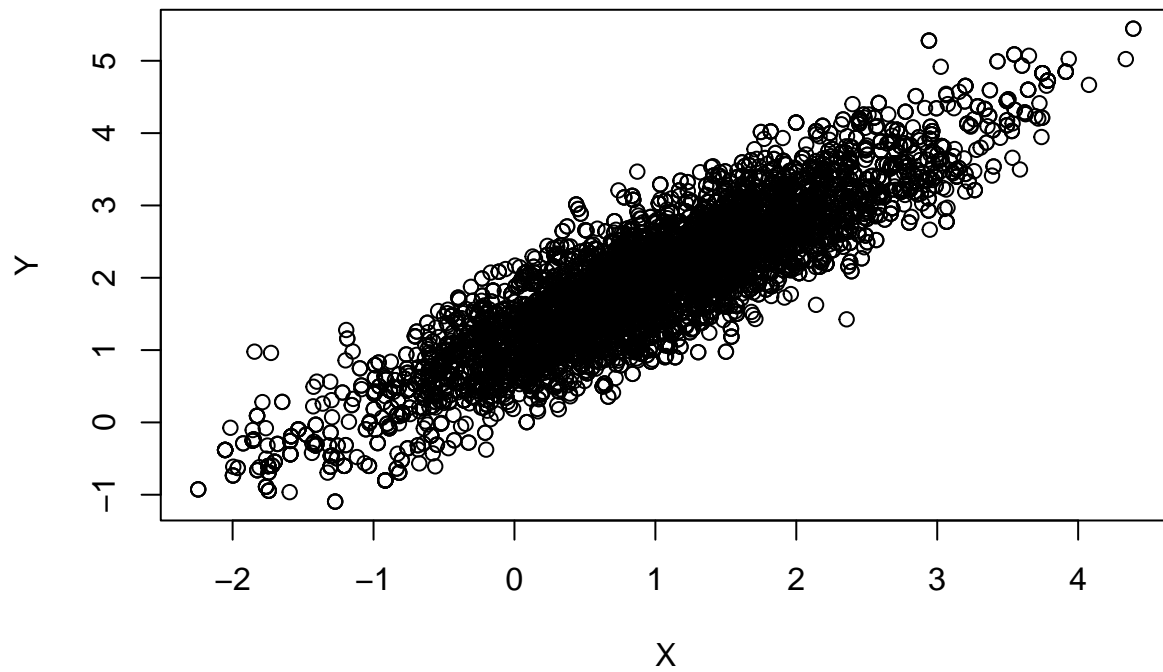
```
# make looping algorithm
WALK.N2 <- function(N,nburn){
```

```

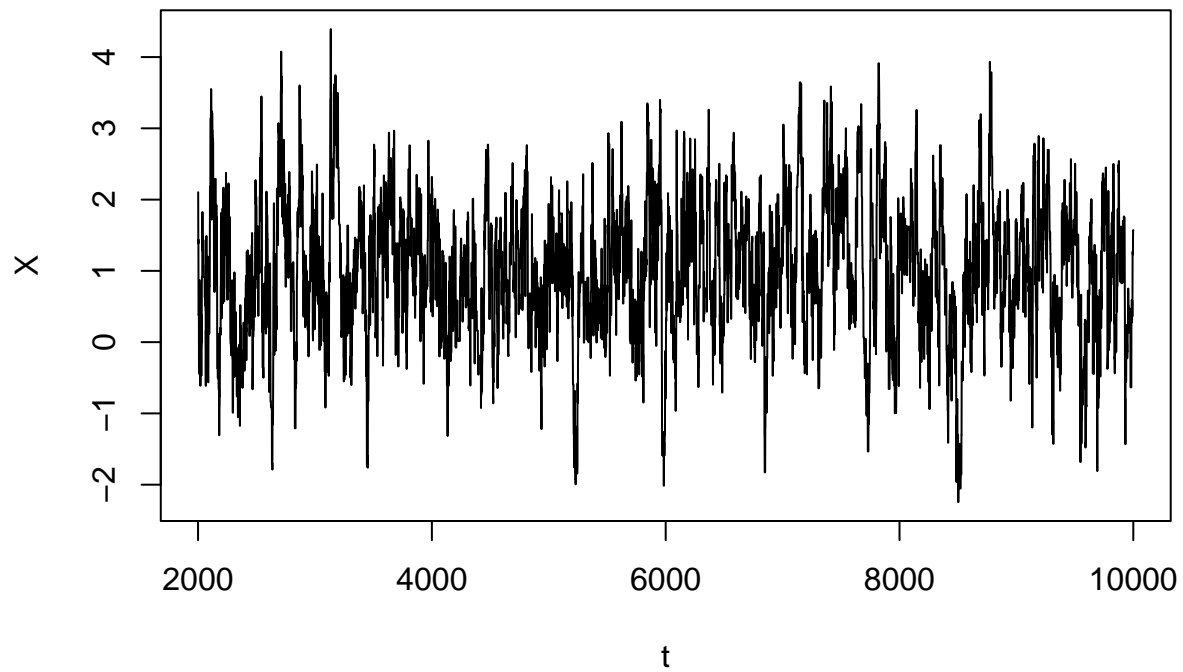
# make a sample vector
vec <- matrix(0,N,2)
vec_bar = vec
vec[1,] <- mvrnorm(1,c(0,0),diag(c(.6,.4)))
accept = 0
# loop
for(i in 2:N){
  # render z
  z = mvrnorm(1,c(0,0),diag(c(.6,.4)))
  vecprime = z + vec[i-1,]
  # while(x1 < 0){rnorm(1,vec[i-1],s) -> x1}
  runif(1) -> u
  min(P(vecprime)/P(vec[i-1,]),1) -> alpha
  if(u < alpha){
    vec[i,] = vecprime
    accept = accept+1
    #x1 -> x0
  } else {
