

# How to use `nma` S3 methods

## Introduction

This document describes how to use the main functions of `NMA` to run a network meta-analysis.

## Example

```
library(NMA)
library(dplyr)
library(purrr)
```

## Settings

Define the BUGS parameters for MCMC.

```
bugs_params <-
  list(
    PROG = "openBugs",
    N.BURNIN = 10, #00,
    N.SIMS = 150, #0,
    N.CHAINS = 2,
    N.THIN = 1,
    PAUSE = TRUE)
```

Define the scenario we will use for the analysis. We will load in a dataframe of values.

```
analyses_params <-
  read.csv(
    here::here("raw_data", "AnalysisList.csv"),
    as.is = TRUE,
    na.strings = c("NR", "NA")) %>%
  filter(Endpoint_type == "Surv") %>%
  dplyr::rename(name = Analysis_name,
               type = Analysis_Type)
```

For demonstration purposes we will select the first scenario to run.

```
analysis <- analyses_params[1, ]

# fixed effects RANDOM=FALSE, random effects RANDOM=TRUE
RANDOM <- analysis$Model_effects == "RE"

REFTX <- analysis$REFTX

# indicator for availability of binary endpoint data
is_bin <- analysis$BinData == "YES"

# indicator for availability of median endpoint data
is_med <- analysis$MedData == "YES"
```

## Read in datasets

The trials data consist of upto 3 separate dataframes. A main table, `subData`, and optional tables for median event time and binary data, `subDataMed` and `subDataBin` respectively.

```
file_name <- paste0(here::here("raw_data"), "/survdata_", analysis$Endpoint, "_")

subData <-
  read.csv(paste0(file_name, analysis$type, ".csv"),
           header = TRUE,
           as.is = TRUE)

subDataBin <-
  if (is_bin) {
    read.csv(paste0(file_name, "bin.csv"),
             header = TRUE,
             as.is = TRUE)
  } else {NA}

subDataMed <-
  if (is_med) {
    read.csv(paste0(file_name, "med.csv"),
             header = TRUE,
             as.is = TRUE) %>%
    mutate(medR = floor(medR))
  } else {NA}
```

