

Causal Model Selection Hypothesis Tests in Systems Genetics: a tutorial

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1 Motivation

Current efforts in systems genetics have focused on the development of statistical approaches that aim to disentangle causal relationships among molecular phenotypes in segregating populations. Model selection criteria, such as the AIC and BIC, have been widely used for this purpose, in spite of being unable to quantify the uncertainty associated with the model selection call. In this tutorial we illustrate the use of software implementing the causal model selection hypothesis tests proposed by Chaibub Neto et al. (2012).

2 Overview

This tutorial illustrates the basic functionality of the CMST routines in the `qtlhot` R package using few simulated toy examples. The analysis of a yeast genetical genomics data-set presented in Chaibub Neto et al. (2012) is reproduced in a separate package, `R/qtl yeast`. The `R/qtlhot` package depends on `R/qtl` (Broman et al. 2003), and we assume the reader is familiar with it.

3 Basic functionality

Here, we illustrate the basic functionality of the CMST routines in the `R/qtlhot` package in a toy simulated example.

```
> library(qtlhot)
```

We first use the `SimCrossCausal` function to simulate a `cross` object with 3 phenotypes, y_1 , y_2 and y_3 , where y_1 has a causal effect on both y_2 and y_3 . The simulated cross data set, `Cross`, is composed of: 100 individuals (`n.ind = 100`); 3 chromosomes of length 100cM (`len = rep(100, 3)`); 101 unequally spaced markers per chromosome (`n.mar = 101` and `eq.spacing = FALSE`); additive genetic effect set to 1 (`add.eff = 1`); dominance genetic effect set to 0 (`dom.eff =`

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0); residual variances for y_1 (`sig2.1`) and the other phenotypes (`sig2.2`) set to 0.4 and 0.1, respectively; backcross cross type (`cross.type = "bc"`); and phenotype data transformed to normal scores (`normalize = TRUE`). The argument `beta = rep(0.5, 2)`, represents the causal effect of y_1 on the other phenotypes (i.e., coefficients of the regressions of $y_2 = 0.5 y_1 + \epsilon$ and $y_3 = 0.5 y_1 + \epsilon$). The length of `beta` controls the number of phenotypes to be simulated.

```
> set.seed(987654321)
> CMSTCross <- SimCrossCausal(n.ind = 100,
+                             len = rep(100, 3),
+                             n.mar = 101,
+                             beta = rep(0.5, 2),
+                             add.eff = 1,
+                             dom.eff = 0,
+                             sig2.1 = 0.4,
+                             sig2.2 = 0.1,
+                             eq.spacing = FALSE,
+                             cross.type = "bc",
+                             normalize = TRUE)
```

We compute the genotype conditional probabilities using Haldane's map function, genotype error rate of 0.0001, and setting the maximum distance between positions at which genotype probabilities were calculated to 1cM.

```
> CMSTCross <- calc.genoprob(CMSTCross, step = 1)
```

We perform QTL mapping using Haley-Knott regression (Haley and Knott 1992), and summarize the results for the 3 phenotypes. Figure 1 presents the LOD score profiles for all 3 phenotypes. The black, blue and red curves represent the LOD profiles of phenotypes y_1 , y_2 and y_3 , respectively.

```
> Scan <- scanone(CMSTCross, pheno.col = 1 : 3, method = "hk")
> summary(Scan[, c(1, 2, 3)], thr = 3)
```

```
      chr pos   y1
c1.loc55   1  55 12.6
```

```
> summary(Scan[, c(1, 2, 4)], thr = 3)
```

```
      chr pos   y2
c1.loc55   1  55  5.27
```

```
> summary(Scan[, c(1, 2, 5)], thr = 3)
```

```
      chr pos   y3
D1M50   1 55.5  7.58
```

```
> plot(Scan, lodcolumn = 1 : 3, ylab = "LOD")
```