    vec[i,] = vec[i-1,]
  }
  vec_bar[i,] <- mean(vec[1:i,])
}
# burn
vec = vec[(nburn+1):N,]
vec_bar = vec_bar[(nburn+1):N]
# return sample vector
list(vec = vec, means = vec_bar, ratio = accept/N)
}

WALK.N2(10000,2000) -> chain
X = chain$vec[,1]
Y = chain$vec[,2]
plot(X,Y)

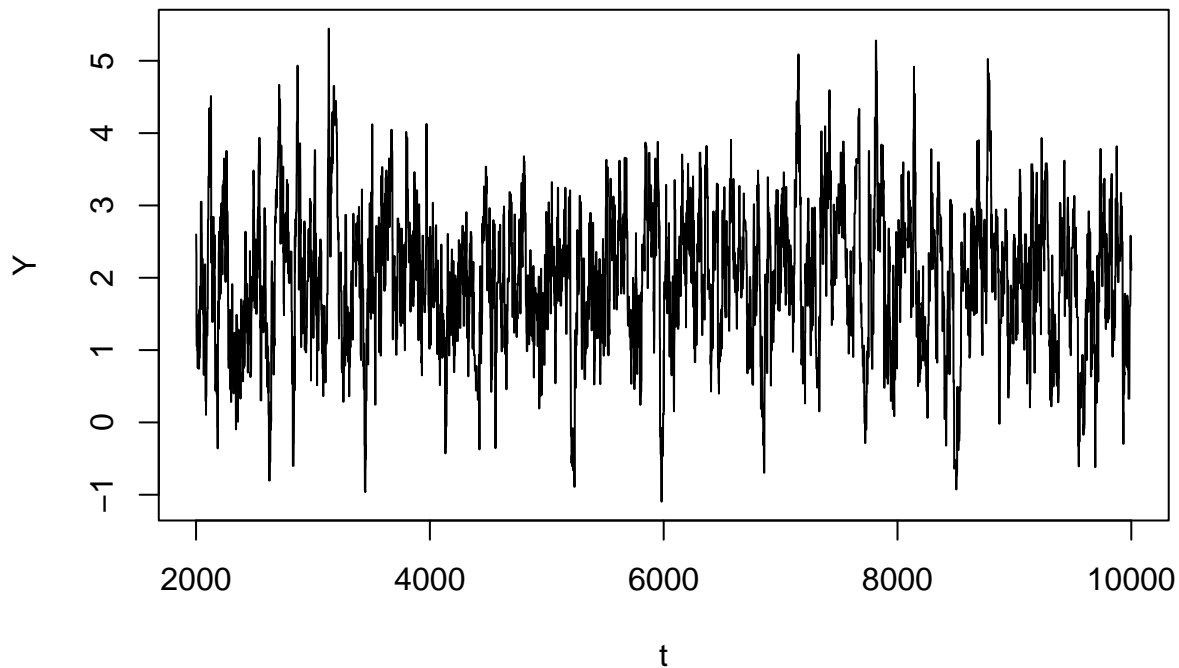
```



```
t = 2001:10000  
plot(t,X,type = 'l')
```



```
plot(t,Y,type = "l")
```



```
sprintf("Acceptance rate is for system 2 is %f",chain$ratio)
```

```
## [1] "Acceptance rate is for system 2 is 0.439300"
```

system 3

```
