

Solution to Exercises

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1 Rejection Sampling - Solution

1.1 Code

```
### Result object
y <- numeric()

### number of iterations
niter<-50000

### Define candidate distribution
cand <- function(x) {
  dunif(x,-3,3)
}

### Define target distribution
target <-function(x) {
  exp(-(x^2+sin(2*x))^4-0.473)
}

### Define M
M <- 0.44
M <- target(0)/cand(0)

### Counter
counter <- 1

for(i in 1:niter){
  ### Sample candidate value
  yCand <- runif(1,-3,3)

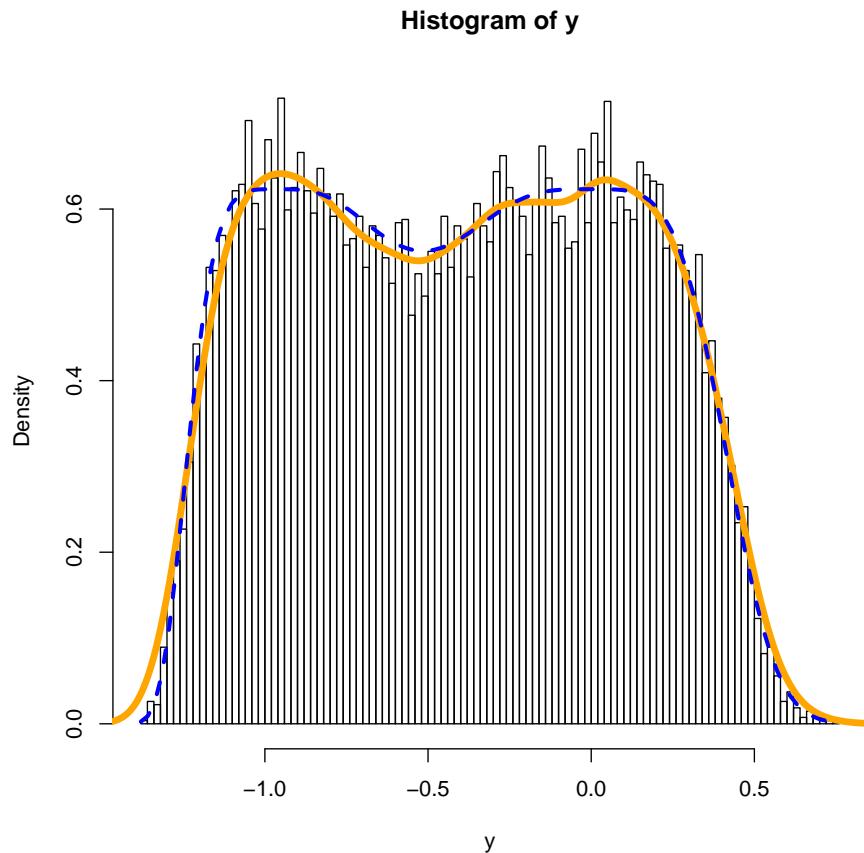
  ### Calculate acceptance probability
  p <- target(yCand)/(M * cand(yCand))
  ### Sample a value from uniform distribution
```

```
U <- runif(1)

if(U < p){
  ### Accept candidate value
  y[counter] <- yCand
  ### Increase counter
  counter <- counter + 1
}
```

1.2 Graphical results

```
### Histogram
hist(y, breaks=100, freq=FALSE)
### Density plot of the true function
lines(density(y), lwd=5, col="orange")
### Sampled density plot
curve(target, col="blue", lwd=3, lty=2, add=TRUE)
```



2 Sample a distribution using a Metropolis-Hastings Algorithm

2.1 Distribution

```
### Distribution to sample
distriEx1<-function(x) {exp(-(x+sin(3*x))^2+0.195)/2}
```

2.2 Code

```
### Number of iterations
niter<-50000
```

```

### Starting value
thetaStart <- 0

### Candidate value
theta_c <- 0

### Vector of saved value
theta<-numeric()

### Initiate result vector
theta[1]<-thetaStart

### acceptance probability
r_c<-numeric()

for(i in 2:niter){
  ### Sample candidate value from jumping distribution
  theta_c <- rnorm(1,mean=theta[i-1],sd=1)

  ### Sample from target distribution using candidate value
  distri_c <- distriEx1(theta_c)

  ### Sample from target distribution using reference value
  distri_Ref <- distriEx1(theta[i-1])

  ### Calculate acceptance probability
  r_c <- distri_c/distri_Ref

  ### Sample a value from uniform distribution
  U <- runif(1)
  if(U < r_c){
    ### Accept candidate value
    theta[i]<-theta_c
  }else{
    ### Keep reference value
    theta[i]<-theta[i-1]
  }
}

