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## mTADA

This notebook describes steps used to jointly analyze two traits by mTADA .

## I. Introduction

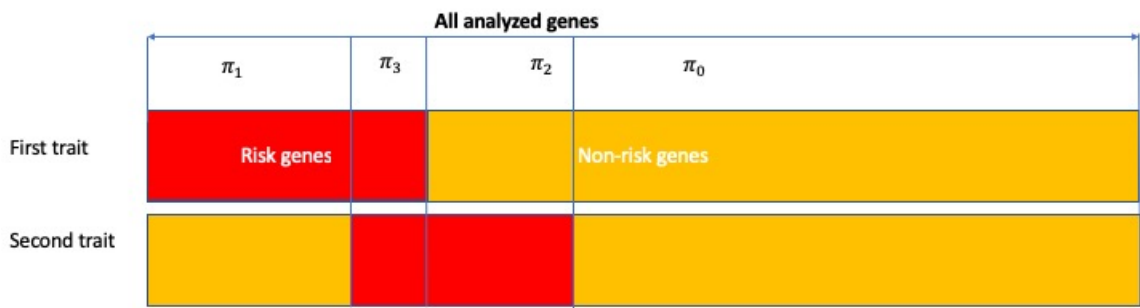
mTADA jointly analyze de novo mutations (DNMs) of two traits to 1) estimate the gene-level genetic overlap of the two traits; 2) report shared and specific risk genes; and 3) identify additional risk genes for each analyzed trait.

The method requires genetic parameters from single-trait analyses (the third and fourth columns in Table 1 below). Users can obtain single-trait parameters from extTADA/TADA methods.

Table 1. mTADA model for one variant category at the  $i^{th}$  gene.

Hypothesis	Proportion	First trait	Second trait
$H_0$	$\pi_0$	$x_{i1} \sim \text{Poisson}(2N_1\mu_i)$	$x_{i2} \sim \text{Poisson}(2N_2\mu_i)$
$H_1$	$\pi_1$	$x_{i1} \sim \text{Poisson}(2N_1\gamma_1\mu_i); \gamma_1 \sim \text{Gamma}(\tilde{\gamma}_1\beta_1, \beta_1)$	$x_{i2} \sim \text{Poisson}(2N_2\mu_i)$
$H_2$	$\pi_2$	$x_{i1} \sim \text{Poisson}(2N_1\mu_i)$	$x_{i2} \sim \text{Poisson}(2N_2\gamma_2\mu_i); \gamma_2 \sim \text{Gamma}(\tilde{\gamma}_2\beta_2, \beta_2)$
$H_3$	$\pi_3$	$x_{i1} \sim \text{Poisson}(2N_1\gamma_1\mu_i); \gamma_1 \sim \text{Gamma}(\tilde{\gamma}_1\beta_1, \beta_1)$	$x_{i2} \sim \text{Poisson}(2N_2\gamma_2\mu_i); \gamma_2 \sim \text{Gamma}(\tilde{\gamma}_2\beta_2, \beta_2)$

Figure 1. mTADA framework.



## Data for reproducible analyses

Data used in the main manuscript are inside the folder data (data):

1. FullDataSet\_DenovoMutations\_for\_mTADA.txt (data/FullDataSet\_DenovoMutations\_for\_mTADA.txt): all gene-level de novo mutations. These DNMs are used in the main manuscript.
2. SingleTrait\_Parameters.txt (data/SingleTrait\_Parameters.txt): all single-trait parameters. We used extTADA to estimate these parameters from the DNMs above.

Note: Users can re-run all these single-trait analyses by following an example here: <https://github.com/hoangtn/extTADA> (<https://github.com/hoangtn/extTADA>).

## II. Requirements

**mTADA** is written in **R**. Other **R** packages are required to run **mTADA** :

- **rstan** : <https://mc-stan.org/rstan/> (<https://mc-stan.org/rstan/>).
- **locfit** : <https://cran.r-project.org/web/packages/locfit/index.html> (<https://cran.r-project.org/web/packages/locfit/index.html>).