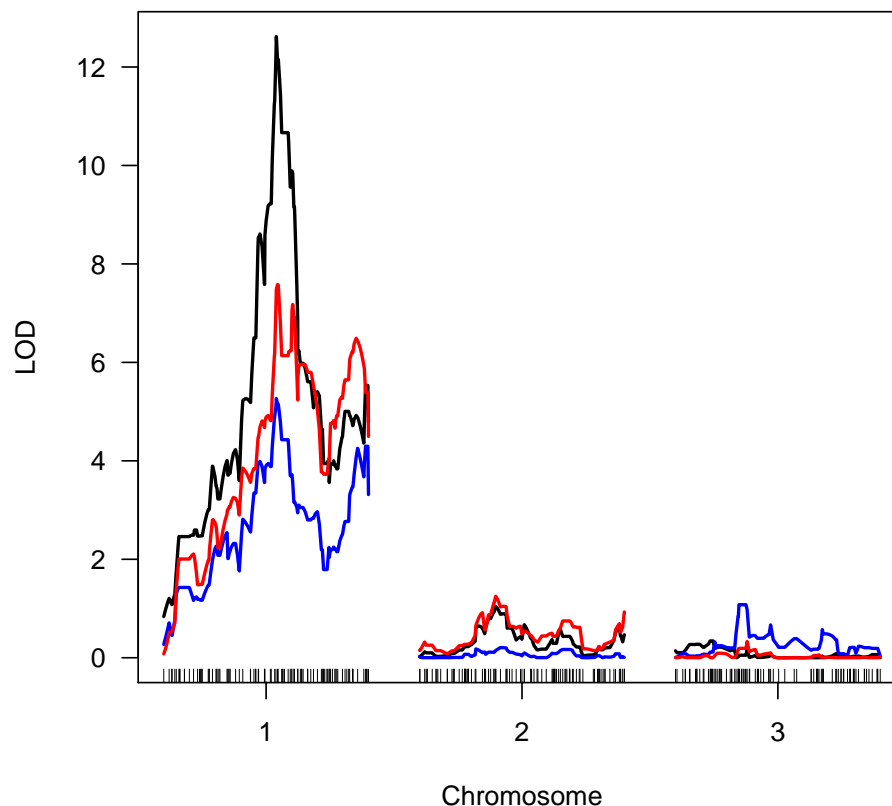


Figure 1: LOD score profiles for phenotypes y_1 (black curve), y_2 (blue curve) and y_3 (red curve).

Phenotypes y_1 and y_2 map to exactly same QTL at position 55 cM on chromosome 1. Phenotype y_3 maps to a QTL at position 55.5 cM. Whenever two phenotypes map to close, but not exactly identical, positions we are faced with the question of which QTL to use as causal anchor. Instead of making a (sometimes) arbitrary choice, our approach is to compute the joint LOD profile of both phenotypes and use the QTL detected by this joint mapping approach as the causal anchor. The function `GetCommonQtls` performs the joint QTL mapping for phenotypes whose marginal LOD peak positions are higher than a certain LOD threshold (`thr`), and are less than a fixed distance apart (`peak.dist`). The function can also handle separate additive and interacting covariates for each phenotype (`addcov1`, `intcov1`, `addcov2`, `intcov2`). In this simulated example the QTL detected by the joint analysis agreed with phenotype's y_1 QTL.

```

> commqtls <- GetCommonQtls(CMSTCross,
+                           pheno1 = "y1",
+                           pheno2 = "y3",
+                           thr = 3,
+                           peak.dist = 5,
+                           addcov1 = NULL,
+                           addcov2 = NULL,
+                           intcov1 = NULL,
+                           intcov2 = NULL)
> commqtls

```

```

      Q Q.chr Q.pos
1 c1.loc55      1   55

```

Now, we fit our causal model selection tests for phenotypes y_1 and y_2 using the **CMSTtests** function. The **Q.chr** and **Q.pos** arguments specify the chromosome and position (in cM) of the QTL to be used as a causal anchor. The argument **method** specify which version of the CMST test should be used. The options "par", "non.par" and "joint" represent, respectively, the parametric, non-parametric, joint parametric versions of the CMST test. The option "all" fits all three versions. The **penalty** argument specifies whether we should test statistics based on the AIC ("aic"), BIC ("bic"), or both ("both") penalties. In this particular call we computed all 3 versions using both penalties fitting 6 separate CMST tests.

```

> nms <- names(CMSTCross$pheno)
> out1 <- CMSTtests(CMSTCross,
+                   pheno1 = nms[1],
+                   pheno2 = nms[2],
+                   Q.chr = 1,
+                   Q.pos = 55,
+                   addcov1 = NULL,
+                   addcov2 = NULL,
+                   intcov1 = NULL,
+                   intcov2 = NULL,
+                   method = "all",
+                   penalty = "both")

```

The output of the **CMSTtests** function is composed of a list with 17 elements. It returns the names of the phenotypes and number of individuals (**n.ind**):

```

> out1[1:3]

$pheno1
[1] "y1"

$pheno2

```

```
[1] "y2"
```

```
$n.ind  
[1] 100
```

The log-likelihood scores (`loglik`) of models M_1 , M_2 , M_3 , and M_4 (see Chaibub Neto et al. 2012 for details):

```
> out1[4]  
  
$loglik  
[1] -123.5318 -140.4604 -141.5803 -123.4834
```

