MAST30027 Modern Applied Statistics Assignment 4 $$\operatorname{Tutorial:Wed}\ 1\text{-}2PM},\ Yidi\ Deng$

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Question 1

```
X = scan(file="assignment4_prob1_2023.txt", what=double())
length(X)

## [1] 100

mean(X)

## [1] 75.726
```

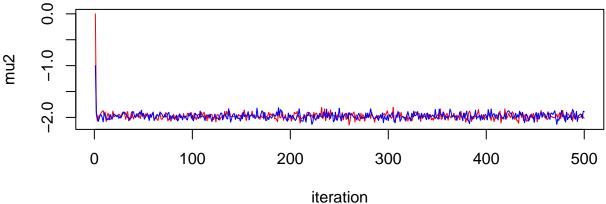
1a

Evaluating the parameters in the posterior distribution of the precision τ

Question 2

```
x = scan(file="assignment4_prob2_x_2023.txt", what=double())
y = scan(file="assignment4_prob2_y_2023.txt", what=double())
length(x)
## [1] 100
length(y)
## [1] 150
mean(x)
## [1] 3.196441
mean(y)
## [1] -1.979781
2b
GibbsS <- function(mu1, mu2, nreps){</pre>
  Gsamples <- matrix(nrow=nreps, ncol=2)</pre>
  Gsamples[1,] <- c(mu1, mu2)</pre>
  # main loop
  for (i in 2:nreps) {
    mu1 \leftarrow rnorm(1, (sum(x) - 2*mu2)/103, sqrt(1/103))
    mu2 \leftarrow rnorm(1, 2*(sum(y) - mu1)/303, sqrt(1/303))
    Gsamples[i,] <- c(mu1, mu2)</pre>
  return(Gsamples=Gsamples)
set.seed(456)
# sample size
nreps <- 500
# initial values
mu1 <- 0
mu2 <- 0
GibbsS1 = GibbsS(mu1, mu2, nreps)
```

```
# initial values
mu1 <- 2
mu2 <- -1
GibbsS2 = GibbsS(mu1, mu2, nreps)
par(mfrow=c(2,1), mar=c(4,4,1,1))
plot(1:nreps, GibbsS1[,1], type="l", col="red", ylim = c(min(GibbsS1[,1],GibbsS2[,1]), max(GibbsS1[,1],
    xlab = "iteration", ylab ="mu1")
points(1:nreps, GibbsS2[,1], type="l", col="blue")
plot(1:nreps, GibbsS1[,2], type="l", col="red", ylim = c(min(GibbsS1[,2],GibbsS2[,2]), max(GibbsS1[,2],
    xlab = "iteration", ylab ="mu2")
points(1:nreps, GibbsS2[,2], type="l", col="blue")
             1.5
                       100
           0
                                   200
                                                300
                                                             400
                                                                          500
                                        iteration
     0.0
     -1.0
     -2.0
```



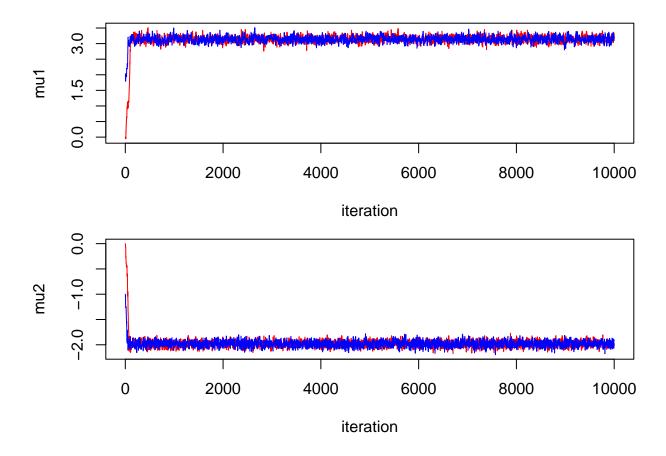
-2.065780 -1.891366

```
par(mfrow=c(2,1), mar=c(4,4,1,1))
plot(density(GibbsS1[-(1:50),1]), ylab="posterior dist", xlab=expression(mu[1]), main="")
plot(density(GibbsS1[-(1:50),2]), ylab="posterior dist", xlab=expression(mu[2]), main="")
posterior dist
      3
      ^{\circ}
                           2.9
                2.8
                                      3.0
                                                3.1
                                                           3.2
                                                                      3.3
                                                                                 3.4
                                                                                           3.5
                                                    \mu_1
posterior dist
      9
      ^{\circ}
      0
                            -2.1
                                              -2.0
                                                                -1.9
                                                                                  -1.8
          -2.2
                                                    \mu_2
mean(GibbsS1[-(1:50),1])
## [1] 3.146983
mean(GibbsS1[-(1:50),2])
## [1] -1.978406
quantile(GibbsS1[-(1:50),1], probs= c(0.05, 0.95))
          5%
                  95%
##
## 2.992497 3.313051
quantile(GibbsS1[-(1:50),2], probs= c(0.05, 0.95))
           5%
```

