

mTADA

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

I. Introduction

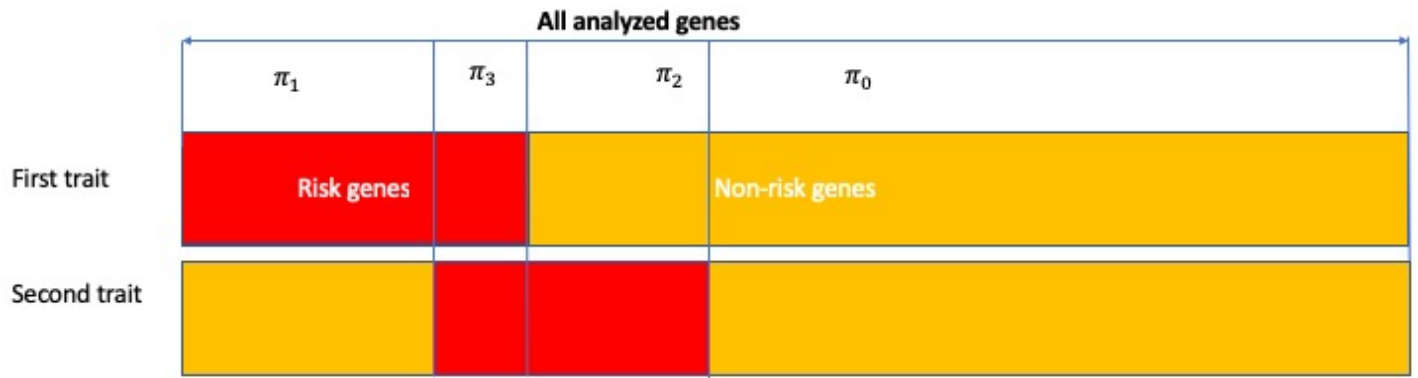
mTADA jointly analyze de novo mutations (DNMs) of two traits to 1) estimate the gene-level genetic overlap of the two traits; 2) report shared and specific risk genes; and 3) identify additional risk genes for each analyzed trait.

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	π_0	$x_{i1} \sim \text{Poisson}(2N_1\mu_i)$	$x_{i2} \sim \text{Poisson}(2N_2\mu_i)$
H_1	π_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	π_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	π_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: *ntrio*;
- the mean and dispersion parameters of relative risks: *bargamma_j* and β_j ($j=1, 2$);
- the proportion of risk genes: π_1^S and π_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  $RR \sim \text{Gamma}(\text{meanRR} * \text{beta}, \text{beta})$ 
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: 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)

## =====
## 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
## ===

```

Get 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 π_j , ($j = 0..3$) in Table 1.
3. `pars` : the estimated value and credible interval of π_3 (described as p12 in the our code).
4. `mcmcData` : MCMC sampling results for π_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 posteior probabilities (PPs) of four models)

We demonstrate how to choose top proritized 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 0.9783601
## 2 A1BG-AS1          0          0          0          0 0.9646035
## 3      A1CF          0          0          0          0 0.9892745
## 4      A2M          0          0          1          0 0.7687196
## 5  A2M-AS1          0          0          0          0 0.9636099
## 6   A2ML1          0          0          0          0 0.9918769
##           BOTH          FIRST          SECOND
## 1 0.0027968521 0.0103170918 0.008525977
## 2 0.0059043959 0.0206076714 0.008884411
## 3 0.0006301115 0.0027151990 0.007380160
## 4 0.0024240791 0.0002620490 0.228594301
## 5 0.0061341390 0.0213601262 0.008895786
## 6 0.0002035984 0.0009286126 0.006990863
```

