11.3

Given the following data:

Starting points

Select 10 θ_i randomly from the y_{ij} sample.

```
theta_start <- sapply(1:6,function(x) sample(Data$measure[Data$machine==x],
10, replace=TRUE))
```

1. Conditional posterior of τ^2

```
<- function(theta) {
TauHat2
 mu
               <- mean(theta)
 Tau2
               <- (1/(J-1)) * sum((theta - mu)^2)
 return(Tau2)
}
Tau CondPosterior
                      <- function(theta) {
 Tau2
               <- TauHat2(theta)
 Tau Post
               <- (J - 1) * (Tau2)/rchisq(1,J-1)
 return(Tau Post)
 }
```

2. Conditional posterior of σ^2

```
FsigmaHat2 <- function(theta) {
  sigmaHat2 <- sapply(1:6, function(x) (Data$measure[Data$machine==x] - theta[x])^2)
  sigmaHat2 <- (1/n) * sum(unlist(sigmaHat2))
  return(sigmaHat2)
}

Sigma2_CodPosterior <- function(theta) {
  Sigma2_Hat <- FsigmaHat2(theta)
  Sigma2_Post <- (n) * (Sigma2_Hat)/rchisq(1,n)
  return(Sigma2_Post)
}</pre>
```

3. Conditional posterior of μ

4. Conditional posterior of θ

```
<- function(j,mu,sigma2,tau2) {
Theta_Hat_j
 Yavg_j
                <- mean(Data$measure[Data$machine==j])</pre>
 N_{oldsymbol{-}}j
                 <- length(Data$measure[Data$machine==j])</pre>
  ((1/tau2) * mu + (N_j/sigma2) * Yavg_j) / ((1/tau2) + (N_j/sigma2))
}
VTheta_Hat_j <- function(j,mu,sigma2,tau2) {</pre>
                 <- length(Data$measure[Data$machine==j])</pre>
 N_{oldsymbol{-}}j
  (1)/((1/tau2) + (N_j/sigma2))
}
Theta_CondPosterior
                              <- function(mu,sigma2,tau2) {
  theta
                 <- NULL
  for (j in 1:J) {
    T Hat
                 <- Theta_Hat_j(j,mu,sigma2,tau2)
    V_T_Hat
                <- VTheta_Hat_j(j,mu,sigma2,tau2)
    theta[j] <- rnorm(1,T_Hat,sqrt(V_T_Hat))</pre>
  return(theta)
}
```

^{**} Hierarchical Model: Sample using Gibbs Sampler **

```
<- 200
sims
Gibbs Sampler
                   <- function(start pt seq No) {
  param
                <- 9
                           <- matrix(NA, ncol = param, nrow = sims )
  sample parameters
  colnames(sample parameters)<- c("theta1", "theta2", "theta3",</pre>
                          "theta4", "theta5", "theta6",
                          "mu", "sigma2", "tau2")
  sample_parameters[1,1:6]<- theta_start[start_pt_seq_No,]</pre>
  sample_parameters[1,9] <- Tau_CondPosterior(theta_start[start_pt_seq_No,])</pre>
  sample_parameters[1,8] <- Sigma2_CodPosterior(theta_start[start_pt_seq_No,])</pre>
  sample parameters[1,7] <- Mu_CondPosterior(theta_start[start_pt_seq_No,],sample_param</pre>
eters[1,9])
  for (s in 2:sims) {
    sample parameters[s,1:6]<- Theta CondPosterior(sample parameters[s-1,7],sample param</pre>
eters[s-1,8], sample parameters[s-1,9])
    sample_parameters[s,9] <- Tau_CondPosterior(sample_parameters[s,1:6])</pre>
    sample parameters[s,8] <- Sigma2 CodPosterior(sample parameters[s,1:6])</pre>
    sample_parameters[s,7] <- Mu_CondPosterior(sample_parameters[s,1:6],sample_paramete</pre>
rs[s,9])
  }
return(sample parameters)
#Warm-up
}
sample_parameters
                             <- lapply(1:10, function(x) Gibbs_Sampler(x))
                             <- sample parameters[[1]][101:200, ]
sample parameters.1
sample parameters.combined <- rbind(sample parameters[[1]][101:200, ], sample parameters</pre>
[[2]][101:200, ], sample parameters[[3]][101:200, ], sample parameters[[4]][101:200, ],
sample parameters[[5]][101:200, ], sample parameters[[6]][101:200, ], sample parameters
[[7]][101:200, ], sample parameters[[8]][101:200, ], sample parameters[[9]][101:200, ],
 sample parameters[[10]][101:200, ])
#Transform the variance in to sd.
sample parameters.combined[,8:9]
                                   <- sqrt(sample parameters.combined[,8:9])
# Ouantiles
t(apply(sample parameters.combined,2, function(x) quantile(x, c(.025,.25,.5,.75,.975))))
                 2.5%
                             25%
                                       50%
                                                  75%
                                                          97.5%
##
## theta1 69.33451180 77.057104 81.58411 86.78668 95.51058
## theta2 89.45782851 97.007670 101.53710 106.49968 114.83650
```