## Build model

Now we can create the NMA object to use in the modelling.

```
nma_model <-
  new_NMA(subData = subData,
          subDataMed = subDataMed,
          subDataBin = subDataBin,
          bugs_params = bugs_params,
          is_random = RANDOM,
          refTx = REFTX ,
          effectParam = "beta",
          modelParams = "totresdev",
          label = analysis$name,
          endpoint = analysis$Endpoint)

nma_model
#> $dat
#> $dat$inits
#> function() {
#>   list(
#>     beta = c(NA, rnorm(nTx - 1, 0, 2)),
#>     sd = 0.1,
#>     alpha = rnorm(nStudies)) %>%
#>     .[param_names]
#>   }
#> <bytecode: 0x00000174580ede80>
#> <environment: 0x000001745825eed8>
#>
```

```

#> $dat$subData
#>      X               study               base               tx               Lmean               Ls
#> 1    6      ARCHER 1050 (Wu, 2017)      ERL/GEF      DAC -0.47803580 0.113440
#> 2    9      CONVINCe (Shi 2017)      CIS+PEM      ICO -0.43078292 0.154626
#> 3   26      CTRI/2015/08/006113 (Patil 2017)      CARBO+PEM      ERL/GEF -0.41551544 0.129116
#> 4   15      CTRI/2016/08/007149 (Noronha 2019b)      ERL/GEF      GEF+CARBO+PEM -0.67330000 0.134210
#> 5   22      ENSURE (Wu 2015)      GEM+CIS      ERL/GEF -1.07880966 0.214485
#> 6    5      FLAURA (Soria 2018)      ERL/GEF      OSI -0.77652879 0.110238
#> 7    4      GOAL (Campelo 2018)      ERL/GEF      GEF+OLA -0.28768207 0.186450
#> 8    3      INCREASE (Li 2018)      ICO      ICO high-dose -0.30110509 0.175849
#> 9   17      J025567 (JapicCTI-111390) (Seto 2014)      ERL/GEF      ERL+BEV -0.61618614 0.200492
#> 10   2      LUX-Lung 3 (Sequist 2013)      CIS+PEM      AFA -0.71334989 0.143742
#> 11  24      LUX-Lung 6 (Wu 2014a)\n      GEM+CIS      AFA -1.34707365 0.163030
#> 12  25      LUX-Lung 7 (Park 2016)      ERL/GEF      AFA -0.24846136 0.123532
#> 13  20      NCT01017874 (Yang, 2014)      ERL/GEF      CIS+PEM+GEF_m -0.18632958 0.344369
#> 14   7      NCT01221077 (Leighl 2017)      ERL/GEF      LIN+ERL 0.31188676 0.297077
#> 15  18      NCT01469000 (Yang, 2020)      ERL/GEF      GEF+PEM -0.40047757 0.149945
#> 16  16      NCT01532089 (Stinchcombe 2019)      ERL/GEF      ERL+BEV -0.21072103 0.245707
#> 17  21      NCT01769066 (Yu 2014)      CIS+PEM      CIS+PEM+GEF_m -1.60943791 0.690829
#> 18  28      NCT01864681 (Li 2019)      ERL/GEF      GEF+MET 0.03922071 0.168174
#> 19   8      NCT01897480 (Scagliotti, 2020)      ERL/GEF      EMI+ERL -0.11653382 0.165827
#> 20  12      NCT02148380 (Han, 2017)      ERL/GEF      CARBO+PEM 1.04982212 0.470613
#> 21  10      NCT02148380 (Han, 2017)      ERL/GEF      ERL/GEF 0.00000000 0.215255
#> 22  11      NCT02148380 (Han, 2017)      ERL/GEF      GEF+CARBO+PEM -0.73396918 0.453945
#> 23  13      NEJ005/TCOG0902 (Sugawara, 2015)      GEF+CARBO+PEM (Alter)      GEF+CARBO+PEM -0.34249031 0.267811
#> 24  27      NEJ009 (UMIN000006340) (Hosomi 2019)      ERL/GEF      GEF+CARBO+PEM -0.71334989 0.118258
#> 25  19      NEJ026 (Saito 2019)      ERL/GEF      ERL+BEV -0.50252682 0.189648
#> 26   1      RELAY (Nakagawa, 2019)      ERL/GEF      RAM+ERL -0.52593926 0.127530
#> 27  14      SWOG S1403 (Goldberg 2018)      AFA      AFA+CET 0.15700375 0.196751
#> 28  23      TORCH (Gridelli 2012)      GEM+CIS      ERL/GEF -0.51082562 0.353646
#>
#> $dat$subDataBin
#>      study      base      tx BinR BinN Btx Bbase Bstudy
#> 1 NCT01039948 (Mok, 2016) ERL/GEF ERL/GEF 34 38 1 1 33
#> 2 NCT01039948 (Mok, 2016) ERL/GEF GEF+FIC 27 33 14 1 33
#>
#> $dat$subDataMed
#>      study      base      tx median medN medR mediantx medi
#> 1      An 2016      ERL/GEF      ERL/GEF 14.0 45 22 1
#> 2      An 2016      ERL/GEF      GEF+PEM 18.0 45 22 17
#> 3 CALGB 30406 (NCT00126581) (Janne 2012)      ERL/GEF      ERL/GEF 14.1 33 16 1
#> 4 CALGB 30406 (NCT00126581) (Janne 2012)      ERL/GEF      ERL+PAC+CARBO 17.2 33 16 10
#> 5      GENOA / NCT02319577 (Genova, 2019)      ERL/GEF      ERL/GEF 9.5 21 10 1
#> 6      GENOA / NCT02319577 (Genova, 2019)      ERL/GEF      VIN+GEF 6.2 23 11 24
#> 7      IFCT-1503 ACE-Lung (Cortot 2019)      AFA      AFA 11.1 59 29 2
#> 8      IFCT-1503 ACE-Lung (Cortot 2019)      AFA      AFA+CET 12.8 59 29 3
#> 9      NCT01502202 (Lee 2016)      CIS+PEM+GEF_m      CIS+PEM 7.8 37 18 5
#> 10     NCT01502202 (Lee 2016)      CIS+PEM+GEF_m      CIS+PEM+GEF_m 13.3 39 19 6
#> 11     UMIN000013586 (Kitagawa, 2019)      ERL/GEF      ERL/GEF 15.1 10 5 1
#> 12     UMIN000013586 (Kitagawa, 2019)      ERL/GEF      GEF+BEV 5.4 6 3 11
#>
#> $dat$bugsData
#> $dat$bugsData$Lstudy