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

```
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 3.156368e-04 0.9931599 4.013926e-03 2.510560e-03
## 3201 4.668500e-10 0.9349822 6.501777e-02 2.158151e-10
## 6254 2.546173e-03 0.9507336 1.729651e-03 4.499059e-02
## 6265 9.338741e-04 0.9792444 1.614628e-03 1.820708e-02
## 6610 1.622213e-08 0.9983506 1.649042e-03 3.157130e-07
## 7165 1.954506e-06 0.8884849 1.115127e-01 5.006059e-07
## 7426 8.875660e-13 0.9343115 6.568851e-02 4.058226e-13
## 8283 3.288808e-13 0.9981550 1.845015e-03 5.719657e-12
## 8284 4.359755e-03 0.9104263 8.368933e-02 1.524650e-03
## 10146 1.495782e-48 0.8634529 1.365471e-01 3.040590e-49
## 12480 1.482913e-02 0.8877874 9.282421e-02 4.559283e-03
## 14673 3.156474e-18 0.9963123 3.687715e-03 2.741407e-17
## 14681 4.280269e-06 0.9958090 4.153687e-03 3.298729e-05
## 16228 7.756999e-24 1.0000000 1.016192e-08 2.453867e-17
```

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

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

##	geneName	dn_damaging_DD	dn_lof_DD	dn_damaging_EE	dn_lof_EE
## 347	ADNP	1	19	0	0
## 681	ANKRD11	0	32	0	0
## 1000	ARID1A	1	2	0	0
## 1001	ARID1B	0	30	0	0
## 1002	ARID2	0	3	0	0
## 1153	ASXL1	0	4	0	0
## 1155	ASXL3	0	14	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
## 4903	EEF1A2	3	0	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
## 6351	GATAD2B	0	7	0	0
## 6606	GNAI1	5	0	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
## 9821	MBD5	0	3	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
##	13599	QRICH1	0	3	0	0
##	14605	SATB2	4	8	0	0
##	14894	SETD2	1	2	0	0
##	14897	SETD5	2	14	0	0
##	15010	SHANK3	0	3	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
##	16537	TBL1XR1	2	4	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
##	347	4.076700e-37	0.19465193	0.8053481	3.167503e-39
##	681	2.288871e-60	0.13400221	0.8659978	1.138544e-62
##	1000	8.444503e-02	0.11265787	0.8025160	3.810791e-04
##	1001	1.698387e-56	0.14147299	0.8585270	8.996828e-59
##	1002	2.188395e-03	0.16914194	0.8286553	1.435940e-05
##	1153	1.840748e-05	0.16713313	0.8328483	1.187474e-07
##	1155	2.518451e-25	0.19412114	0.8058789	1.950158e-27
##	1317	1.131522e-05	0.17891246	0.8210761	7.925989e-08
##	1450	7.443686e-07	0.18498008	0.8150192	5.430983e-09
##	1630	7.088960e-05	0.12826197	0.8716668	3.353229e-07
##	2355	4.889546e-02	0.08598278	0.8649655	1.562480e-04
##	2434	1.009580e-02	0.16477452	0.8250649	6.481503e-05
##	3202	5.950790e-02	0.10715368	0.8330924	2.460491e-04
##	3203	5.507747e-04	0.08451237	0.9149352	1.635449e-06
##	3206	4.681431e-02	0.09757541	0.8554386	1.716577e-04
##	3457	6.312271e-05	0.11373702	0.8861996	2.604289e-07
##	3516	1.530866e-04	0.17182201	0.8280239	1.021189e-06
##	3599	1.570226e-03	0.17954423	0.8188745	1.106750e-05
##	3773	1.295155e-10	0.09018929	0.9098107	4.127231e-13
##	3876	8.939816e-04	0.19122750	0.8078717	6.802519e-06
##	3924	3.486621e-05	0.18720809	0.8127568	2.581678e-07
##	3942	1.537751e-19	0.17648890	0.8235111	1.059418e-21
##	4632	3.842403e-05	0.16607543	0.8338859	2.459999e-07
##	4832	5.179249e-31	0.18200362	0.8179964	3.704492e-33
##	4861	8.597727e-07	0.18381289	0.8161862	6.224487e-09
##	4903	1.657449e-02	0.18034688	0.8029590	1.196710e-04
##	4948	2.497223e-05	0.14442457	0.8555503	1.355146e-07
##	4974	2.133419e-13	0.14195132	0.8580487	1.134585e-15

```

