Exercise1

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Objectives

Practicing with rjags, a package to enables us work with JAGS(Just Another Gibbs Sampler) in R, JAGS is a program for analysis of Bayesian hierarchical models using Markov Chain Monte Carlo(MCMC) simulation.

System setup

install the current JAGS version install rjags package from CRAN

#Step1: The data

Several studies suggest that cognitive behavioral therapy is an effective treatment for Post-Traumatic Stress Disorder (PTSD) in male veterans. Suppose that you did a study to compare Prolonged Exposure (PE), a type of cognitive behavioral therapy, with Present-Centered therapy (PC), a supportive intervention. It was a randomized controlled trial, where 284 veterans suffering from PTSD were assigned randomly to receive either PE or PC. The outcome measure of interest was loss of diagnosis (LD), a dichotomous variable. The resulting data are displayed in Table ??. # Step1 Read data

```
# You can specify the data in this manner:
dat <-list(y.PE=58, n.PE=141, y.PC=40, n.PC=143)

#this will be useful when using bigger datasets later on.
```

OR

```
library('rjags')
```

```
## Warning: package 'rjags' was built under R version 4.1.2
```

```
## Loading required package: coda
```

```
## Linked to JAGS 4.3.0
```

```
## Loaded modules: basemod,bugs
```

```r
source('DataExe1.txt')
```

step 2: Specify the model

This step is done is a notepad file with an extention .txt

C. Step 3: Obtain initial values.

For this particular model, it is not necessary to provide any initial values manually. JAGS automatically generates initial values when the model is specified, and no initial vales are provided. These are chosen to be a typical value from the prior distribution.

#D. Step 4: Obtain samples from the posterior distribution of the parameters. For the next steps in the analysis you will run JAGS from R using the rjags package. First load

```r
library(rjags)
```

Next, create a model object in R by means of the jags.model function. We need to specify a model .txt-file, data and number of chains:

```r
model.def <- jags.model(file = "Exercise1Model.txt", data = dat, n.chains = 2)
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 2
##    Unobserved stochastic nodes: 2
##    Total graph size: 8
##
## Initializing model
```

Subsequently, use the update() function to run a large number of burn-in iterations (for example 1000 iterations) for your model:

```r
# burn-in period :
update(object = model.def, n.iter =1000 )
```

Then, use the *coda.samples()* function to set monitors on the parameters of interest and draw a large number of samples from the posterior distribution, (for example 10000): obtain samples from the posterior distribution of the parameters and monitor these:

```r
parameters <- c('theta.PE', 'theta.PC', 'RR')
res <- coda.samples(model = model.def, variable.names = parameters, n.iter = 10000)
summary(res)
```

```
##
## Iterations = 2001:12000
```

```
## Thinning interval = 1
## Number of chains = 2
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##            Mean      SD  Naive SE Time-series SE
## RR       0.6928 0.11724 0.0008290      0.0010735
## theta.PC 0.2824 0.03760 0.0002659      0.0003438
## theta.PE 0.4119 0.04124 0.0002916      0.0003781
##
## 2. Quantiles for each variable:
##
##            2.5%    25%    50%    75%  97.5%
## RR       0.4870 0.6102 0.6853 0.7658 0.9448
## theta.PC 0.2120 0.2564 0.2818 0.3073 0.3587
## theta.PE 0.3313 0.3842 0.4115 0.4395 0.4950
```

Interpretation

The posterior mean is **0.69**, CI is $[0.49, 0, 94]$, lie below 1, thus we are certain or believe that **PE** therapy gives a higher change of recovery than **PC** therapy. Since, posterior mean of PC is **0.28** with Central Credible Interval is $[0.21, 0, 36]$, laying below 1, and posterior mean of PE is **0.41** with Central Credible interval is $[0.33, 0.49]$.

Comparing the non-informative priors and informative prior(historical data)

The first historic data to compare with is Ronald's data, so in the model step we change the priors, in the notepad.

a model .txt-file, data and number of chains:

```
model.def <- jags.model(file = "Exercise2Model.txt", data = dat, n.chains = 2)
```

```
## Compiling model graph
##    Resolving undeclared variables
##    Allocating nodes
## Graph information:
##    Observed stochastic nodes: 2
##    Unobserved stochastic nodes: 2
##    Total graph size: 11
##
## Initializing model
```

Subsequently, use the update() function to run a large number of burn-in iterations (for example 1000 iterations) for your model:

```r
# burn-in period :
update(object = model.def, n.iter =1000 )
```

Then, use the *coda.samples()* function to set monitors on the parameters of interest and draw a large number of samples from the posterior distribution, (for example 10000): obtain samples from the posterior distribution of the parameters and monitor these:

```r
parameters <- c('theta.PE', 'theta.PC', 'RR')
res <- coda.samples(model = model.def, variable.names = parameters, n.iter = 10000)
summary(res)
```

```
##
## Iterations = 2001:12000
## Thinning interval = 1
## Number of chains = 2
## Sample size per chain = 10000
##
## 1. Empirical mean and standard deviation for each variable,
##    plus standard error of the mean:
##
##            Mean      SD  Naive SE Time-series SE
## RR       0.7864 0.09400 0.0006646      0.0008505
## theta.PC 0.3121 0.02811 0.0001988      0.0002527
## theta.PE 0.3993 0.03100 0.0002192      0.0002839
##
## 2. Quantiles for each variable:
##
##            2.5%    25%    50%    75%  97.5%
## RR       0.6161 0.7211 0.7807 0.8467 0.9842
## theta.PC 0.2585 0.2930 0.3115 0.3307 0.3689
## theta.PE 0.3396 0.3783 0.3991 0.4197 0.4620
```

Interpretation

The posterior mean is **0.79**, CI is $[0.62, 0, 99]$, lie below 1, thus we are certain or believe that **PE** therapy gives a higher change of recovery than **PC** therapy. Since, posterior mean of PC is **0.31** with Central Credible Interval is $[0.25, 0, 37]$, laying below 1, and posterior mean of PE is **0.34** with Central Credible interval is $[0.34, 0.46]$.The 95% CCIs of the RR are smaller, and still do not include 1. Therefore, the RR is still in favor of PE, but less strongly than with uninformative priors.