# render bivariate normal function
ch <- function(v){
  v[1] -> X
  v[2] -> Y
  x = matrix(c(X,Y),nrow=2)
  mu = matrix(c(1,2),nrow=2)
  S = diag(c(2,2))
  0.9/(2*pi*sqrt(det(S)))*exp(-.5*t(x-mu)%*%solve(S)%*(x-mu))
}

# make looping algorithm
WALK.P3 <- function(N,nburn){
  # make a sample vector
  vec <- matrix(0,N,2)
  vec_bar = vec
  #vec[1,] <- mvrnorm(1,c(0,0),diag(2))
  vec[1,] <- c(rnorm(1,0,2),rnorm(1,0,2))
  accept = 0
  # loop
  for(i in 2:N){
    # render vecprime
    vecprime <- mvrnorm(1,c(0,0),diag(2))
    c(rnorm(1,0,2),rnorm(1,0,2)) -> vecprime
    runif(1) -> u
    # render alphas
    if(P(vec[i-1,]) < ch(vec[i-1,])){ #C1
      alpha = 1
    }
  }
}
```

```

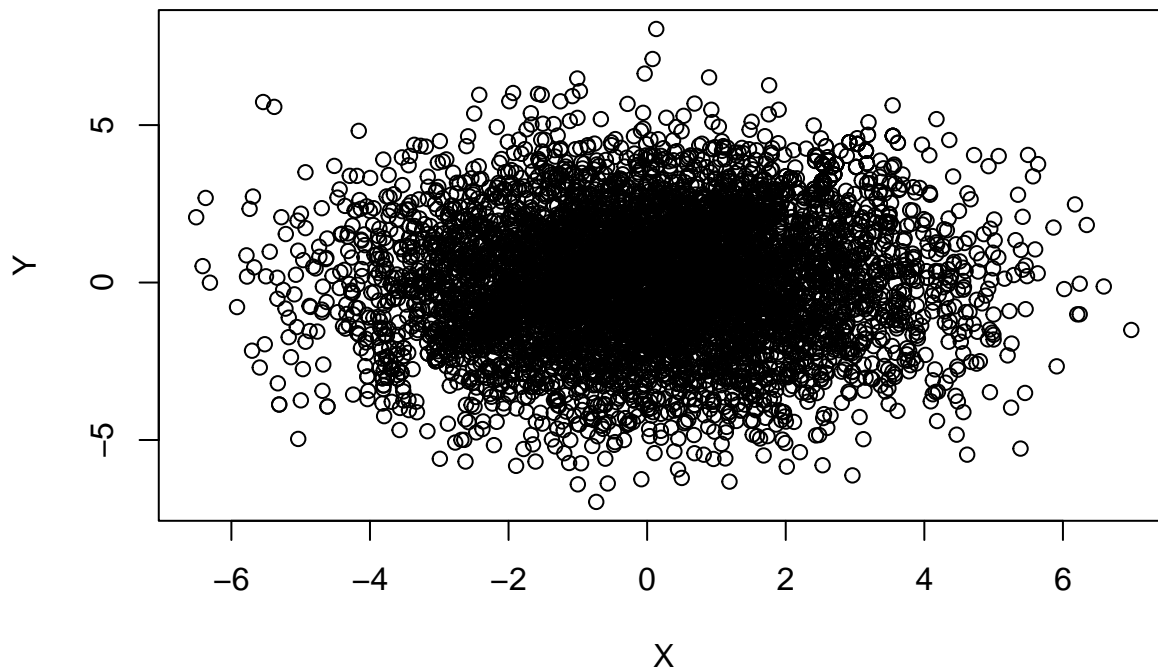
    } else if(P(vec[i-1,]) >= cH(vec[i-1,]) && P(vecprime) < cH(vecprime)){ #C2
      alpha = cH(vec[i-1,])/P(vec[i-1,])
    } else{ #C3
      alpha = min(1,(P(vecprime)*cH(vec[i-1,]))/(cH(vecprime)*P(vec[i-1,])))
    }
    # accept-reject
    if(u < alpha){
      vec[i,] = vecprime
      accept = accept+1
    } else {
      vec[i,] = vec[i-1,]
    }
    vec_bar[i,] <- mean(vec[1:i,])