Software versions were used in our analyses: **R** version 3.5.2, **locfit** version 1.5-9.1, and **rstan** version 2.18.2.

## III. An example: joint analysis of DD and EE DNMs

Only one function **mTADA** (in the **Run mTADA** section) is used to obtain results. Therefore, users can go directly to the **Run mTADA** section to run **mTADA**. However, some additional steps are described here.

### Load the source codes

```
dataDir <- "./data/"
source("script/mTADA.R")
```

```
## locfit 1.5-9.1    2013-03-22
```

### Read the data and single-trait parameters

```
## De novo data
data <- read.table(paste0(dataDir, "FullDataSet_DenovoMutations_for_mTADA.txt"), header = TRUE, as.is = TRUE)
## Single-trait parameters
sPar <- read.table(paste0(dataDir, "SingleTrait_Parameters.txt"), as.is = TRUE, header = TRUE)

trait1 = "DD"
trait2 = "EE"
##Take a quick look at the single-trait parameters of DD and EE
sPar[grep(trait1, sPar[, 1]), ] ##Trait 1
```

```
##           Parameter EstimatedValue
## 8           DD_pi[1]      0.02936283
## 9 DD_hyperGammaMeanDN[1]  22.31762802
## 10 DD_hyperGammaMeanDN[2] 86.03966530
## 11      DD_hyperBetaDN[1]   0.82594514
## 12      DD_hyperBetaDN[2]   0.80689775
```

```
sPar[grep(trait2, sPar[, 1]), ] ##Trait 2
```

```
##           Parameter EstimatedValue
## 18           EE_pi[1]      0.01548789
## 19 EE_hyperGammaMeanDN[1]  51.08181282
## 20 EE_hyperGammaMeanDN[2]  65.15189031
## 21      EE_hyperBetaDN[1]   0.80906448
## 22      EE_hyperBetaDN[2]   0.80774192
```

### Set parameters for two traits

As described above, **mTADA** needs single-trait parameters:

- the number of trios:  $n_{trio}$ ;
- the mean and dispersion parameters of relative risks:  $\bar{\gamma}_j$  and  $\beta_j$  ( $j=1,2$ );
- the proportion of risk genes:  $\pi_1^S$  and  $\pi_2^S$ .

**All these parameters are shown above.**

```

### Trait-1 INFORMATION
ntrio1 = 4293 #family numbers
p1 = 0.02936283 #The proportion of risk genes, this is p1S
meanGamma1 = c(22.31762802, 86.03966530) #Mean Gamma of two categories
beta1 = c(0.82594514, 0.80689775) #Beta values inside the distribution RR ~ Gamma(meanRR*beta, beta)
dataT1 <- data[, paste0(c("dn_damaging_", "dn_lof_"), trait1)] #De novo data
muDataT1 <- data[, c("mut_damaging", "mut_lof")] #Mutation data of the first trait
#####
### Trait-2 INFORMATION
ntrio2 = 356
p2 = 0.01548789 #This is p2S
meanGamma2 = c(51.08181282, 65.15189031)
beta2 = c(0.80906448, 0.80774192)
dataT2 <- data[, paste0(c("dn_damaging_", "dn_lof_"), trait2)]
muDataT2 <- muDataT1

```

## Run mTADA

In this example, we only use a small number of iterations and two MCMC chains. However, users can change these parameters to obtain more reliable results.

```

nIteration = 2000 #This should be higher to obtain better results.
nChain = 2 #The number of MCMC chains

#####MAIN ANALYSIS
mTADAResults <- mTADA(geneName = data[, 1],
  #####Trait-1 information
  ntrio1 = ntrio1, # Trio number of Trait 1
  p1 = p1, #Risk-gene proportion of Trait 1
  dataDN1 = data.frame(dataT1), #De novo data of Trait 1
  mutRate1 = data.frame(muDataT1), # Mutation rates of Trait 1
  hyperGammaMeanDN1 = c(meanGamma1), # Mean relative risks of Trait 1
  hyperBetaDN01 = beta1, #NULL, #array(c(1, 1)),
  #####Trait-2 information
  ntrio2 = ntrio2, # Trio number of Trait 2
  p2 = p2, #Risk-gene proportion of Trait 2
  dataDN2 = data.frame(dataT2), # De novo data of Trait 2
  mutRate2 = data.frame(muDataT2), # Mutation rates of Trait 2
  hyperGammaMeanDN2 = c(meanGamma2), # Mean relative risks of Trait 2
  hyperBetaDN02 = beta2, #NULL, #array(c(1, 1)),
  ###Other parameters
  nIteration = nIteration,
  useMCMC = TRUE, #If FALSE, it will use the 'Variational Bayes' approach.
  nChain = nChain
)