Estimated marginal posterior mean for $\mu_1=3.1470$ Estimated marginal posterior mean for $\mu_2=-1.9784$ 90% credible interval for $\mu_1=(2.9925,\,3.3131)$ 90% credible interval for $\mu_2=(-2.0658,\,-1.8914)$

```
dbinorm <- function(x, mu, Si) {</pre>
    # x and mu are vectors length 2 and Si a 2x2 matric
    # returns the density at x of a bivariate normal (mean mu, var Si)
    \exp(-t(x - mu)%*%solve(Si, x - mu)/2)/2/pi/sqrt(det(Si))
}
####### MH algorithm ##############
run metropolis MCMC <- function(startvalue, iterations){</pre>
    chain = array(dim = c(iterations+1,2))
    chain[1,] = startvalue
    for (i in 1:iterations){
        proposal = proposalfunction(chain[i,])
        probab = exp(posterior(proposal) - posterior(chain[i,]))
        if (runif(1) < probab){</pre>
            chain[i+1,] = proposal
        }else{
            chain[i+1,] = chain[i,]
    return(chain)
}
# propose new parameter values
proposalfunction <- function(param){</pre>
    return(rnorm(2, mean = param, sd = c(0.1, 0.1)))
}
# evaluate log posterior at given parameter values
posterior <- function(param){</pre>
   return (likelihood(param) + prior(param))
# evaluate log prior at given parameter values
prior <- function(param){</pre>
    mu_vec = c(0, 0)
    sigma_matrix = matrix(c(3/5, -2/5, -2/5, 3/5), ncol=2)
    return(log(dbinorm(param, mu_vec, sigma_matrix)))
}
# evaluate log likelihood at given parameter values
likelihood <- function(param){</pre>
    mu1 = param[1]
    mu2 = param[2]
    11_x = sum(dnorm(x, mean=mu1, sd=1, log = TRUE))
    11_y = sum(dnorm(y, mean=mu2, sd=1/sqrt(2), log = TRUE))
    return(ll_x + ll_y)
}
```

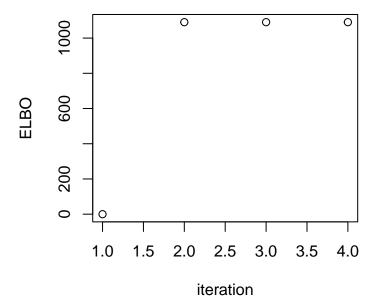
```
set.seed(456)
nreps = 10000
# initial values
startvalue = c(0,0)
# simulate 10000 samples
MHchain1 = run_metropolis_MCMC(startvalue, nreps)
# initial values
startvalue = c(2,-1)
# simulate another 10000 samples
MHchain2 = run_metropolis_MCMC(startvalue, nreps)
# remove the first 5000 as burn-in
burnIn = 5000
# computing average acceptance probability
(acceptance1 = 1-mean(duplicated(MHchain1[-(1:burnIn),])))
## [1] 0.4373125
(acceptance2 = 1-mean(duplicated(MHchain2[-(1:burnIn),])))
## [1] 0.4435113
par(mfrow=c(2,1), mar=c(4,4,1,1))
plot(1:(nreps+1), MHchain1[,1], type="l", col="red", ylim = c(min(MHchain1[,1], MHchain2[,1]), max(MHchain1[,1], ma
                xlab = "iteration", ylab ="mu1")
points(1:(nreps+1), MHchain2[,1], type="l", col="blue")
plot(1:(nreps+1), MHchain1[,2], type="l", col="red", ylim = c(min(MHchain1[,2], MHchain2[,2]), max(MHch
                xlab = "iteration", ylab ="mu2")
points(1:(nreps+1), MHchain2[,2], type="l", col="blue")
```



```
par(mfrow=c(2,1), mar=c(4,4,1,1))
plot(density(MHchain1[-(1:burnIn),1]), ylab="posterior dist", xlab=expression(mu[1]), main="")
plot(density(MHchain1[-(1:burnIn),2]), ylab="posterior dist", xlab=expression(mu[2]), main="")
posterior dist
      \alpha
                 2.8
                                     3.0
                                                         3.2
                                                                            3.4
                                                   \mu_1
      9
posterior dist
      \alpha
      0
                             -2.1
             -2.2
                                              -2.0
                                                              -1.9
                                                                               -1.8
                                                    \mu_2
mean(MHchain1[-(1:burnIn),1])
## [1] 3.150803
mean(MHchain1[-(1:burnIn),2])
## [1] -1.982535
quantile(MHchain1[-(1:burnIn),1], probs= c(0.05, 0.95))
         5%
##
                  95%
## 2.988247 3.312308
quantile(MHchain1[-(1:burnIn),2], probs= c(0.05, 0.95))
          5%
## -2.077089 -1.883055
```