  }
  # burn
  vec = vec[(nburn+1):N,]
  vec_bar = vec_bar[(nburn+1):N]
  # return sample vector
  list(vec = vec, means = vec_bar, ratio = accept/N)
}

```

```

WALK.P3(10000,2000) -> chain
X = chain$vec[,1]
Y = chain$vec[,2]
plot(X,Y)

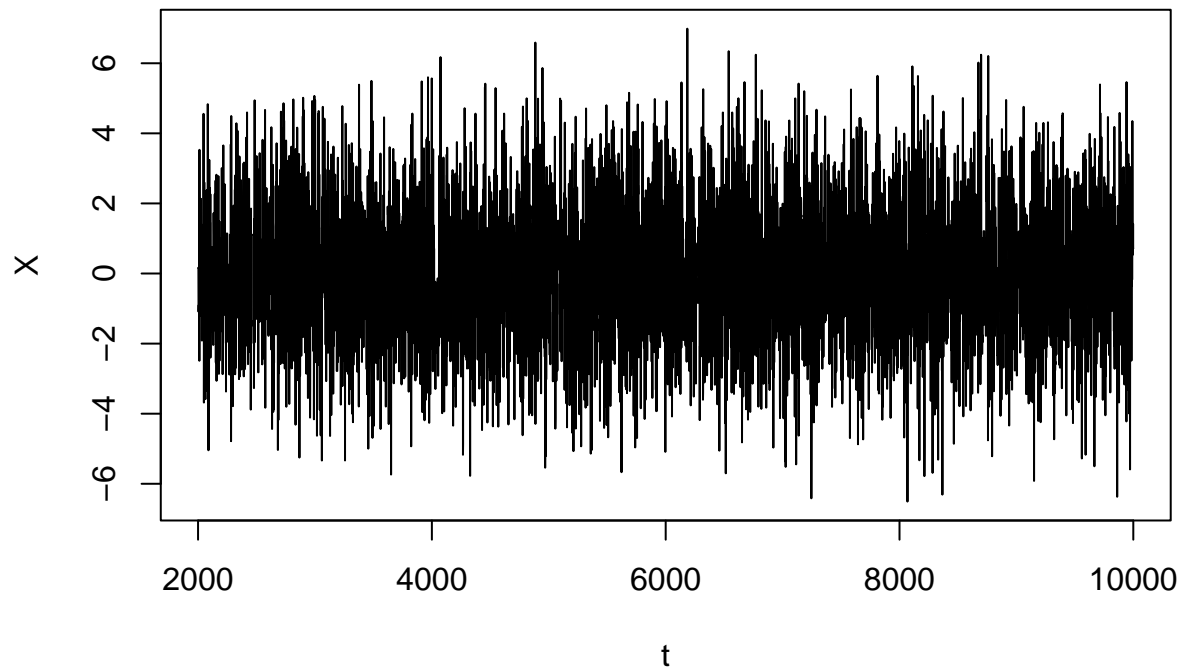
```



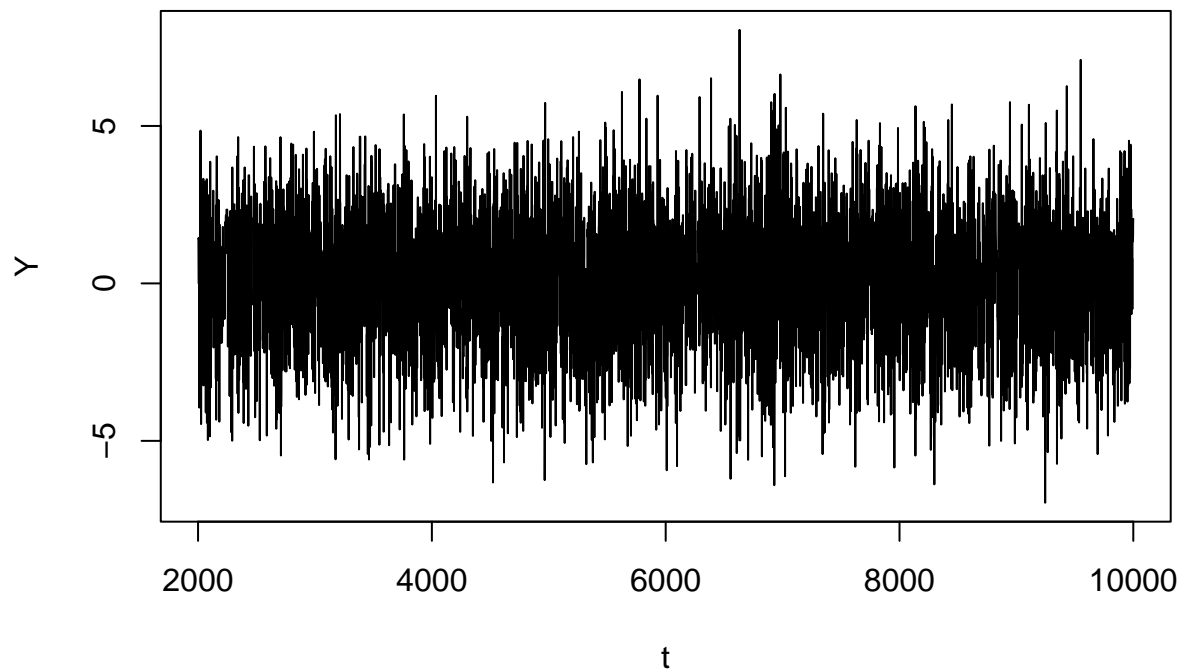
```

t = 2001:10000
plot(t,X,type = 'l')

```



```
plot(t,Y,type = "l")
```



```
sprintf("Acceptance rate is for system 3 is %f",chain$ratio)
```

```
## [1] "Acceptance rate is for system 3 is 0.744300"
```