```

2.3 Graphical results

```
par(mfrow=c(2,1))
```

```

### Trace plot
plot(theta,main="trace plot",type="l")

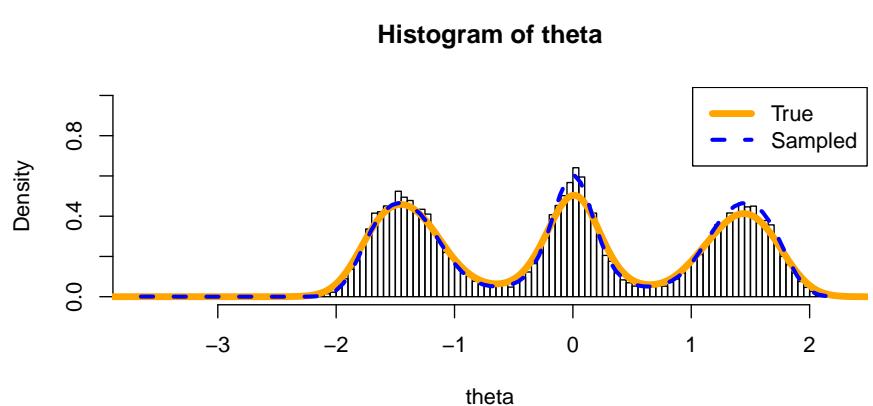
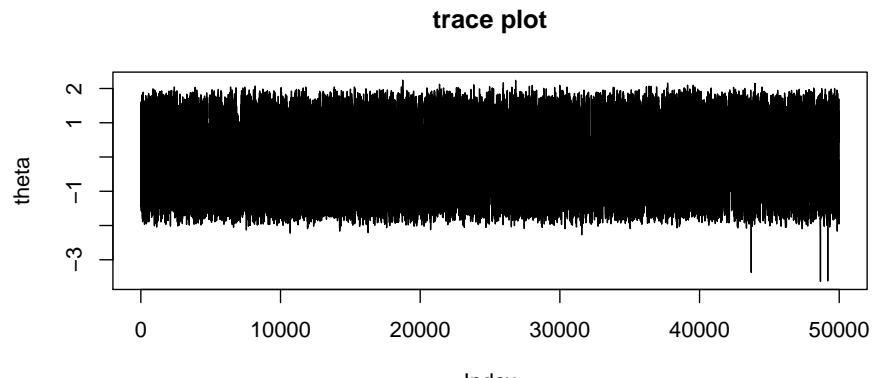
### Histogram
hist(theta,freq=FALSE,breaks=100,ylim=c(0,1))

### Density plot of the true function
lines(density(theta),lwd=5,col="orange")

### Sampled density plot
curve(distriEx1(x),add=TRUE,col="blue",lwd=3,lty=2)

### Legende
legend("topright",legend=c("True","Sampled"),lwd=c(5,3),
      lty=c(1,2),col=c("orange","blue"))

```



3 Sample a distribution using an adaptative Metropolis-Hasting Algorithm

3.1 Distribution

```
### Distribution to sample
distriEx2<-function(x) {exp(-(x^2+sin(3*x))^4-0.344)}
```

3.2 Code

```
### Number of iterations
niter <- 50000

### Number of burnin iterations
burnin <- 20000

### Starting value
thetaStart <- 0

### Candidate value
theta_c <- 0

### Vector of saved value
theta<-numeric()

### Initiate result vector
theta[1]<-thetaStart

### acceptance probability
r_c<-numeric()

### Adatptation value
A <- 1

for(i in 2:niter){
  ### Sample candidate value from jumping distribution
  theta_c <- rnorm(1,mean=theta[i-1],sd=A)

  ### Sample from target distribution using candidate value
  distri_c <- distriEx2(theta_c)

  ### Sample from target distribution using reference value
  distri_Ref <- distriEx2(theta[i-1])}
```

```

### Calculate acceptance probability
r_c <- distri_c/distri_Ref

### Sample a value from uniform distribution
U <- runif(1)
if(U < r_c){
  ### Accept candidate value
  theta[i]<-theta_c
  if(burnin < i){
    ### Modify adaptation value
    A = A * 1.01
  }
}else{
  ### Keep reference value
  theta[i]<-theta[i-1]
  if(burnin < i){
    ### Modify adaptation value
    A = A / 1.01
  }
}
}