## 5157 4.059543e-23 0.10747500 0.8925250 1.571439e-25
## 6120 9.986252e-19 0.17037605 0.8296239 6.592696e-21
## 6121 5.419903e-03 0.17079259 0.8237514 3.612415e-05
## 6351 4.185648e-12 0.19940945 0.8005905 3.351439e-14
## 6606 1.518612e-05 0.19831115 0.8016735 1.207618e-07
## 7330 1.633915e-03 0.13646603 0.8618917 8.316382e-06
## 7333 2.798275e-03 0.13933118 0.8578559 1.461025e-05
## 8168 1.944443e-13 0.17756475 0.8224352 1.349533e-15
## 8177 2.067784e-12 0.14564487 0.8543551 1.133170e-14
## 8178 9.984733e-13 0.15292481 0.8470752 5.794630e-15
## 8211 8.645342e-03 0.17169806 0.8195984 5.822101e-05
## 8228 2.397887e-03 0.16493385 0.8326530 1.526890e-05
## 8336 3.002908e-02 0.11887309 0.8509630 1.348491e-04
## 9618 2.088935e-02 0.15756325 0.8214186 1.288097e-04
## 9727 2.175722e-04 0.12260477 0.8771767 9.775905e-07
## 9821 3.826780e-04 0.19855968 0.8010546 3.049268e-06
## 9906 1.520409e-28 0.11989470 0.8801053 6.658233e-31
## 9935 2.498053e-11 0.17545536 0.8245446 1.708784e-13
## 10670 5.462293e-04 0.15094353 0.8485071 3.123685e-06
## 10978 2.417674e-07 0.17716742 0.8228323 1.673414e-09
## 11282 2.430649e-11 0.13265511 0.8673449 1.195054e-13
## 12004 5.405960e-09 0.16906919 0.8309308 3.535946e-11
## 12831 1.674672e-09 0.18664209 0.8133579 1.235353e-11
## 12994 5.305667e-08 0.18842472 0.8115752 3.959883e-10
## 13062 5.245261e-15 0.16915721 0.8308428 3.432986e-17
## 13250 8.661032e-03 0.15901633 0.8322694 5.319620e-05
## 13538 2.903560e-04 0.19099780 0.8087096 2.204448e-06
## 13540 8.164386e-03 0.15626495 0.8355216 4.908634e-05
## 13541 2.495618e-16 0.19213465 0.8078654 1.907999e-18
## 13599 3.047342e-04 0.19867545 0.8010174 2.429722e-06
## 14605 1.812297e-19 0.19537655 0.8046235 1.414628e-21
## 14894 4.838585e-02 0.14535955 0.8059741 2.805267e-04
## 14897 1.790489e-27 0.16390034 0.8360997 1.128305e-29
## 15010 5.826150e-04 0.19892791 0.8004848 4.654333e-06
## 15074 2.368229e-04 0.14355836 0.8562035 1.276464e-06
## 15133 5.030627e-02 0.14061877 0.8087938 2.811647e-04
## 15440 2.192661e-10 0.18073311 0.8192669 1.554952e-12
## 15546 1.411983e-08 0.10979924 0.8902007 5.598529e-11
## 15752 3.825791e-03 0.16164559 0.8345048 2.382262e-05
## 15985 3.757334e-05 0.12272212 0.8772401 1.689730e-07
## 16337 1.013209e-22 0.14737786 0.8526221 5.629995e-25
## 16537 5.960269e-09 0.19714085 0.8028591 4.704748e-11
## 16578 3.097313e-03 0.17215594 0.8247260 2.078407e-05
## 16581 1.276101e-07 0.18552553 0.8144743 9.344249e-10
## 16587 1.133537e-20 0.16373717 0.8362628 7.134659e-23
## 17284 6.721918e-03 0.16853741 0.8246965 4.415995e-05
## 17548 4.269484e-05 0.13434232 0.8656148 2.130085e-07
## 18337 1.975758e-03 0.18114678 0.8168634 1.408472e-05
## 18420 3.972860e-03 0.14586602 0.8501392 2.191293e-05

```

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

```
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 2.00889e-12 0.1159578 8.470647e-15 0.8840422
```

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

```
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 0.9151739
## 1001   ARID1B           0          30           0           0 1.0000000
## 1002   ARID2           0           3           0           0 0.9977972
```

Trait 2

```
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 0.9956704
## 3201    CHD2           0           6           0           1 0.9349822
## 6254   GABBR2           2           0           2           0 0.9957242
## 6265   GABRB3           2           0           2           0 0.9974515
## 6610    GNAO1           4           1           2           0 0.9983509
## 7165   HECW2           5           1           1           0 0.8884854
```

Other information

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

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

The proportions of risk genes

piValue is a vector of π values. In the result below, pNO, pFIRST, pSECOND, and pBOTH are π_0 , π_1 , π_2 and π_3 respectively in **Table 1**.

```
piValue
```

```
##          pNO          pFIRST          pSECOND          pBOTH
## 0.961721614 0.022790496 0.008915556 0.006572334
```

Estimated information of π_3 .