system 4

```
# make looping algorithm
WALK.BVU4 <- function(N,nburn){
  # make a sample vector
```

```

vec <- matrix(0,N,2)
vec_bar = vec
vec[1,1] <- runif(1,-.75,.75)
vec[1,2] <- runif(1,-1,1)
accept = 0
mu = c(1,2)
# loop
for(i in 2:N){
  # render z
  z = c(runif(1,-1,1),runif(1,-1,1))

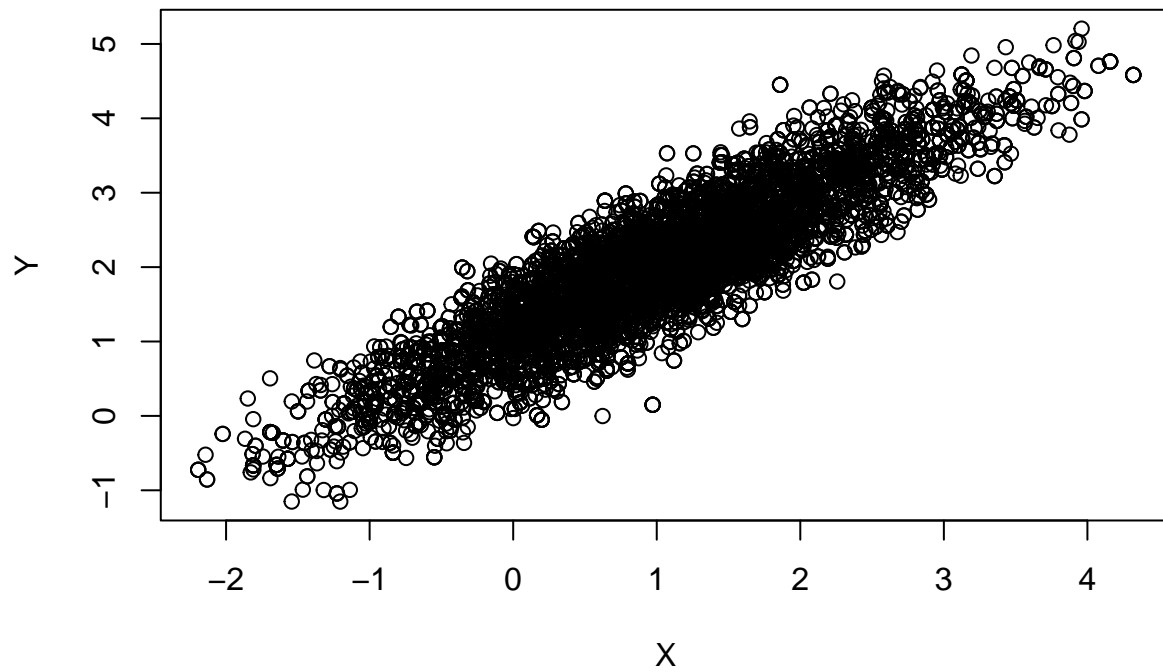
  # walk
  vecprime = z + 2*mu - vec[i-1,]
  runif(1) -> u
  min(P(vecprime)/P(vec[i-1,]),1) -> alpha
  if(u < alpha){
    vec[i,] = vecprime
    accept = accept+1
    #x1 -> x0
  } else {
    vec[i,] = vec[i-1,]
  }