```

```
## No information for core numbers (nCore); therefore, nCore = nChain: 2 core(s) is/are used

## Loading required package: ggplot2

## Loading required package: StanHeaders

## rstan (Version 2.18.2, GitRev: 2elf913d3ca3)

## 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)

## =====
## Building the model
## =====

##
## =====Use MCMC=====

## recompiling to avoid crashing R session

## ====
## Only pi, alpha and hyper parameters are estimated in this step
## The method does not calculate HPDs for hyper betas, just their medians
## ==
```

## Obtain analysis results

`mTADA` 's output includes:

1. `data` : main gene-level results (posterior probabilities for the four models as described in the main manuscript: PP0, PP1, PP2 and PP3).
2. `probModel` : a vector of  $\pi_j$ , ( $j = 0..3$ ) in Table 1.
3. `pars` : the estimated value and credible interval of  $\pi_3$  (described as p12 in the our code).
4. `mcmcData` : MCMC sampling results for  $\pi_3$ .

The most important information is from `data` . **Users can use this information to obtain top prioritized genes for downstream analyses (e.g., top shared/specific genes, top genes for each trait)**. However, we will also take a quick look at all these information.

### Results for downstream analyses (gene-level posterior probabilities (PPs) of four models)

We will demonstrate how to choose top prioritized genes from `mTADA` 's results using a PP threshold of 0.8. These genes can be shared genes, specific genes; or genes for single traits.

```
fData <- mTADAResults$data ## Full analysis results of the two-trait analysis.
head(fData)
```

```
##   geneName dn_damaging_DD dn_lof_DD dn_damaging_EE dn_lof_EE      NO
## 1    A1BG           0           0           0           0 0.9785638
## 2 A1BG-AS1           0           0           0           0 0.9648110
## 3    A1CF           0           0           0           0 0.9894511
## 4     A2M           0           0           1           0 0.7728022
## 5 A2M-AS1           0           0           0           0 0.9638173
## 6   A2ML1           0           0           0           0 0.9920417
##
##           BOTH          FIRST          SECOND
## 1 0.0028849335 0.0102232990 0.008327935
## 2 0.0060903853 0.0204204671 0.008678102
## 3 0.0006499363 0.0026904350 0.007208518
## 4 0.0025131770 0.0002609915 0.224423609
## 5 0.0063273659 0.0211660881 0.008689214
## 6 0.0002100015 0.0009201318 0.006828191
```