```

```

#> [1] 6 9 24 13 20 5 4 3 15 2 22 23 18 7 16 14 19 26 8 10 10 10 11 25 17 1 12 21
#>
#> $dat$bugsData$Ltx
#> [1] 7 19 1 12 1 22 16 20 9 2 2 2 6 21 17 9 6 15 8 4 1 12 12 12 9 23 3 1
#>
#> $dat$bugsData$Lbase
#> [1] 1 5 4 1 18 1 1 19 1 5 18 1 1 1 1 1 5 1 1 1 1 1 13 1 1 1 2 18
#>
#> $dat$bugsData$Lmean
#> [1] -0.47803580 -0.43078292 -0.41551544 -0.67330000 -1.07880966 -0.77652879 -0.28768207 -0.30110509
#> [17] -1.60943791 0.03922071 -0.11653382 1.04982212 0.00000000 -0.73396918 -0.34249031 -0.71334989
#>
#> $dat$bugsData$Lse
#> [1] 0.1134403 0.1546265 0.1291164 0.1342100 0.2144855 0.1102381 0.1864509 0.1758496 0.2004921 0.143
#> [21] 0.2152550 0.4539455 0.2678118 0.1182584 0.1896482 0.1275307 0.1967513 0.3536465
#>
#> $dat$bugsData$multi
#> [1] 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0
#>
#> $dat$bugsData$LnObs
#> [1] 28
#>
#> $dat$bugsData$nTx
#> [1] 24
#>
#> $dat$bugsData$nStudies
#> [1] 33
#>
#> $dat$bugsData$medianStudy
#> [1] 27 27 30 30 32 32 29 29 31 31 28 28
#>
#> $dat$bugsData$medianTx
#> [1] 1 17 1 10 1 24 2 3 5 6 1 11
#>
#> $dat$bugsData$medianBase
#> [1] 1 1 1 1 1 1 2 2 6 6 1 1
#>
#> $dat$bugsData$Bstudy
#> [1] 33 33
#>
#> $dat$bugsData$Btx
#> [1] 1 14
#>
#> $dat$bugsData$Bbase
#> [1] 1 1
#>
#> $dat$bugsData$medianN
#> [1] 45 45 33 33 21 23 59 59 37 39 10 6
#>
#> $dat$bugsData$medianR
#> [1] 22 22 16 16 10 11 29 29 18 19 5 3
#>
#> $dat$bugsData$median