```

3.3 Graphical results

```

par(mfrow=c(2,1))

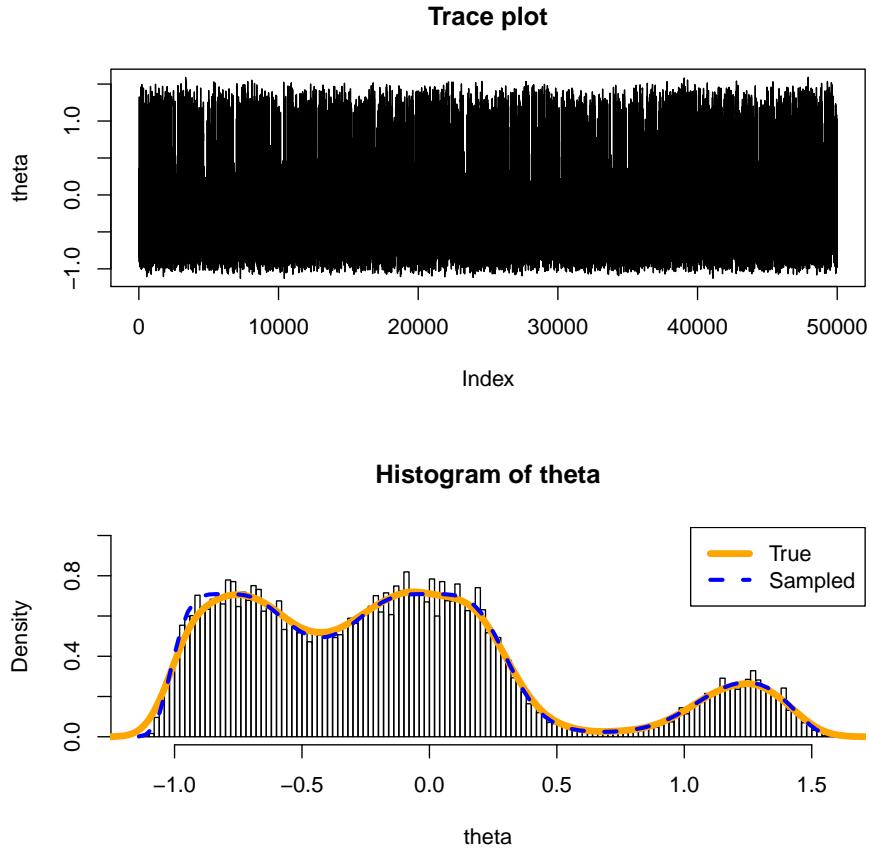
### Trace plot
plot(theta,main="Trace plot",type="l")

### Histogram
hist(theta,freq=FALSE,breaks=100,ylim=c(0,1))

### Density plot of the true function
lines(density(theta),lwd=5,col="orange")
### Sampled density plot
curve(distriEx2(x),add=TRUE,col="blue",lwd=3,lty=2)

### Legend
legend("topright",legend=c("True","Sampled"),lwd=c(5,3),
      lty=c(1,2),col=c("orange","blue"))

```



4 Sample a distribution using a single component adaptive Metropolis-Hastings Algorithm

4.1 Distribution

```
### Define target distribution (bivariate normal distribution)
library(mvtnorm)

### Mean of the bivariate normal distribution
mu <- c(10,30)

### Covariance of the bivariate normal distribution
sigma <- matrix(c(1,0.7,0.7,2),2,2)
```

```

### Distribution
distriEx3<-function(x) {
  dmvnorm(x,mean=mu,sigma=sigma)
}

```

4.2 Code

```

### Number of iterations
niter <- 10000

### Number of burnin iterations
burnin <- 5000

### Vector of starting value
thetaStart <- c(0,0)

### Vector of candidate values
theta_c <- thetaStart

### Matrix of results value
theta <- matrix(NA,ncol=2,nrow=niter)

### Initiate result matrix
theta[1,] <- thetaStart

### Number of parameters
nparam <- length(mu)

### Acceptance probability
r_c <- numeric()

### Adaptation values
A <- c(1,1)

for(i in 2:niter){
  for(j in 1:nparam){
    ### Sample candidate value from jumping distribution
    theta_c[j] <- rnorm(1,mean=theta[i-1,j],sd=A)

    ### Sample from target distribution using candidate value
    distri_c <- distriEx3(theta_c)

    ### Sample from target distribution using reference value
  }
}