### Genes with PP3 > 0.8 (Posterior probabilities of Model 3)

Shared risk genes between DD and EE.

```
fData[fData$BOTH > 0.8, ]
```

```
##      geneName dn_damaging_DD dn_lof_DD dn_damaging_EE dn_lof_EE
## 2348  CACNA1A           5           0           2           0
## 3201   CHD2            0           6           0           1
## 6254  GABBR2           2           0           2           0
## 6265  GABRB3           2           0           2           0
## 6610   GNAO1           4           1           2           0
## 7165  HECW2           5           1           1           0
## 7426  HNRNPU           0           7           0           1
## 8283   KCNQ2           9           0           2           0
## 8284   KCNQ3           3           0           1           0
## 10146  MLL             1          26           1           0
## 12480  PHIP            1           2           0           1
## 14673  SCN2A           9           4           2           0
## 14681  SCN8A           6           0           2           0
## 16228  STXBP1          6           5           4           1
##      NO      BOTH      FIRST      SECOND
## 2348 3.061557e-04 0.9934586 3.857158e-03 2.378089e-03
## 3201 4.538516e-10 0.9373802 6.261984e-02 2.048901e-10
## 6254 2.475216e-03 0.9531470 1.665815e-03 4.271197e-02
## 6265 9.065089e-04 0.9802813 1.552743e-03 1.725944e-02
## 6610 1.573114e-08 0.9984154 1.584264e-03 2.989837e-07
## 7165 1.903578e-06 0.8924003 1.075973e-01 4.761376e-07
## 7426 8.628766e-13 0.9367325 6.326751e-02 3.852893e-13
## 8283 3.189291e-13 0.9982274 1.772551e-03 5.416619e-12
## 8284 4.242399e-03 0.9136293 8.067943e-02 1.448846e-03
## 10146 1.458250e-48 0.8681168 1.318832e-01 2.894838e-49
## 12480 1.444210e-02 0.8916606 8.956108e-02 4.336247e-03
## 14673 3.061183e-18 0.9964569 3.543136e-03 2.596351e-17
## 14681 4.151136e-06 0.9959737 3.990920e-03 3.124247e-05
## 16228 7.521732e-24 1.0000000 9.762103e-09 2.323688e-17
```

## Genes with PP1 > 0.8 (Posterior probabilities of Model 1)

Specific risk genes for DD.

```
fData[fData$FIRST > 0.8, ]
```

##	geneName	dn_damaging_DD	dn_lof_DD	dn_damaging_EE	dn_lof_EE
## 681	ANKRD11	0	32	0	0
## 1001	ARID1B	0	30	0	0
## 1002	ARID2	0	3	0	0
## 1153	ASXL1	0	4	0	0
## 1317	AUTS2	0	4	0	0
## 1450	BCL11A	2	3	0	0
## 1630	BRPF1	0	4	0	0
## 2355	CACNA1E	2	2	0	0
## 2434	CAMTA1	1	2	0	0
## 3202	CHD3	3	1	0	0
## 3203	CHD4	5	1	0	0
## 3206	CHD7	2	2	0	0
## 3457	CLTC	2	3	0	0
## 3516	CNOT3	2	2	0	0
## 3599	COL4A3BP	4	0	0	0
## 3773	CREBBP	7	3	0	0
## 3876	CSNK2A1	4	0	0	0
## 3924	CTCF	5	0	0	0
## 3942	CTNNB1	0	11	0	0
## 4632	DNMT3A	4	1	0	0
## 4832	DYRK1A	4	14	0	0
## 4861	EBF3	2	3	0	0
## 4948	EFTUD2	3	2	0	0
## 4974	EHMT1	2	7	0	0
## 5157	EP300	3	12	0	0
## 6120	FOXP1	4	8	0	0
## 6121	FOXP2	1	2	0	0
## 7330	HIVEP2	2	2	0	0
## 7333	HK1	3	1	0	0
## 8168	KANSL1	0	8	0	0
## 8177	KAT6A	0	8	0	0
## 8178	KAT6B	0	8	0	0
## 8211	KCNB1	2	1	0	0
## 8228	KCNH1	4	0	0	0
## 8336	KDM5B	0	3	0	0
## 9618	LZTR1	2	1	0	0
## 9727	MAP4K4	3	2	0	0
## 9906	MED13L	5	13	0	0
## 9935	MEF2C	4	4	0	0
## 10670	MYT1L	2	2	0	0
## 10978	NFIX	1	4	0	0
## 11282	NSD1	1	7	0	0
## 12004	PACS1	8	0	0	0
## 12831	POGZ	0	6	0	0
## 12994	PPM1D	0	5	0	0
## 13062	PPP2R5D	12	0	0	0
## 13250	PRPF40A	1	2	0	0
## 13538	PUF60	0	3	0	0
## 13540	PUM2	1	2	0	0
## 13541	PURA	3	7	0	0
## 14894	SETD2	1	2	0	0
## 14897	SETD5	2	14	0	0
## 15074	SIN3A	1	3	0	0
## 15133	SLC12A2	2	1	0	0
## 15440	SLC6A1	6	2	0	0
## 15546	SMARCA2	9	0	0	0
## 15752	SON	0	3	0	0
## 15985	SRCAP	1	4	0	0
## 16337	SYNGAP1	0	13	0	0
## 16578	TCF12	1	2	0	0
## 16581	TCF20	0	5	0	0
## 16587	TCF4	4	9	0	0
## 17284	TNPO3	1	2	0	0
## 17548	TRIP12	2	3	0	0
## 18337	WDR26	1	2	0	0
## 18420	WHSC1	0	3	0	0