```

```

#> [1] 14.0 18.0 14.1 17.2 9.5 6.2 11.1 12.8 7.8 13.3 15.1 5.4
#>
#> $dat$bugsData$medianNObs
#> [1] 12
#>
#> $dat$bugsData$Bn
#> [1] 38 33
#>
#> $dat$bugsData$Br
#> [1] 34 27
#>
#> $dat$bugsData$BnObs
#> [1] 2
#>
#>
#> $dat$txList
#> [1] "ERL/GEF" "AFA" "AFA+CET" "CARBO+PEM"
#> [9] "ERL+BEV" "ERL+PAC+CARBO" "GEF+BEV" "GEF+CARBO+PEM"
#> [17] "GEF+PEM" "GEM+CIS" "ICO" "ICO high-dose"
#>
#>
#> $is_med
#> [1] TRUE
#>
#> $is_bin
#> [1] TRUE
#>
#> $bugs_params
#> $bugs_params$PROG
#> [1] "openBugs"
#>
#> $bugs_params$N.BURNIN
#> [1] 10
#>
#> $bugs_params$N.SIMS
#> [1] 150
#>
#> $bugs_params$N.CHAINS
#> [1] 2
#>
#> $bugs_params$N.THIN
#> [1] 1
#>
#> $bugs_params$PAUSE
#> [1] TRUE
#>
#> $bugs_params$run_bugs
#> [1] TRUE
#>
#>
#> $bugs_fn
#> function(...)
#> bugs(program = "openbugs", ...)

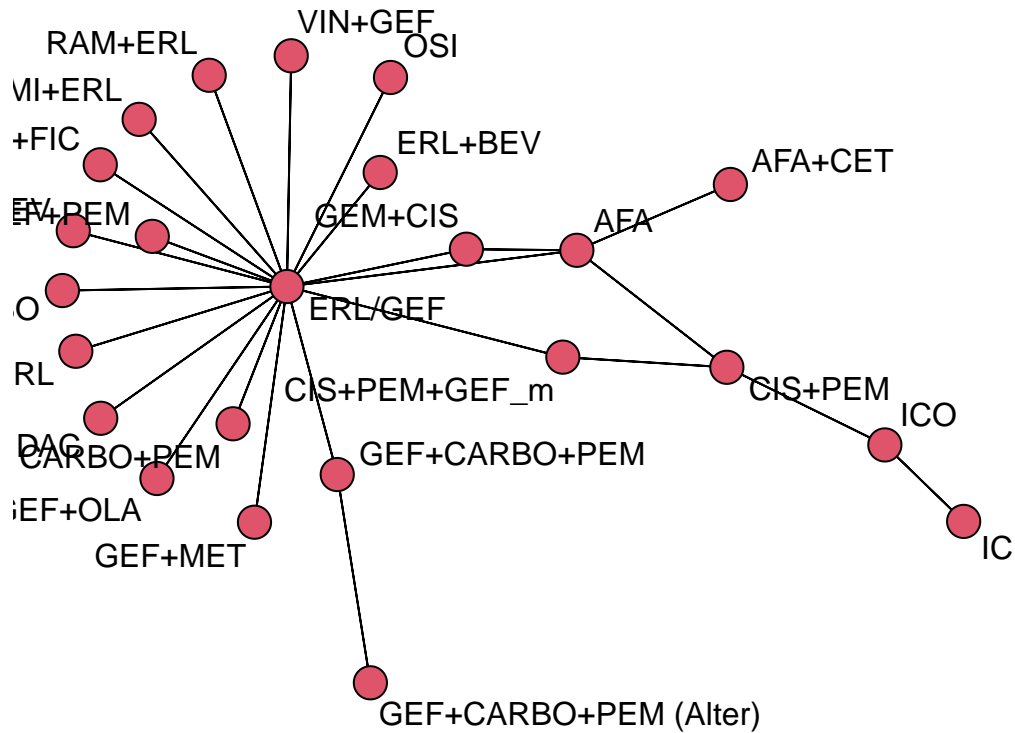
```

```

#> <bytecode: 0x000001745392bbc8>
#> <environment: 0x000001745e367750>
#>
#> $is_random
#> [1] FALSE
#>
#> $refTx
#> [1] "ERL/GEF"
#>
#> $effectParam
#> [1] "beta"
#>
#> $modelParams
#> [1] "totresdev"
#>
#> $label
#> [1] "BC_PFS_mFE"
#>
#> $endpoint
#> [1] "PFS"
#>
#> attr("class")
#> [1] "nma"
#> attr("CALL")
#> attr("CALL")$subData
#> subData
#>
#> attr("CALL")$subDataMed
#> subDataMed
#>
#> attr("CALL")$subDataBin
#> subDataBin
#>
#> attr("CALL")$bugs_params
#> bugs_params
#>
#> attr("CALL")$is_random
#> RANDOM
#>
#> attr("CALL")$refTx
#> REFTX
#>
#> attr("CALL")$effectParam
#> [1] "beta"
#>
#> attr("CALL")$modelParams
#> [1] "totresdev"
#>
#> attr("CALL")$label
#> analysis$name
#>
#> attr("CALL")$endpoint
#> analysis$Endpoint