The dimensions of the models (`model.dim`):

```
> out1[5]  
  
$model.dim  
[1] 6 6 6 7
```

The R^2 values (`R2`) relative to the regression of phenotypes 1 and 2 on the causal anchor:

```
> out1[6]  
  
$R2  
[1] 0.4407170 0.2153583
```

The covariance matrix (`S.hat`) with the variances and covariances of the penalized log-likelihood ratios of models $M_1 \times M_2$, $M_1 \times M_3$, $M_1 \times M_4$, $M_2 \times M_3$, $M_2 \times M_4$, and $M_3 \times M_4$:

```
> out1[7]  
  
$S.hat  
      [,1]      [,2]      [,3]      [,4]      [,5]      [,6]  
[1,] 0.26221327 -0.01323094 0.010924311 -0.275444212 -0.251288963 0.02415525  
[2,] -0.01323094 0.36275299 0.012080993 0.375983930 0.025311930 -0.35067200  
[3,] 0.01092431 0.01208099 0.001115354 0.001156681 -0.009808958 -0.01096564  
[4,] -0.27544421 0.37598393 0.001156681 0.651428142 0.276600893 -0.37482725  
[5,] -0.25128896 0.02531193 -0.009808958 0.276600893 0.241480006 -0.03512089  
[6,] 0.02415525 -0.35067200 -0.010965639 -0.374827248 -0.035120888 0.33970636
```

The BIC scores (`BICs`):

```
> out1[8]  
  
$BICs  
[1] 274.6946 308.5518 310.7917 279.2030
```

The BIC-based penalized log-likelihood test statistics (`Z.bic`):

```
> out1[9]
```

```
$Z.bic
```

	[,1]	[,2]	[,3]	[,4]
[1,]	NA	3.305926	2.9966507	6.749745
[2,]	NA	NA	0.1387598	-2.986200
[3,]	NA	NA	NA	-2.709873
[4,]	NA	NA	NA	NA

The BIC-based model selection p-values for the parametric CMST (`pvals.p.BIC`), non-parametric CMST (`pvals.np.BIC`) and joint parametric CMST (`pvals.j.BIC`):

```
> out1[10:12]
```

```
$pvals.p.BIC
```

```
[1] 0.001364817 0.999526684 0.998635183 1.000000000
```

```
$pvals.np.BIC
```

```
[1] 6.289575e-06 9.999977e-01 9.999999e-01 1.000000e+00
```

```
$pvals.j.BIC
```

```
[1] 0.003779474 0.999946885 0.999669186 1.000000000
```

The analogous AIC-based quantities:

```
> out1[13:17]
```

```
$AICs
```

```
[1] 259.0636 292.9208 295.1606 260.9668
```

```
$Z.aic
```

	[,1]	[,2]	[,3]	[,4]
[1,]	NA	3.305926	2.9966507	2.849429
[2,]	NA	NA	0.1387598	-3.251273
[3,]	NA	NA	NA	-2.933361
[4,]	NA	NA	NA	NA

```
$pvals.p.AIC
```

```
[1] 0.002189889 0.999526684 0.998635183 0.997810111
```

```
$pvals.np.AIC
```

```
[1] 6.289575e-06 9.999977e-01 1.000000e+00 9.999977e-01
```

```
$pvals.j.AIC
```

```
[1] 0.005993868 0.999946885 0.999669186 1.000000000
```

The function `CMSTtests` can also compute CMST tests of a single phenotype against a list of phenotypes. Its output is less detailed though. In this particular call we test y_1 against y_2 and y_3 .

```
> out2 <- CMSTtests(CMSTCross,
+                   pheno1 = nms[1],
+                   pheno2 = nms[-1],
+                   Q.chr = 1,
+                   Q.pos = 55.5,
+                   addcov1 = NULL,
+                   addcov2 = NULL,
+                   intcov1 = NULL,
+                   intcov2 = NULL,
+                   method = "all",
+                   penalty = "both")
> out2
```

\$R2s

	R2.Y1 ~ Q	R2.Y2 ~ Q
y1_y2	0.4286585	0.2112760
y1_y3	0.4286585	0.2945801

\$AIC.stats

	AIC.1	AIC.2	AIC.3	AIC.4	z.12	z.13	z.14	z.23
y1_y2	261.1967	293.4397	297.8127	263.0819	3.136952	3.034372	2.6436961	0.2659898
y1_y3	256.9466	278.0272	311.4368	258.2783	2.177343	3.876750	0.8229369	2.0030490

	z.24	z.34
y1_y2	-3.084095	-2.975873
y1_y3	-2.329987	-4.023391

\$BIC.stats

	BIC.1	BIC.2	BIC.3	BIC.4	z.12	z.13	z.14	z.23
y1_y2	276.8278	309.0707	313.4437	281.3181	3.136952	3.034372	6.297065	0.2659898
y1_y3	272.5777	293.6583	327.0678	276.5145	2.177343	3.876750	2.432884	2.0030490

	z.24	z.34
y1_y2	-2.819431	-2.752652
y1_y3	-2.022629	-3.826214

\$pvals.j.BIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	0.003366319	0.9998806	0.9997017	1
y1_y3	0.035842249	0.9974573	0.9999900	1