##	NO	BOTH	FIRST	SECOND
## 681	2.297741e-60	0.13872908	0.8612709	1.116175e-62
## 1001	1.704450e-56	0.14641883	0.8535812	8.817382e-59
## 1002	2.193691e-03	0.17485453	0.8229377	1.405687e-05
## 1153	1.845391e-05	0.17279546	0.8271860	1.162575e-07
## 1317	1.133833e-05	0.18488529	0.8151033	7.756077e-08
## 1450	7.457047e-07	0.19110833	0.8088909	5.313246e-09
## 1630	7.118090e-05	0.13281732	0.8671112	3.288114e-07
## 2355	4.915877e-02	0.08914968	0.8615381	1.534086e-04
## 2434	1.012129e-02	0.17035744	0.8194578	6.345614e-05
## 3202	5.977087e-02	0.11099360	0.8289942	2.413456e-04
## 3203	5.540230e-04	0.08766979	0.9117746	1.606548e-06
## 3206	4.704508e-02	0.10112344	0.8516630	1.684619e-04
## 3457	6.341962e-05	0.11784625	0.8820901	2.555229e-07
## 3516	1.534432e-04	0.17760910	0.8222365	9.995846e-07
## 3599	1.573369e-03	0.18553072	0.8128851	1.082981e-05
## 3773	1.302498e-10	0.09353761	0.9064624	4.053376e-13
## 3876	8.953515e-04	0.19751095	0.8015870	6.653305e-06
## 3924	3.492562e-05	0.19339259	0.8065722	2.525481e-07
## 3942	1.541043e-19	0.18239881	0.8176012	1.036809e-21
## 4632	3.852259e-05	0.17170928	0.8282520	2.408519e-07
## 4832	5.189173e-31	0.18805603	0.8119440	3.624622e-33
## 4861	8.613568e-07	0.18991149	0.8100876	6.089838e-09
## 4948	2.505835e-05	0.14945560	0.8505192	1.327957e-07
## 4974	2.140993e-13	0.14691102	0.8530890	1.111933e-15
## 5157	4.079682e-23	0.11138649	0.8886135	1.542231e-25
## 6120	1.001012e-18	0.17612505	0.8238750	6.453606e-21
## 6121	5.432492e-03	0.17654382	0.8179883	3.535965e-05
## 7330	1.640057e-03	0.14126349	0.8570883	8.152047e-06
## 7333	2.808436e-03	0.14421099	0.8529663	1.431972e-05
## 8168	1.948521e-13	0.18350266	0.8164973	1.320675e-15
## 8177	2.074813e-12	0.15071096	0.8492890	1.110380e-14
## 8178	1.001571e-12	0.15819723	0.8418028	5.676406e-15
## 8211	8.664847e-03	0.17746796	0.8138102	5.698508e-05
## 8228	2.404097e-03	0.17053318	0.8270478	1.494974e-05
## 8336	3.015563e-02	0.12310789	0.8466042	1.322444e-04
## 9618	2.094615e-02	0.16293339	0.8159943	1.261336e-04
## 9727	2.185163e-04	0.12698830	0.8727922	9.588267e-07
## 9906	1.527178e-28	0.12419530	0.8758047	6.531170e-31
## 9935	2.503506e-11	0.18133828	0.8186617	1.672388e-13
## 10670	5.479651e-04	0.15615945	0.8432895	3.060186e-06
## 10978	2.422783e-07	0.18309500	0.8169048	1.637657e-09
## 11282	2.440202e-11	0.13734200	0.8626580	1.171639e-13
## 12004	5.419168e-09	0.17478338	0.8252166	3.461530e-11
## 12831	1.677565e-09	0.19281239	0.8071876	1.208490e-11
## 12994	5.314446e-08	0.19463984	0.8053601	3.873495e-10
## 13062	5.258058e-15	0.17487375	0.8251263	3.360725e-17
## 13250	8.685049e-03	0.16444484	0.8268180	5.209380e-05
## 13538	2.908053e-04	0.19727664	0.8024304	2.156125e-06
## 13540	8.187980e-03	0.16161836	0.8301456	4.807471e-05
## 13541	2.499371e-16	0.19844222	0.8015578	1.866093e-18
## 14894	4.852918e-02	0.15035019	0.8008459	2.747650e-04
## 14897	1.795241e-27	0.16947547	0.8305245	1.104792e-29
## 15074	2.376476e-04	0.14856417	0.8511969	1.250895e-06
## 15133	5.046412e-02	0.14547211	0.8037883	2.754382e-04
## 15440	2.196975e-10	0.18675291	0.8132471	1.521505e-12
## 15546	1.418853e-08	0.11378454	0.8862154	5.493950e-11
## 15752	3.836161e-03	0.16715345	0.8289871	2.332748e-05
## 15985	3.773627e-05	0.12710945	0.8728526	1.657293e-07
## 16337	1.016582e-22	0.15249346	0.8475065	5.516375e-25
## 16578	3.104402e-03	0.17794702	0.8189282	2.034353e-05
## 16581	1.278363e-07	0.19166762	0.8083323	9.141475e-10
## 16587	1.136552e-20	0.16930787	0.8306921	6.986022e-23
## 17284	6.738068e-03	0.17422658	0.8189921	4.322883e-05
## 17548	4.285968e-05	0.13907921	0.8608777	2.088205e-07
## 18337	1.979577e-03	0.18717380	0.8108328	1.378128e-05
## 18420	3.986182e-03	0.15093289	0.8450595	2.147124e-05