```

```
library(sna)
plotNetwork(nma_model)
```



```
nma_res <- NMA_run(nma_model)
#> Loading required namespace: BRugs
#> Welcome to BRugs connected to OpenBUGS version 3.2.3
#> model is syntactically correct
#> data loaded
#> model compiled
#> Initializing chain 1:
#> initial values loaded and chain initialized but another chain contain uninitialized variables
#> Initializing chain 2:
#> model is initialized
```

```

#> model is already initialized
#> Sampling has been started ...
#> 10 updates took 0 s
#> deviance set
#> monitor set for variable 'beta'
#> monitor set for variable 'totresdev'
#> monitor set for variable 'deviance'
#> 150 updates took 0 s
#> Warning in dir.create(path = here(folder)): 'C:\Users\Nathan\Documents\ICON\NMA\output' already exists

nma_res
#> Inference for Bugs model at "C:/Users/Nathan/Documents/ICON/NMA/inst/FE_med_bin.txt", fit using OpenBUGS
#> 2 chains, each with 160 iterations (first 10 discarded)
#> n.sims = 300 iterations saved
#>
#>      mean      sd  2.5%  25%   50%   75%  97.5% Rhat n.eff
#> beta[2]    0.2    0.7  -0.7  -0.5   0.1   0.7   1.3  2.2    4
#> beta[3]   -0.9    0.9  -2.2  -2.0  -0.5  -0.1   0.0  7.0    2
#> beta[4]    0.5    0.1   0.2   0.4   0.4   0.5   0.7  1.0  210
#> beta[5]    1.4    0.6   0.1   1.2   1.4   1.8   2.3  2.0    4
#> beta[6]    0.8    0.7  -0.2   0.4   0.9   1.1   2.8  1.5    6
#> beta[7]   -0.5    0.1  -0.7  -0.5  -0.5  -0.4  -0.2  1.0  300
#> beta[8]   -0.1    0.2  -0.4  -0.2  -0.1   0.0   0.2  1.0  190
#> beta[9]   -0.5    0.1  -0.7  -0.6  -0.5  -0.4  -0.3  1.0  210
#> beta[10]  -0.2    0.7  -1.3  -0.5  -0.2   0.1   0.7  1.2  230
#> beta[11]   0.9    0.8  -0.6   0.4   1.0   1.4   2.2  1.1   26
#> beta[12]  -0.7    0.1  -0.9  -0.8  -0.7  -0.6  -0.5  1.0  300
#> beta[13]  -0.4    0.3  -0.9  -0.6  -0.4  -0.2   0.3  1.0  150
#> beta[14]  -0.3    0.2  -0.7  -0.4  -0.3  -0.2   0.2  1.1   21
#> beta[15]   0.0    0.2  -0.3  -0.1   0.0   0.1   0.3  1.0  110
#> beta[16]  -0.3    0.2  -0.6  -0.4  -0.3  -0.2   0.1  1.0  300
#> beta[17]  -0.9    0.6  -2.1  -1.5  -0.6  -0.4  -0.2  1.0   91
#> beta[18]   1.3    0.4   0.7   0.9   1.3   1.6   1.9  2.1    4
#> beta[19]   0.9    0.6  -0.4   0.6   0.9   1.4   1.9  2.8    3
#> beta[20]   0.6    0.6  -0.7   0.3   0.7   1.1   1.7  2.6    3
#> beta[21]   0.3    0.3  -0.3   0.1   0.3   0.5   0.8  1.0  300
#> beta[22]  -0.8    0.1  -1.0  -0.8  -0.8  -0.7  -0.6  1.0  300
#> beta[23]  -0.5    0.1  -0.8  -0.6  -0.5  -0.4  -0.3  1.0  200
#> beta[24]   0.4    0.6  -0.7   0.0   0.3   0.8   1.4  1.2   11
#> totresdev 655.5 578.3 110.6 293.6 385.8 919.6 1813.1 1.1   41
#> deviance  670.8 578.7 126.9 309.2 400.9 933.8 1833.6 1.1   45
#>
#> For each parameter, n.eff is a crude measure of effective sample size,
#> and Rhat is the potential scale reduction factor (at convergence, Rhat=1).
#>
#> DIC info (using the rule,  $pD = \bar{D} - \hat{D}$ )
#>  $pD = 349.8$  and  $DIC = 1021.0$ 
#> DIC is an estimate of expected predictive error (lower deviance is better).

# diagnostics(nma_res)
# nma_outputs(nma_res)

