Bayesian data analysis - Assignment 9

Contents

1 Stan model

```
data{
  int<lower=0> N;
  int<lower=0> J;
  vector<lower=0>[J] y[N];
}
parameters{
  vector[J] mu;
  real mu_P;
  real<lower=0> sigma_P;
  real<lower=0> sigma;
}
model{
  // priors
  mu_P ~ normal(0,100);
  sigma_P ~ inv_chi_square(0.1);
  sigma ~ inv_chi_square(0.1);

  // likelihood
  for (j in 1:J){
    mu[j] ~ normal(mu_P, sigma_P);
    y[,j] ~ normal(mu[j], sigma);
  }

}
generated quantities{
  real ypred1;
  real ypred2;
  real ypred3;
  real ypred4;
  real ypred5;
  real ypred6;
  real ypred7;
  real mu7;
  vector[N*J] log_lik;

```

```
  // Compute predictive distribution
  ypred1 = normal_rng(mu[1], sigma);
  ypred2 = normal_rng(mu[2], sigma);
  ypred3 = normal_rng(mu[3], sigma);
  ypred4 = normal_rng(mu[4], sigma);
  ypred5 = normal_rng(mu[5], sigma);
  ypred6 = normal_rng(mu[6], sigma);

  // Compute posterior mean of new machine
  mu7 = normal_rng(mu_P, sigma_P);
  ypred7 = normal_rng(mu7, sigma);

  // compute log-likelihood of each observation for each posterior draw of parameters
  for (j in 1:J){
    for (n in 1:N){
      log_lik[N*(j-1)+n] = normal_lpdf(y[n,j] | mu[j], sigma);
    }
  }
}
```

2 Compute utility for each machine

```r
library(aaltobda)
data("factory")

utility <- function(draws){
  U <- c()
  for (i in 1:length(draws)){
    if (draws[i] < 85){U[i] = -106}
    else {U[i] = 94}
  }
  return(mean(U))
}


y_pred <- c(123.80, 85.23, 70.16, 80.57, 84.91)
utility(draws = y_pred)
```

```
## [1] -26
```

Apply above function of utility to posterior predictive draws from hierachical for each machine.

```r
hm_stan_data <- list(
    y = factory,
    N = nrow(factory),
    J = ncol(factory)
  )
hm <- sampling(hierarchical_factory, data=hm_stan_data, seed=1000, iter=5000, chains=5)
hm_sims <- extract(hm, permuted = TRUE)

utility_1 <- utility(draws = hm_sims$ypred1)
utility_2 <- utility(draws = hm_sims$ypred2)
```

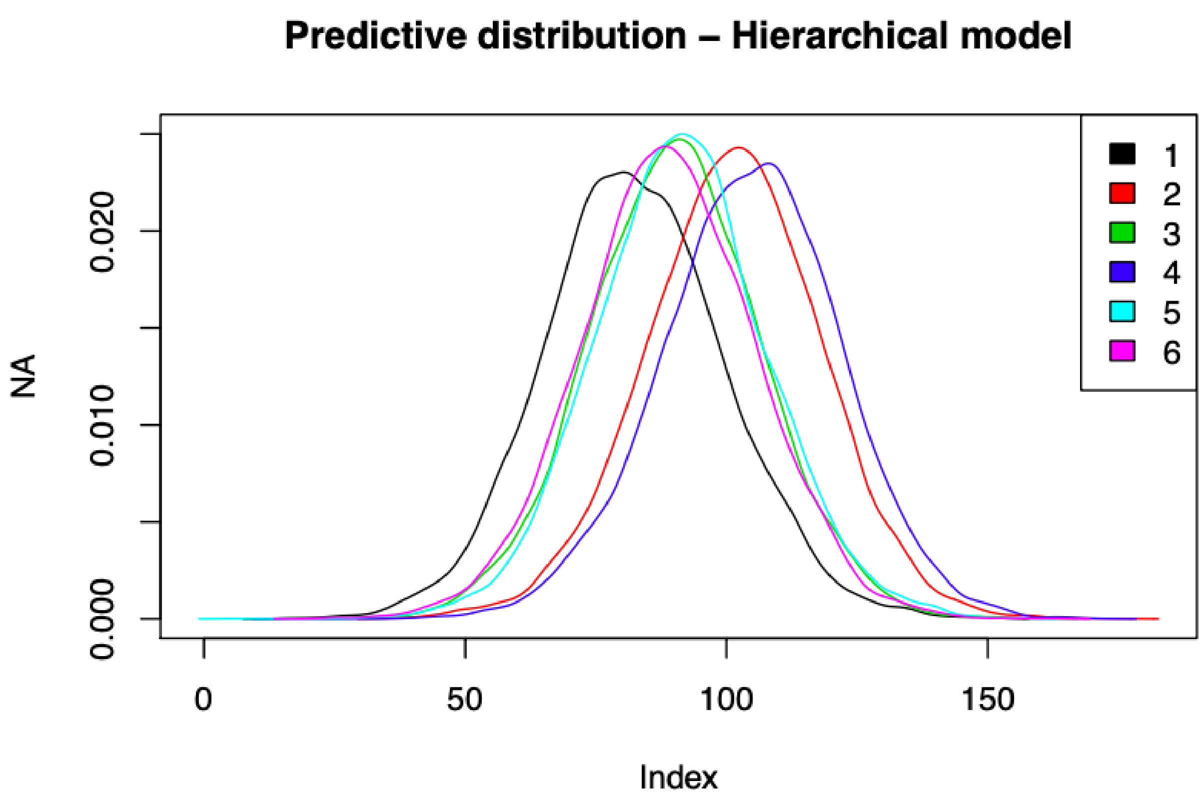
```r
utility_3 <- utility(draws = hm_sims$ypred3)
utility_4 <- utility(draws = hm_sims$ypred4)
utility_5 <- utility(draws = hm_sims$ypred5)
utility_6 <- utility(draws = hm_sims$ypred6)

U <- data.frame(matrix(c(utility_1, utility_2, utility_3, utility_4, utility_5, utility_6)
                          , ncol=6)
                 )
colnames(U) <- c("machine 1", "machine 2", "machine 3", "machine 4", "machine 5", "machine 6")
print(U[, order(U[1,])])
```

```
##   machine 1 machine 6 machine 3 machine 5 new machine machine 2 machine 4
## 1   -19.216    12.112    18.848    24.096       25.44    61.504    69.072
```

As a result, it's reasonable to say that machine 4 is the most profitable one since its utility is the highest; and machine 1 is the only non-profitable machine since its utility is negative. Otherwise, other machines are still profitable but less than machine 4.

The order of machine in term of utility value is exactly equivalent to their order in term of predictive chart from left to right. The more to the right distribution is, the higher probability of having sufficient quality machine has.
Since machine 1 has predictive distribution where its quality is satisfied with about 50%, while it's more than 80% for machine 2 and 4. Therefore, we observe an highly outstanding utility of mahince 2 and 4 compared to machine 1.



3 Decision on new machine

```
utility_7 <- utility(draws = hm_sims$ypred7)
U[1,"new machine"] <- utility_7
print(U[, order(U[1,])])
```

```
##   machine 1 machine 6 machine 3 machine 5 new machine machine 2 machine 4
## 1   -19.216    12.112    18.848    24.096       25.44    61.504    69.072
```

We observe that the new machine probably has utility approximate to 25 which means that it can be profitable. Even its profitability might be significantly less than machine 2 and 4, but at least it's profitable. Therefore, it's worth to buy new machine if company only cares about added money.