## Genes with PP2 > 0.8 (Posterior probabilities of Model 2)

Specific risk genes for EE.

```
fData[fData$SECOND > 0.8, ]
```

```
##      geneName dn_damaging_DD dn_lof_DD dn_damaging_EE dn_lof_EE
## 14671     SCN1A           2         0           4           4
##              NO      BOTH      FIRST      SECOND
## 14671 2.043814e-12 0.1216637 8.537782e-15 0.8783363
```

## Use mTADA's results for single-trait analyses.

We can obtain single-trait results by summing PP1 and PP3 (Trait 1) or PP2 and PP3 (Trait 2).

### Trait 1

Top prioritized genes of DD.

```
fData[, 'pTrait1'] <- fData[, 'BOTH'] + fData[, 'FIRST']
fData1 <- fData[fData$pTrait1 > 0.8, ]
head(fData1[, c(1:5, 10)])
```

```
##      geneName dn_damaging_DD dn_lof_DD dn_damaging_EE dn_lof_EE  pTrait1
## 347      ADNP           1         19           0           0 1.0000000
## 447     AHDC1           0           8           0           0 1.0000000
## 681    ANKRD11           0         32           0           0 1.0000000
## 1000   ARID1A           1           2           0           0 0.9148468
## 1001   ARID1B           0         30           0           0 1.0000000
## 1002   ARID2           0           3           0           0 0.9977923
```

### Trait 2

Top prioritized genes of EE.

```
fData[, 'pTrait2'] <- fData[, 'BOTH'] + fData[, 'SECOND']
fData2 <- fData[fData$pTrait2 > 0.8, ]
head(fData2[, c(1:5, 11)])
```

```
##      geneName dn_damaging_DD dn_lof_DD dn_damaging_EE dn_lof_EE  pTrait2
## 2348  CACNA1A           5           0           2           0 0.9958367
## 3201    CHD2           0           6           0           1 0.9373802
## 6254  GABBR2           2           0           2           0 0.9958590
## 6265  GABRB3           2           0           2           0 0.9975407
## 6610   GNAO1           4           1           2           0 0.9984157
## 7165   HECW2           5           1           1           0 0.8924008
```