```

```

distri_Ref <- distriEx3(theta[i-1,])

### Calculate acceptance probability
r_c <- distri_c/distri_Ref

### Sample value from a uniform distribution
U <- runif(1)
if(U < r_c){
  ### Accept candidate value
  theta[i,j] <- theta_c[j]
  if(burnin < i){
    ### Modify adaptation value
    A[j] = A[j] * 1.01
  }
} else{
  ### Keep reference value
  theta[i,j] <- theta[i-1,j]
  if(burnin < i){
    ### Modify adaptation value
    A[j] = A[j] / 1.01
  }
}
}
}
}

```

4.3 Graphical results

```

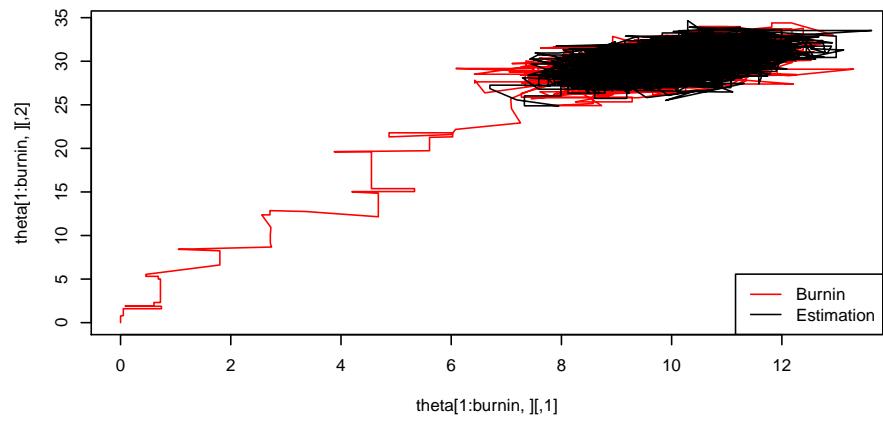
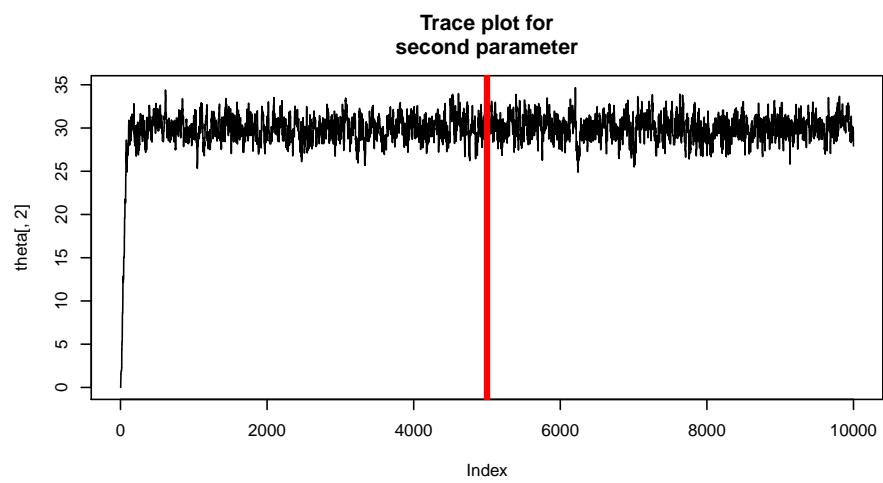
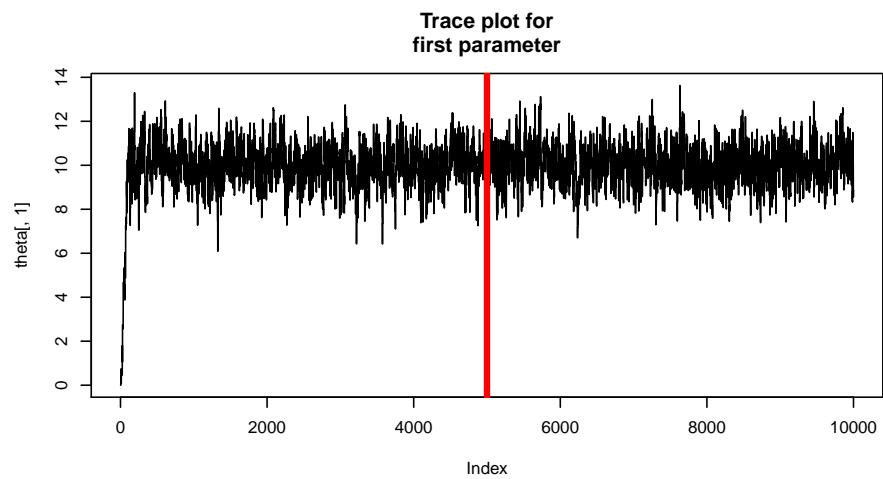
par(mfrow=c(3,1))

### Trace plot of the first parameter
plot(theta[,1],main="Trace plot for\nfirst parameter",type="l")
abline(v=burnin,col="red",lwd=4)

### Trace plot of the second parameter
plot(theta[,2],main="Trace plot for\nsecond parameter",type="l")
abline(v=burnin,col="red",lwd=4)

### Distribution of both parameters
plot(theta[1:burnin,],type="l",col="red")
lines(theta[burnin:niter,],type="l")
legend("bottomright",legend=c("Burnin","Estimation"),lty=c(1,1),col=c("red","black"))

