

*Homework Notes:* I did not work with anyone else on this homework or refer to resources other than the course notes, textbook, and course Piazza page.

### Problem 1

**A** To update the sample of  $\mu_k$  at iteration  $m + 1$ , we can sample  $\mu_{k,m+1} \sim \text{Unif}(l, u)$  where  $l = \min(0, \mu_k - \epsilon)$  and  $u = \max(5, \mu_k + \epsilon)$ . This prevents us from sampling outside the range defined by the prior. In my samples, I set the ‘step’  $\epsilon = 0.1$ .

The MH acceptance probability is the ratio of the likelihood of the new and old samples:  

$$p(\text{keep}) = \frac{\mathcal{L}(X|\mu_{k,m+1})}{\mathcal{L}(X|\mu_{k,m})}.$$

### B

**C** I ran 500 rounds of burn-in and 3,000 iterations of sampling. Parameters were initialized as:

Listing 1: R Code for Initial Parameters

```
1 # set hyperparameters
2 BURN = 500
3 M = 3000+BURN
4 STEP = 0.1
5 MIN = 0
6 MAX = 5
7 K = 2
8
9 # helper functions
10 sum.sq.err = function(x, mu){
11   errs = (x-mu)
12   sq.errs = errs %*% t(errs)
13   sse = sum(sq.errs)
14   return(sse)
15 }
16
17 log.lik = function(x, mu){
18   ll = sum(log(dnorm(x, mu, 1)))
19   return(ll)
20 }
21
22 # initialize
23 pis = mus = matrix(NA, nrow=M, ncol=K)
24 mus[1, ] = sample(X, 2)
25 mus[1, ]
```

```

26 Z = matrix(NA, nrow=nrow(X), ncol=K)
27 Z[1,] = pis[1,] = rep(1/K, K)
28 N = x.bar = rep(0, K)
29 z = rep(0, nrow(X))
30 alpha = rep(1, K)
31 S_0 = rep(3, K)
32 v_0 = rep(5, K)
33 v = rep(0, K)
34 S = rep(0, K)
35 Sigma.inv = rgamma(K, shape=v_0, rate=S_0)

```

The following code runs the burn-in and sampling iterations:

Listing 2: R Code for MH

```

37 for(m in 2:M){
38   # step 1 - simulate proportion vector from Dirichlet
39   pisamp = rdirichlet(1, c(alpha[1]+N[1], alpha[2]+N[2]))
40   pis[m,] = pisamp[1,]
41
42   # step 2 - sample latent indicators
43   for(i in 1:nrow(Z)){
44     for(j in 1:ncol(Z)){
45       Z[i, j] = pis[m, j] * dnorm(X[i], mus[m-1, j], 1/Sigma.inv[j])
46     }
47     Z[i,] = Z[i,]/sum(Z[i,])
48
49     # step 3 - calculate new z's based on Z draws
50     z[i] = sample(seq(1:K), size=1, prob=Z[i,])
51   }
52
53   # step 4 - update mean and variance
54   for(k in 1:K){
55     want = which(z==k)
56     N[k] = length(want)
57     subset = X[want]
58     x.bar[k] = mean(subset)
59     v[k] = v_0[k] + N[k]
60     S[k] = S_0[k] + sum.sq.err(subset, mus[m-1,k]) # test this
61     Sigma.inv[k] = rgamma(1, shape=v[k], rate=S[k])
62
63     lower = max(c(MIN, mus[m-1, k]-STEP))
64     upper = min(c(MAX, mus[m-1, k]+STEP))
65     new.mu = runif(1, lower, upper)
66     ll.new.mu = log.lik(subset, new.mu)

```

```

67     ll.old.mu = log.lik(subset, mus[m-1,k])
68     acceptance.prob = ll.new.mu / ll.old.mu
69     acceptance.prob = min(1, acceptance.prob, na.rm=TRUE)
70     if(runif(1,0,1) < acceptance.prob){
71         mus[m, k] = new.mu
72     } else {
73         mus[m, k] = mus[m-1, k]
74     }
75
76 }
77 if(n%%10==0){ print(m) }
78 }

```

**D**

**E** It appears that  $K = 2$  is a reasonable fit for the data, with  $\mu \approx (1.5, 3)$ . Label switching did occur in my samples.

**F** I would use a composite from all three samples, weighted by the likelihood of each.

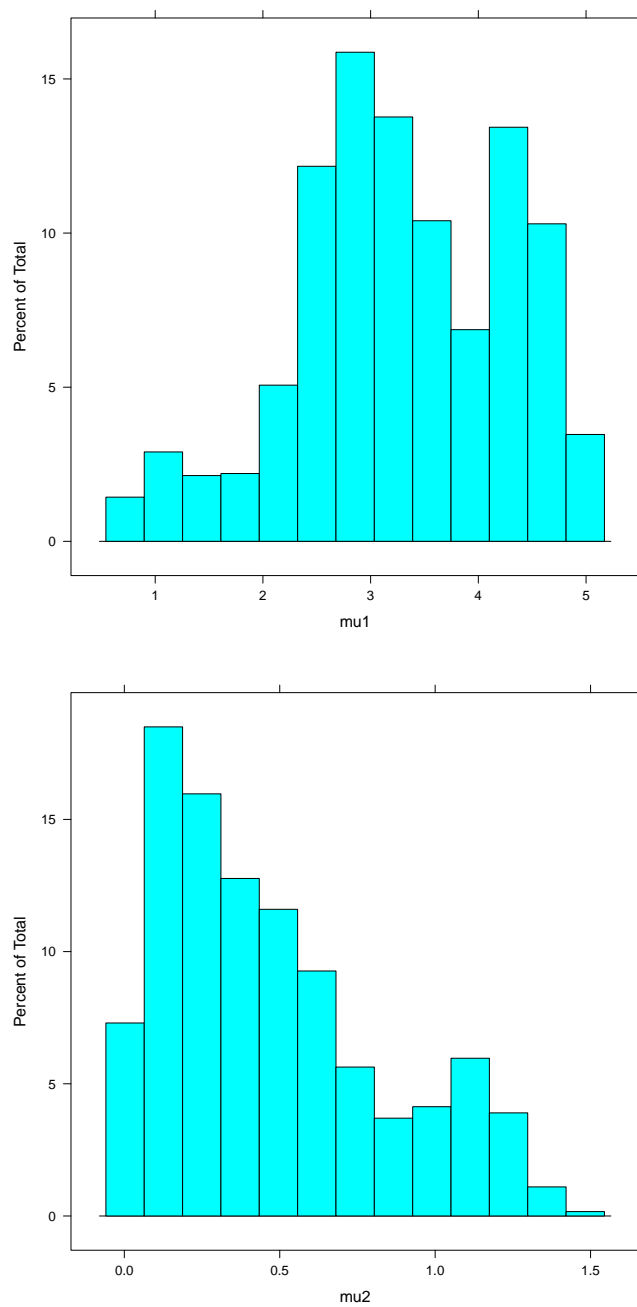


Figure 1: Histogram of Posterior Samples