```



## Reconfigure model

It is simple to modify an existing analysis without repeating the previous steps. For example, we can run the NMA for a random effects model version of the same model.

```
nma_model2 <-
  NMA_update(nma_model,
             is_random = TRUE)

nma_res2 <- NMA_run(nma_model2,
                   output_dir = "RE output")

#> model is syntactically correct
#> data loaded
#> model compiled
#> Initializing chain 1:
#> initial values loaded but chain contain uninitialized variables
#> Initializing chain 2:
#> initial values loaded but chain contain uninitialized variables
#> initial values generated, model initialized
#> Sampling has been started ...
#> 10 updates took 0 s
#> deviance set
#> monitor set for variable 'beta'
#> monitor set for variable 'totresdev'
#> monitor set for variable 'deviance'
#> 150 updates took 0 s
#> Warning in dir.create(path = here(folder)): 'C:\Users\Nathan\Documents\ICON\NMA\RE output' already exists

nma_res2
#> Inference for Bugs model at "C:/Users/Nathan/Documents/ICON/NMA/inst/RE_med_bin.txt", fit using OpenBUGS
#> 2 chains, each with 160 iterations (first 10 discarded)
#> n.sims = 300 iterations saved
#>
#>      mean      sd  2.5%   25%   50%   75%  97.5% Rhat n.eff
#> beta[2]   -0.6   5.4  -7.0  -6.3   0.1   4.6   5.9 12.1    2
#> beta[3]   -5.5   3.2 -10.1  -9.2  -3.4  -2.6  -1.8  5.3    2
#> beta[4]    0.4   1.7  -2.1  -1.5   0.9   1.9   2.8  6.3    2
#> beta[5]    1.1   1.1  -0.9   0.4   0.7   2.3   3.1  1.7    6
#> beta[6]    0.8   3.9  -5.4  -3.9   2.6   4.3   5.1  5.2    2
#> beta[7]   -1.1   1.2  -3.5  -2.2  -0.9  -0.1   0.7  1.9    4
#> beta[8]   -2.2   0.9  -3.7  -2.9  -2.3  -1.7  -0.1  1.0   300
#> beta[9]   -0.9   1.0  -2.8  -1.3  -0.7  -0.2   0.7  1.2   26
#> beta[10]  -1.8   1.3  -3.6  -2.6  -2.2  -0.9   0.9  3.5    3
#> beta[11]   2.0   1.3  -1.0   1.3   2.2   2.9   4.3  1.1   15
#> beta[12]  -1.2   0.5  -2.0  -1.5  -1.3  -1.0  -0.3  2.0    4
#> beta[13]  -2.6   2.2  -6.5  -3.8  -2.5  -0.8   0.8  3.6    3
#> beta[14]  -0.7   1.1  -2.1  -1.5  -1.0   0.2   1.6  1.9    4
#> beta[15]   0.1   1.2  -2.0  -0.8  -0.1   1.1   2.2  3.4    3
#> beta[16]   1.7   0.8   0.0   1.1   1.8   2.4   2.9  1.0   260
#> beta[17]   3.2   3.0  -0.3   0.6   0.8   6.2   7.8  4.0    2
#> beta[18]   0.8   2.1  -2.4  -1.1   0.7   2.6   4.4  6.2    2
#> beta[19]   1.7   2.4  -1.2  -0.5   0.8   4.4   5.3  6.0    2
#> beta[20]   1.4   1.3  -0.7   0.3   1.5   2.6   3.7  4.3    2
#> beta[21]   2.0   1.5  -1.7   1.2   2.2   3.2   4.3  1.2   24
#> beta[22]   1.3   1.5  -0.5   0.2   0.7   2.8   4.3  2.7    3
#> beta[23]  -2.3   1.0  -3.8  -2.9  -2.5  -1.9   0.0  1.7    5
```

```

#> beta[24]    0.5    1.2   -1.7  -0.5    0.7    1.7    2.3    3.8    2
#> totresdev 423.5 398.4   69.8 104.6 394.6 580.1 1670.6   5.3    2
#> deviance   440.8 401.0   84.7 121.1 412.8 594.5 1699.7   5.3    2
#>
#> For each parameter, n.eff is a crude measure of effective sample size,
#> and Rhat is the potential scale reduction factor (at convergence, Rhat=1).
#>
#> DIC info (using the rule,  $pD = \bar{D} - \hat{D}$ )
#>  $pD = 216.0$  and  $DIC = 656.8$ 
#> DIC is an estimate of expected predictive error (lower deviance is better).

# diagnostics(nma_res2, save = TRUE)
# nma_outputs(nma_res2, save = TRUE)

```