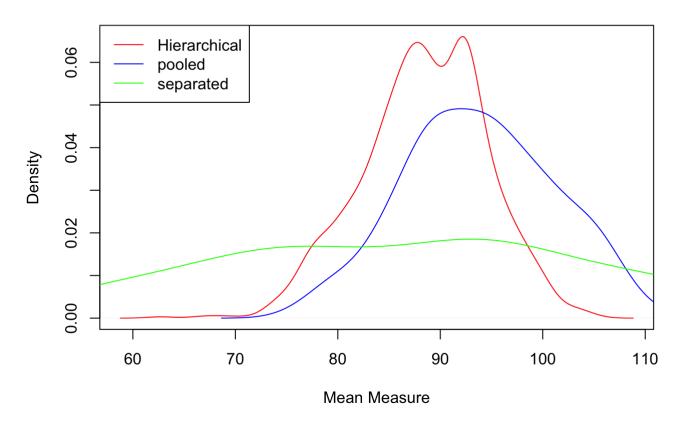
```
## thetal 69.33451180 77.057104 81.58411 86.78668 95.51058
## theta2 89.45782851 97.007670 101.53710 106.49968 114.83650
## theta3 77.27804552 85.883826 90.07689 92.98418 100.38957
## theta4 91.84875536 99.706566 105.39575 110.58712 119.11883
## theta5 79.18944654 87.732601 91.87743 95.24059 102.29602
## theta6 76.44598989 84.747576 88.72221 92.49478 99.68702
## mu 80.35995763 89.911681 92.77493 96.96565 107.01125
## sigma2 11.23766052 13.459499 14.97195 16.77308 21.32504
## tau2 0.03335087 7.141435 10.65701 14.98413 30.76660
```

^{**} Pooled and Separated Model **

** Posterior distribution of the mean of the quality measurements of the sixth machine. For the hierarchical, pooled and separate models **

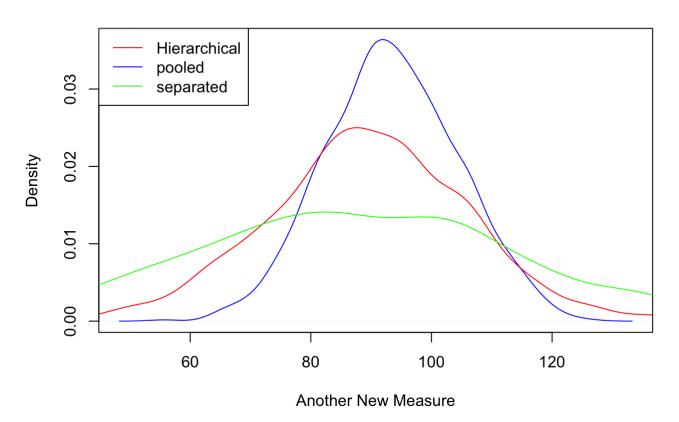
```
plot(density(sample_parameters.combined[,"theta6"]), col="red",
    xlab="Mean Measure",
    ylab="Density",
    main="Posterior Dist of measure mean: 6th Machine, Three Models")
lines(density(Theta_Posterior_Pooled_6), col="blue")
lines(density(Theta_Posterior_Sep_6), col="green")
legend("topleft",col = c("red","blue", "green"),
    legend=c("Hierarchical","pooled", "separated"),
    lty = c(1,1,1))
```

Posterior Dist of measure mean: 6th Machine, Three Models



^{**} Predictive distribution for another quality measurement of the sixth machine. **

Predictive Dist new measure: 6th machine, Three Models



** Posterior distribution of the mean of the quality measurements of the seventh machine. For the hierarchical, pooled and separate models **

```
plot(density(sample_parameters.1[,"mu"]), col="red", xlab="Mean Measure",
    ylab="Density", main="Posterior Dist: 7th Measure, Three Models")
lines(density(Theta_Posterior_Pooled_6), col="blue")
lines(density(Theta_Posterior_Sep_6), col="green")
legend("topleft",col = c("red","blue", "green"),
    legend=c("Hierarchical","pooled", "separated"),
    lty = c(1,1,1))
```

Posterior Dist: 7th Measure, Three Models