  vec_bar[i,] <- mean(vec[1:i,])
}
# burn
vec = vec[(nburn+1):N,]
vec_bar = vec_bar[(nburn+1):N]
# return sample vector
list(vec = vec, means = vec_bar, ratio = accept/N)
}

```

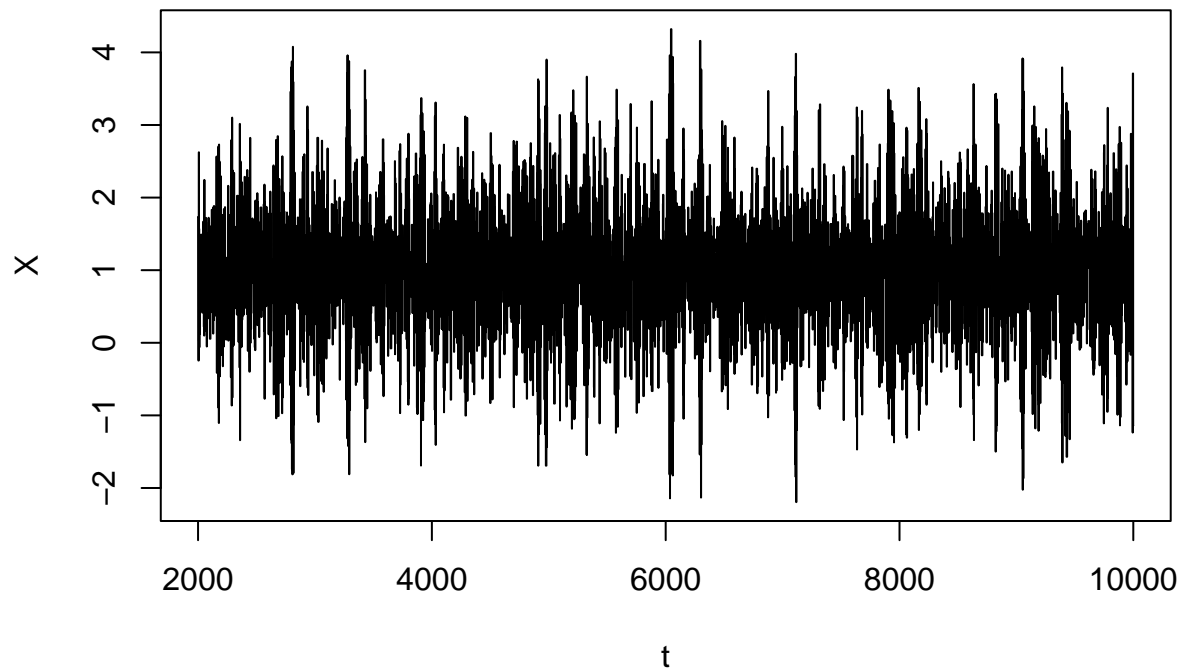
```

WALK.BVU4(10000,2000) -> chain
X = chain$vec[,1]
Y = chain$vec[,2]
plot(X,Y)

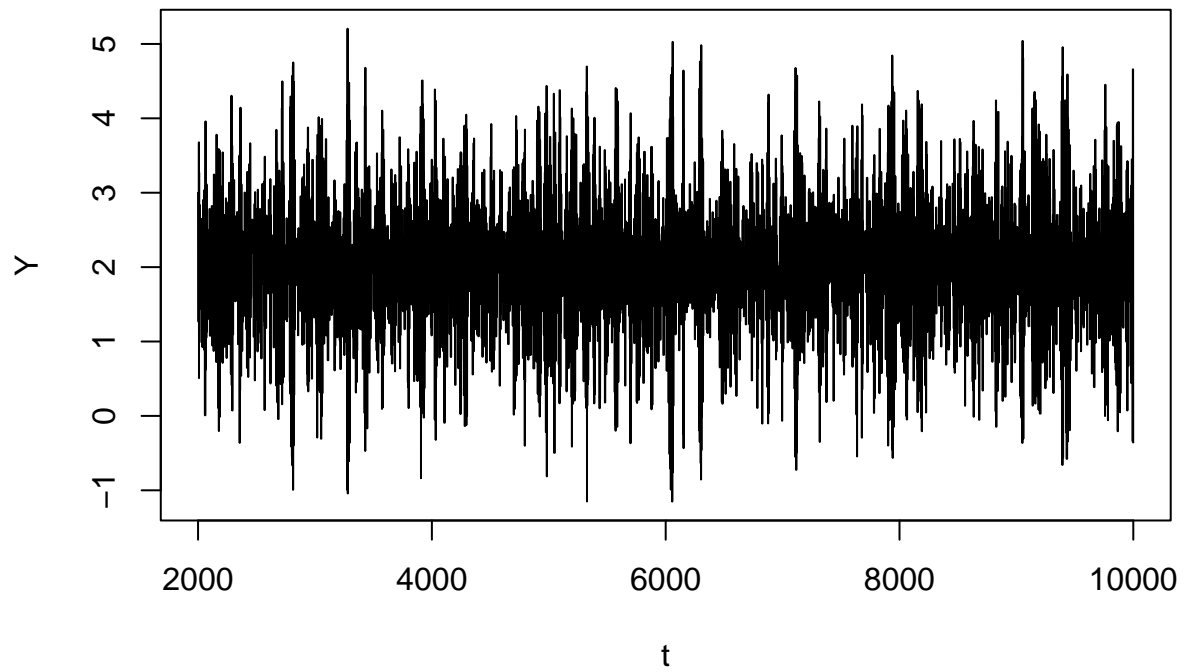
```



```
t = 2001:10000  
plot(t,X,type = 'l')
```



```
plot(t,Y,type = "l")
```

```
sprintf("Acceptance rate is for system 4 is %f",chain$ratio)
```

```
## [1] "Acceptance rate is for system 4 is 0.462700"
```