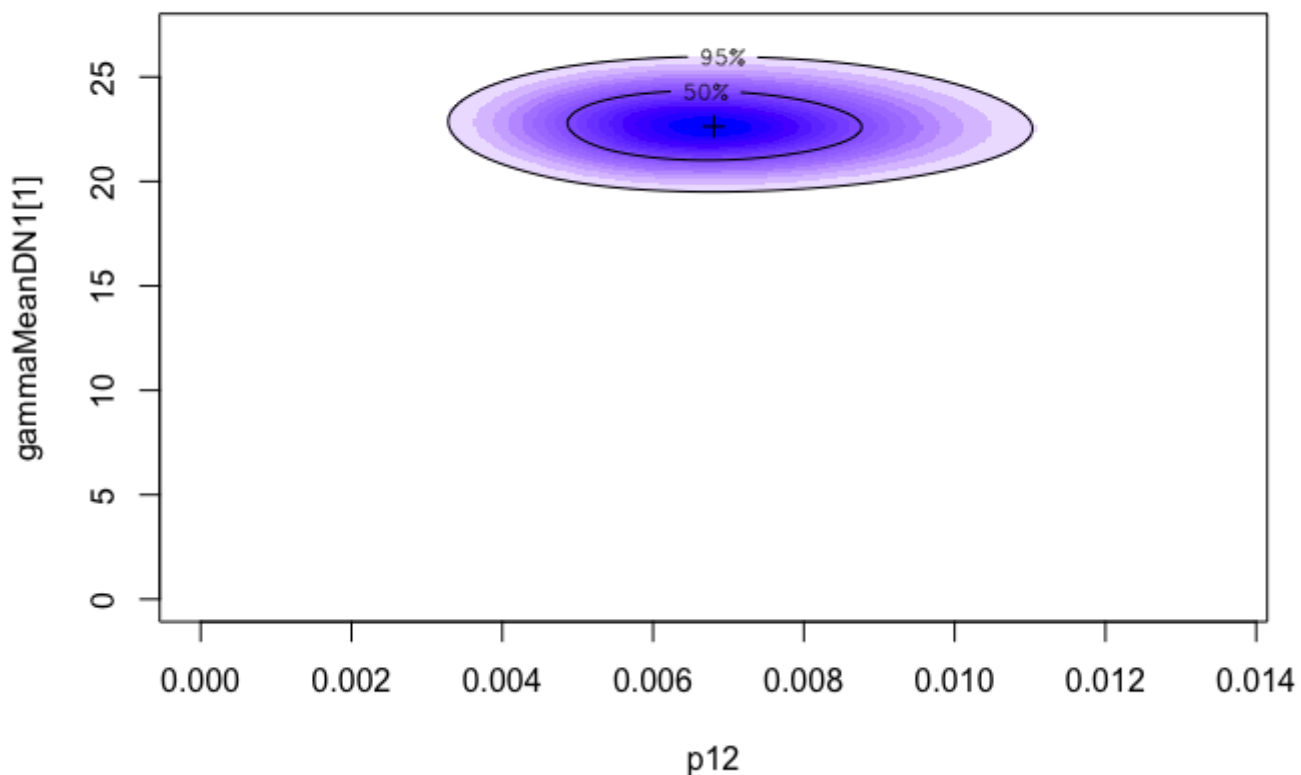
Credible-interval information is from pCI .

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

```
##          Mode          lCI          uCI
## p12          0.006572334 0.003861267 0.01016222
## gammaMeanDN1[1] 22.628526092 20.062524125 25.39720292
```

To check the convergent information of π_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.