\$pvals.p.BIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	0.001205187	0.9991464	0.9987948	1.0000000
y1_y3	0.014727493	0.9852725	0.9999471	0.9925105

\$pvals.np.BIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	2.346206e-06	0.9999992	1	1.0000000
y1_y3	1.758821e-03	0.9991050	1	0.9999607

\$pvals.j.AIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	0.01109575	0.9998806	0.9997017	1
y1_y3	0.38662933	0.9985143	0.9999950	1

\$pvals.p.AIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	0.004100312	0.9991464	0.9987948	0.9958997
y1_y3	0.205271925	0.9900966	0.9999713	0.7947281

\$pvals.np.AIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	1.608001e-05	0.9999992	1	0.9999937
y1_y3	4.431304e-02	0.9991050	1	0.9715560

4 Other Functions

There are several other functions involved in simulation and in data analysis that are not well documented yet. See `R/qtlyeast` available at [GITHUB](#) for further analysis. Here we do scans for the three traits, and create a reduced object with only high LOD values.

```
> CMSTscan <- scanone(CMSTCross, pheno.col = 1:3, method = "hk")
> CMSThigh <- highlod(CMSTscan)
```

For our purposes, we place the three traits on chromosome 1 at some arbitrary positions, with trait y1 having causal “targets” of the other two traits.

```
> traits <- names(CMSTCross$pheno)
> annot <- data.frame(name = traits, traits = traits, chr = rep(1, 3),
+   Mb.pos = c(55,10,100))
> annot$cM.pos <- annot$Mb.pos
> annot
```

	name	traits	chr	Mb.pos	cM.pos
1	y1	y1	1	55	55


```

2  y2      y2    1      10      10
3  y3      y3    1     100     100

```

```
> targets <- list(y1 = c("y2", "y3"))
```

Now we used the scans (via `CMSThigh`) and the annotation to identify candidate regions, the subset of cis-acting candidate regions, and co-mapping targets.

```
> cand.reg <- GetCandReg(CMSThigh, annot, traits)
> cand.reg
```

	gene	phys.chr	phys.pos	peak.chr	peak.pos	peak.lod
1	y1	1	55	1	55.00000	12.618418
2	y2	1	10	1	55.00000	5.266431
3	y3	1	100	1	55.54525	7.577615

```
> cis.cand.reg <- GetCisCandReg(CMSThigh, cand.reg)
> cis.cand.reg
```

	gene	phys.chr	phys.pos	peak.pos	peak.lod	peak.pos.lower	peak.pos.upper
1	y1	1	55	55	12.61842	53	57.61146

```
> comap.targets <- GetCoMappingTraits(CMSThigh, cand.reg)
> comap.targets
```

```
$y1
[1] "y2" "y3"
```

```
$y2
[1] "y1" "y3"
```

```
$y3
[1] "y1" "y2"
```

Next, we perform tests to infer causal relationships.

```
> tests <- list()
> for(k in seq(names(comap.targets))) {
+   tests[[k]] <- FitAllTests(CMSTCross, pheno1 = names(comap.targets)[k],
+                               pheno2 = comap.targets[[k]],
+                               Q.chr = cand.reg[k, 4],
+                               Q.pos = cand.reg[k, 5])
+ }
```

```

pheno2 = 1
pheno2 = 2
CIT pheno2 = y2
CIT pheno2 = y3
pheno2 = 1
pheno2 = 2
CIT pheno2 = y1
CIT pheno2 = y3
pheno2 = 1
pheno2 = 2
CIT pheno2 = y1
CIT pheno2 = y2

```

```

> names(tests) <- names(comap.targets)
> tests <- JoinTestOutputs(comap.targets, tests)
> tests

```

\$R2s

```

      R2.Y1 ~ Q R2.Y2 ~ Q
y1_y2 0.4407170 0.2153583
y1_y3 0.4407170 0.2914979
y2_y1 0.2153583 0.4407170
y2_y3 0.2153583 0.2914979
y3_y1 0.2945801 0.4286585
y3_y2 0.2945801 0.2112760