```



5 Gibbs sampler using conjugate priors

5.1 Data

```
Y <- c(15, 19.59, 15.06, 15.71, 14.65, 21.4, 17.64, 18.31, 15.12, 14.40)
n <- length(Y)
```

5.2 Define hyperparameter

```
hyperParamMu <- c("mu0" = 16, "sigma0" = 0.4)
hyperParamSigma <- c("alpha0" = 1, "beta0" = 3)
```

5.3 Code

```
### Number of iterations
niter <- 10000

### Vector of starting value
mu <- 15
sigma <- 1

### Sample each parameters
for(i in 1:niter){
  #=====
  ### Sample mu
  #=====
  ### Conjugate prior for the mean of sigma
  ConjSigmaMean <- (1/hyperParamMu[2] + n/sigma[i]^2)^(-1)

  ### Conjugate prior for the mean of mu
  ConjMuMean <- (hyperParamMu[1]/hyperParamMu[2] + sum(Y)/sigma[i]^2)/ConjSigmaMean^(-1)

  ### Sample mu
  muSample <- rnorm(1,ConjMuMean, ConjSigmaMean)

  ### Save value
  mu <- c(mu,muSample)
  #=====
  ### Sample sigma
  #=====
  ### Conjugate prior for the mean of sigma
```

```

ConjAlphaSigma <- (hyperParamSigma[1]+n/2)

### Conjugate prior for the mean of mu
ConjBetaSigma <- (hyperParamSigma[2]+sum(Y-mu[i])/2)

### Sample the sigma from the conjugate prior
sigmaSample <- 1/rgamma(1,ConjAlphaSigma, ConjBetaSigma)

### Save value
sigma <- c(sigma, sigmaSample)
}