## Other information

Some additional information can be obtained from mTADA's results.

```
pCI <- mTADAResults$pars ## Genetic parameters
piValue <- mTADAResults$probModel ## Posterior probabilities of genes for four models
mcmcResult <- mTADAResults$mcmcData ##MCMC results
```

## The proportions of risk genes

*piValue* is a vector of  $\pi$  values. In the result below, pNO, pFIRST, pSECOND, and pBOTH are  $\pi_0$ ,  $\pi_1$ ,  $\pi_2$  and  $\pi_3$  respectively in **Table 1**.

```
piValue
```

```
##      pNO      pFIRST      pSECOND      pBOTH
## 0.961928644 0.022583466 0.008708526 0.006779364
```

Estimated information of  $\pi_3$ .



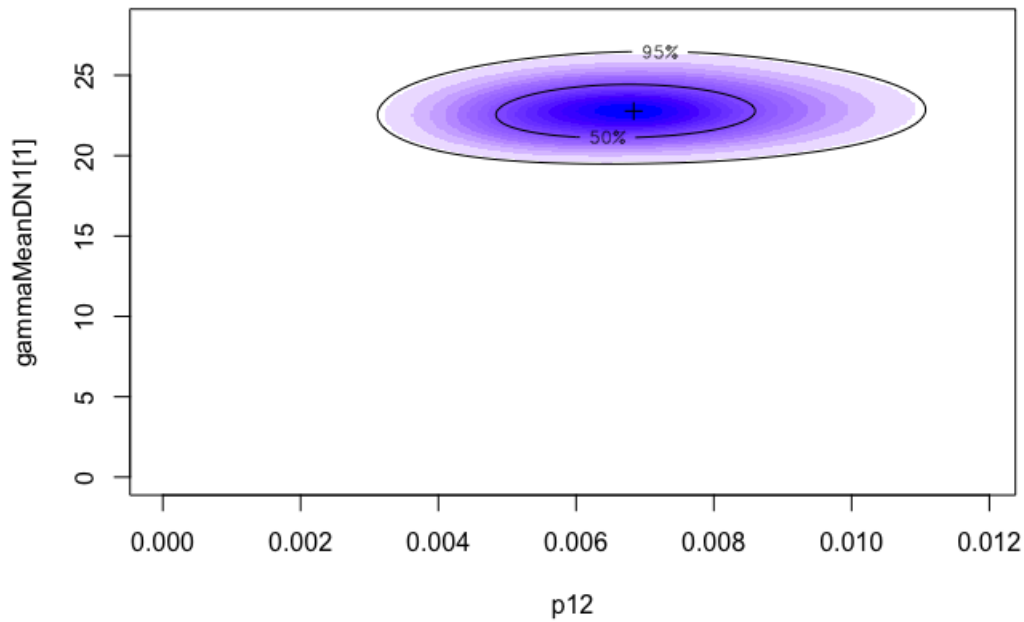
Credible-interval information is from **pCI**.

```
pCI ## Mode: estimated values; CI: credible interval with low (l) and upper (u) values
```

```
##                Mode                lCI                uCI
## p12            0.006779364  0.003786445  0.01006793
## gammaMeanDN1[1] 22.848744547 20.082794919 25.60378408
```

To check the convergent information of  $\pi_3$ , we can visualize MCMC results.

```
## p12 is pi3 in the model
plotParHeatmap1(mcmcResult = mcmcResult, pars = c('p12', 'gammaMeanDN1[1]'))
```



## Citation

**mTADA : a framework for identifying risk genes from de novo mutations in multiple traits.** Hoang T. Nguyen, Amanda Dobbyn, Ruth C. Brown, Brien P. Riley, Joseph Buxbaum, Dalila Pinto, Shaun M Purcell, Patrick F Sullivan, Xin He, Eli A. Stahl.