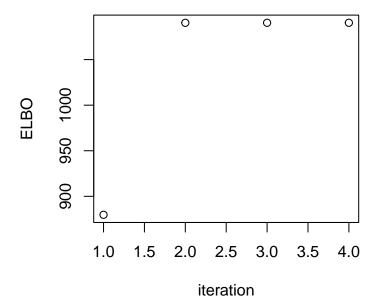
Estimated marginal posterior mean for $\mu_1=3.1508$ Estimated marginal posterior mean for $\mu_2=-1.9825$ 90% credible interval for $\mu_1=(2.9882,\,3.3123)$ 90% credible interval for $\mu_2=(-2.0771,\,-1.8831)$

```
# x,y: data
# mu10, mu20 : prior for mu
# initial values for mu1*, mu2*,: mu1.vi.init, mu2.vi.init
# epsilon : If the ELBO has changed by less than epsilon, the CAVI algorithm will stop
# max.iter : maximum number of iteration
cavi.normal <- function(x, y, mu1.vi.init, mu2.vi.init, epsilon=1e-5, max.iter=100) {</pre>
      mu1.vi = mu1.vi.init
      mu2.vi = mu2.vi.init
       # store the ELBO for each iteration
       elbo = c()
       # I will store mu*, sigma2*, a*, b* for each iteration
      mu1.vi.list = mu2.vi.list = c()
       # compute the ELBO using initial values of mu*
       elbo = c(elbo, (-103/2) * mu1.vi^2 + mu1.vi*sum(x) - (303/2) * mu2.vi^2 + 2*mu2.vi*sum(y) - 2*mu1.vi*sum(x) - (303/2) * mu2.vi^2 + 2*mu2.vi*sum(x) - 2*mu2.vi*sum(x) - (303/2) * mu2.vi*sum(x) - (303/2) * mu2.vi*sum(x
       mu1.vi.list = c(mu1.vi.list, mu1.vi)
      mu2.vi.list = c(mu2.vi.list, mu2.vi)
       # set the change in the ELBO with 1
       delta.elbo = 1
       # number of iteration
      n.iter = 1
       # If the elbo has changed by less than epsilon, the CAVI will stop.
       while((delta.elbo > epsilon) & (n.iter <= max.iter)){</pre>
              # Update mu.vi and sigma2.vi
              mu1.vi = (sum(x) - 2*mu2.vi)/103
              mu2.vi = (2*sum(y)-2*mu1.vi)/303
              # compute the ELBO using the current values of mu*
              elbo = c(elbo, (-103/2) * mu1.vi^2 + mu1.vi*sum(x) - (303/2) * mu2.vi^2 + 2*mu2.vi*sum(y) - 2*mu1.vi*sum(x) - (303/2) * mu2.vi^2 + 2*mu2.vi*sum(x) - (303/2) * mu2.vi*sum(x) - (303/2) * mu2.
              mu1.vi.list = c(mu1.vi.list, mu1.vi)
              mu2.vi.list = c(mu2.vi.list, mu2.vi)
              # compute the change in the elbo
              delta.elbo = elbo[length(elbo)] - elbo[length(elbo)-1]
              # increase the number of iteration
              n.iter = n.iter + 1
      return(list(elbo = elbo, mu1.vi.list = mu1.vi.list,
                                                   mu2.vi.list=mu2.vi.list))
```



[1] 879.7223 1090.3781 1090.3968 1090.3968

```
plot(cavi.res$elbo, ylab='ELBO', xlab='iteration')
```



[1] "mu1* and mu2* = (3.14,-1.98)"