```

5.4 Graphical results

```

par(mfrow=c(2,2))

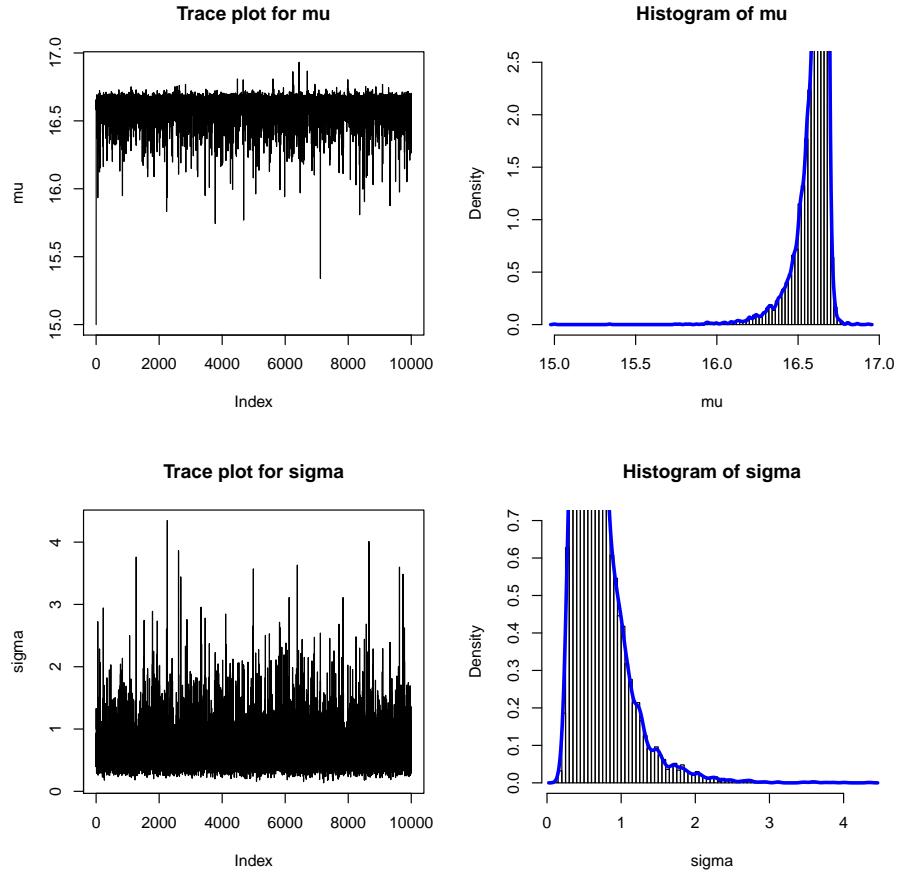
### Trace plot of the first parameter
plot(mu,main="Trace plot for mu",type="l")

### Histogram and density plot
hist(mu,freq=FALSE,breaks=100,ylim=c(0,2.5))
lines(density(mu),col="blue",lwd=3)

### Trace plot of the first parameter
plot(sigma,main="Trace plot for sigma",type="l")

### Histogram and density plot
hist(sigma,freq=FALSE,breaks=100,ylim=c(0,0.7))
lines(density(sigma),col="blue",lwd=3)

```



6 Gibbs sampler using Metropolis algorithm

6.1 Data

```
Y <- c(15, 19.59, 15.06, 15.71, 14.65, 21.4, 17.64, 18.31, 15.12, 14.40)
```

6.2 Define important functions

```
### Function to sample the candidate
cand <- function(params, T, k)
{
  params[k] <- rnorm(1, params[k], T[k])
  return(params)
```

```

}

#### Function to calculate the log-likelihood
loglik <- function(params, data)
{
  if(params[2] <= 0) return(NA)
  sig <- sqrt(1/params[2])
  sum(dnorm(data, params[1], sig, log=TRUE))
}

#### Function to define the log-priors
logprior <- list(
  function(mu) dnorm(mu, 16, 0.4),
  function(tau) dgamma(tau, 1,3)
)

```

6.3 Code

```

#### Basic objects
nsteps <- 10000
nparam <- 2
tuning <- c(1.5, 0.4)
accepts <- 0

#### Result matrix
params <- matrix(nrow=nsteps, ncol=nparam, dimnames = list(1:nsteps, c('mu', 'tau')))

#### Starting value
params[1,] <- c(5, 2)

#### Sample each parameters
for(t in 2:nsteps){
  current <- params[t-1,]
  for(k in 1:nparam){
    # propose a new value based on the current values and candidate distribution
    # returns a parameter vector but only changes param k
    proposal <- cand(current, tuning, k)

    # compute log posterior probabilities
    # this is the target distribution
    lp_proposal <- loglik(proposal, Y) + logprior[[k]](proposal[k])
    lp_previous <- loglik(current, Y) + logprior[[k]](current[k])

    # in case of a numerical error, such as from a negative variance, we automa
  }
}

```

```

    if(! is.finite(lp_proposal)){
        next()
    }

    accept_prob <- exp(lp_proposal - lp_previous)
    U <- runif(1,0,1)

    # if we accept, change the value, otherwise keep the previous
    if(U < accept_prob) {
        current[k] <- proposal[k]
        accepts <- accepts + 1
    }
}
params[t,] <- current
}

```

6.4 Results

```

print(paste("Acceptance Rate:", accepts/((nsteps-1)*nparam)))

## [1] "Acceptance Rate: 0.335483548354835"

par(mfrow=c(2,2))

### Trace plot of the first parameter
plot(1:nsteps, params[,1], type='l', xlab='step', ylab='mu')

### Histogram and density plot
hist(params[,1], freq=FALSE)
lines(density(params[,1]), col='blue')

### Trace plot of the second parameter
plot(1:nsteps, params[,2], type='l', xlab='step', ylab='tau')

### Histogram and density plot
hist(params[,2], freq=FALSE)
lines(density(params[,2]), col='blue')

```

