OPTIMSE (Optimisation of Cardiovascular Management to Improve Surgical Outcome) is a multi-centre randomised controlled trial which was carried out to try and determine if the optimisation of Cardiovascular Management intervention was of benefit.

JAMA. 2014;311(21):2181-2190. doi:10.1001/jama.2014.5305

Patients were randomised to a cardiac output–guided hemodynamic therapy for intravenous fluid and a drug to increase heart muscle contraction (the inotrope, dopexamine) during and 6 hours following surgery (intervention group) or to usual care (control group).

The primary outcome measure was the relative risk (RR) of a composite of 30-day moderate or major complications and mortality.

**Results**

Focusing on the primary outcome measure, there were 158/364 (43.3%) and 134/366 (36.6%) patients with complication/mortality in the control and intervention group respectively.

Using the standard statistical approach, the relative risk (95% confidence interval) = 0.84 (0.70-1.01), p=0.07 and absolute risk difference = 6.8% (−0.3% to 13.9%), p=0.07. The authors reasonably concluded that:

*In a randomized trial of high-risk patients undergoing major gastrointestinal surgery, use of a cardiac output–guided hemodynamic therapy algorithm compared with usual care did not reduce a composite outcome of complications and 30-day mortality.*

**Homework**

Focus on the absolute difference risk groups and repeat the analysis in a Bayesian framework.

(i) Assuming a non-informative prior, for example Beta(1,1), for complication/mortality rate in both groups, derive the posterior distribution for the absolute difference risk.

(ii) Using the posterior distribution of the intervention group complication/mortality rate and the posterior distribution of the usual care group, simulate patients’ outcome to determine the proportion of cases in which the intervention would result in no complication/death while the usual care would result in complication/death:

what is the probability of patients to get benefit from the intervention compared with usual care?

**Solution**

library(R2OpenBUGS)

# Write down the model

mymodel = function(){

# Likelihood for each arm: each complication/death is Bernoulli

for (i in 1 : N1) {y1[i] ~ dbern(theta1)}

for (i in 1 : N2) {y2[i] ~ dbern(theta2)}

# Prior: independent beta distributions

theta1 ~ dbeta(1,1)

theta2 ~ dbeta(1,1)

}

# Write down the data as a list

data = list(

N1 = 366,

y1 = c(rep(1, 134), rep(0, N1-134)),

N2 = 364,

y2 = c(rep(1, 158), rep(0, N2-158))

)

# Specify the parameters to be monitored

parameters = c(“theta1”, “theta2”)

# Initialize the chain: generate random starting values for theta1 and theta2

bugsInits = function(){

list(theta1 = rbeta(1,1,1),

theta2 = rbeta(1,1,1)

}

# Run the chain

resbugs = bugs(data, inits = bugsInits, parameter.to.save = parameter,

n.chains = 1, n.iter = 50000, n.burnin = 10000, n.thin = 1, dbug = TRUE)

# Using the posterior distribution, by simulation determine proportion of cases in which:

(i) using the intervention would result in no complication/death

(ii) using the intervention would result in complication death

theta1.post = resbugs$sims.list$theta1

theta2.post = resbugs$sims.list$theta2

chainLength = length(theta1.post)

# Create a matrix to store simulated outcomes:

yPred = matrix( NA , nrow= chainLength , ncol= 2)

# For each step in chain, use posterior prediction to simulate outcomes

for (i in 1:chainLength){

pDeath1 = theta1.post[i]

yPred[i,1] = sample(x=c(0,1), prob=c(1-pDeath1,pDeath1), size=1)

pDeath2 = theta2.post[i]

yPred[i,2] = sample(x=c(0,1), prob=c(1-pDeath2,pDeath2), size=1)

}

# Finally determine the proportion of casesin which the intervention arm has no complication/death, i.e. y1==0 and the control arm has a complication/death, i.e, y2 == 1

sum(yPred[,1]==0 & yPred[,2]==1)/chainLength