BDA - Assignment 9

Anonymous

```
library(tidyr)
library(rstan)
## Loading required package: StanHeaders
## Loading required package: ggplot2
## rstan (Version 2.19.2, GitRev: 2e1f913d3ca3)
## For execution on a local, multicore CPU with excess RAM we recommend calling
## options(mc.cores = parallel::detectCores()).
## To avoid recompilation of unchanged Stan programs, we recommend calling
## rstan_options(auto_write = TRUE)
\ensuremath{\mbox{\#\#}} For improved execution time, we recommend calling
## Sys.setenv(LOCAL_CPPFLAGS = '-march=native')
## although this causes Stan to throw an error on a few processors.
##
## Attaching package: 'rstan'
## The following object is masked from 'package:tidyr':
##
##
       extract
rstan_options(auto_write = TRUE)
options(mc.cores = parallel::detectCores())
library(loo)
## This is loo version 2.1.0.
## **NOTE: As of version 2.0.0 loo defaults to 1 core but we recommend using as many as possible. Use to
## **NOTE for Windows 10 users: loo may be very slow if 'mc.cores' is set in your .Rprofile file (see h
##
## Attaching package: 'loo'
## The following object is masked from 'package:rstan':
##
##
       100
library(ggplot2)
library(gridExtra)
library(bayesplot)
```

```
## This is bayesplot version 1.7.0
## - Online documentation and vignettes at mc-stan.org/bayesplot
## - bayesplot theme set to bayesplot::theme_default()
##
      * Does _not_ affect other ggplot2 plots
      * See ?bayesplot_theme_set for details on theme setting
##
theme_set(bayesplot::theme_default(base_family = "sans"))
library(shinystan)
## Loading required package: shiny
## Registered S3 method overwritten by 'xts':
    method
                from
##
##
     as.zoo.xts zoo
## This is shinystan version 2.5.0
source('stan_utility.R')
library(aaltobda)
SEED <- 48927 # set random seed for reproducability
data("factory")
```

The data applied to the hierarchical model is:

Hierarchical model

In this model the means of the different machines are assumed to have a common standard deviation σ and means μ that are drawn from a normal distribution with μ_0 and σ_0 . I assumed weekly informative priors for μ_0 and σ_0 and σ_0 and σ_0 . The Stan implementation of the model is as follows:

```
## data {
## int<lower=0> N; // number of data points
## int<lower=0> K; // number of groups
## int<lower=1,upper=K> x[N]; // group indicator
## vector[N] y; //
## }
```

```
## parameters {
##
    real mu0; // prior mean
##
     real<lower=0> sigma0; // prior std
     vector[K] mu; // group means
##
##
     real<lower=0> sigma; // group stds
## }
## model {
     mu ~ normal(mu0, sigma0); // population prior with unknown parameters
##
##
     y ~ normal(mu[x] , sigma);
## }
## generated quantities {
     real ypred[K];
##
##
    for (i in 1:K){
       ypred[i] = normal_rng(mu[i], sigma);
##
##
## }
We fit the separate model in stan as follow:
```

```
fit_hierarchical <- stan(file="hierarchical.stan", data = data_vec, seed = SEED)</pre>
```

```
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
## Warning: Examine the pairs() plot to diagnose sampling problems
## Warning: Bulk Effective Samples Size (ESS) is too low, indicating posterior means and medians may be
## Running the chains for more iterations may help. See
```

Warning: There were 33 divergent transitions after warmup. Increasing adapt_delta above 0.8 may help

```
## Warning: Tail Effective Samples Size (ESS) is too low, indicating posterior variances and tail quant
## Running the chains for more iterations may help. See
## http://mc-stan.org/misc/warnings.html#tail-ess
```

Problem 1: For each of the six machines, compute and report the expected utility of one product of that machine.

For the utility function: - each machine cost is 106 e - if quality above 85, then the customers pay 200 e, otherwise the prouct is not sold.

The following function computes the expected utility of one product of each machine given the measurements:

```
utility <-function(draws) {</pre>
  n <- length(draws)</pre>
  utility <- sum((draws >= 85) *200) / n - 106
  return(utility)
}
#TEST:
y_pred <- c(123.80, 85.23, 70.16, 80.57, 84.91)</pre>
print('expected utility of the test example')
```

[1] "expected utility of the test example"

http://mc-stan.org/misc/warnings.html#bulk-ess

```
print(utility(y_pred))
```

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

Now the posterior predictive data from each machine can be extracted to compute the utility:

```
df = extract(fit_hierarchical)

Util = c()
for(i in 1:6){
  print(sprintf('Expected utility for machine %d:',i))
  Util[i] <- utility(df$ypred[,i])
  print(Util[i])
}</pre>
```

```
## [1] "Expected utility for machine 1:"
## [1] -32.55
## [1] "Expected utility for machine 2:"
## [1] 66.85
## [1] "Expected utility for machine 3:"
## [1] 11.45
## [1] "Expected utility for machine 4:"
## [1] 76.7
## [1] "Expected utility for machine 5:"
## [1] 20.1
## [1] "Expected utility for machine 6:"
## [1] 5.75
```

Problem 2: Rank the machines based on the expected utilities.

```
order(Util)
```

```
## [1] 1 6 3 5 2 4
```

A positive utility means that we expect the machine to be profitable, i.e. it can be operated without losswhen taking all costs into consideration. Of the six machines, #1 is the only one which is not profitable. The other machines are beneficial for the compaby. The ranking: Worst => 1, 6, 3, 5, 2, 4 <= Best

Question 3: Compute and report the expected utility of the products of a new (7th) machine.

For the 7th machine we need to use the posterior predictive of the new machine computed in the Stan code:

```
Utility_7 = utility(df$ypred[,7])
print('Expected utility for machine 7:')
```

```
## [1] "Expected utility for machine 7:"
```

print(Utility_7)

[1] 21.6

Question 4:Based on your analysis, discuss briefly whether the company owner should buy a new (7th) machine.

The 7th machine is expected to be profitable so I would advise the business owner to invest if a) he seesgrowth in demand and b) he has access to financing.