```

\$AIC.stats

	AIC.1	AIC.2	AIC.3	AIC.4	z.12	z.13	z.14
y1_y2	259.0636	292.9208	295.1606	260.9668	3.305926	2.9966507	2.8494289
y1_y3	254.8135	278.4632	309.7396	256.4303	2.339472	4.2078724	1.3197398
y2_y1	292.9208	259.0636	295.1606	260.9668	-3.305926	0.1387598	-3.2512727
y2_y3	226.3940	216.1866	231.6614	213.0150	-1.014912	0.4428305	-2.0302949
y3_y1	278.0272	256.9466	311.4368	258.2783	-2.177343	2.0030490	-2.3299872
y3_y2	215.7506	226.9129	231.7444	212.9632	1.098857	1.2871586	-0.5813799

	z.23	z.24	z.34
y1_y2	0.1387598	-3.2512727	-2.933361
y1_y3	1.9587743	-2.4119422	-4.279798
y2_y1	2.9966507	2.8494289	-2.933361
y2_y3	1.2380872	-0.6314165	-2.084435
y3_y1	3.8767496	0.8229369	-4.023391
y3_y2	0.3909483	-2.0014294	-2.073127

\$BIC.stats

	BIC.1	BIC.2	BIC.3	BIC.4	z.12	z.13	z.14
--	-------	-------	-------	-------	------	------	------

y1_y2	274.6946	308.5518	310.7917	279.2030	3.305926	2.9966507	6.74974480
y1_y3	270.4445	294.0943	325.3707	274.6665	2.339472	4.2078724	3.44622282
y2_y1	308.5518	274.6946	310.7917	279.2030	-3.305926	0.1387598	-2.98619967
y2_y3	242.0250	231.8176	247.2924	231.2511	-1.014912	0.4428305	-1.63495434
y3_y1	293.6583	272.5777	327.0678	276.5145	-2.177343	2.0030490	-2.02262858
y3_y2	231.3816	242.5439	247.3754	231.1994	1.098857	1.2871586	-0.03799597
	z.23	z.24	z.34				
y1_y2	0.1387598	-2.9861997	-2.709873				
y1_y3	1.9587743	-2.1267544	-4.070649				
y2_y1	2.9966507	6.7497448	-2.709873				
y2_y3	1.2380872	-0.1127673	-1.793211				
y3_y1	3.8767496	2.4328842	-3.826214				
y3_y2	0.3909483	-1.6276524	-1.785559				

\$pvals.j.BIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	0.003779474	0.999946885	0.9996692	1.0000000
y1_y3	0.023770207	0.998342606	0.9999985	1.0000000
y2_y1	0.999946885	0.003779474	0.9996692	1.0000000
y2_y3	0.991331495	0.727786029	0.9881747	0.9533151
y3_y1	0.997457264	0.035842249	0.9999900	1.0000000
y3_y2	0.708326515	0.990042453	0.9878292	0.9698693

\$pvals.p.BIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	0.001364817	0.999526684	0.9986352	1.0000000
y1_y3	0.009655499	0.990344501	0.9999871	0.9997158
y2_y1	0.999526684	0.001364817	0.9986352	1.0000000
y2_y3	0.948970690	0.544892461	0.9635304	0.4551075
y3_y1	0.985272507	0.014727493	0.9999471	0.9925105
y3_y2	0.515154554	0.948200693	0.9629147	0.4848454

\$pvals.np.BIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	6.289575e-06	9.999977e-01	0.9999999	1.0000000
y1_y3	2.043886e-04	9.999084e-01	1.0000000	0.9999997
y2_y1	9.999977e-01	6.289575e-06	0.9999999	1.0000000
y2_y3	9.556870e-01	8.643735e-01	0.9997956	0.1841008
y3_y1	9.991050e-01	1.758821e-03	1.0000000	0.9999607
y3_y2	8.158992e-01	9.895106e-01	0.9997956	0.2420592

\$pvals.j.AIC

	pval.1	pval.2	pval.3	pval.4
y1_y2	0.005993868	0.999946885	0.9996692	1.0000000

```

y1_y3 0.195697275 0.998720666 0.9999990 1.0000000
y2_y1 0.999946885 0.005993868 0.9996692 1.0000000
y2_y3 0.997728473 0.880223915 0.9949729 0.6993183
y3_y1 0.998514322 0.386629331 0.9999950 1.0000000
y3_y2 0.875137894 0.997069515 0.9947476 0.7328496

```

\$pvals.p.AIC

```

      pval.1      pval.2      pval.3      pval.4
y1_y2 0.002189889 0.999526684 0.9986352 0.9978101
y1_y3 0.093460955 0.992066102 0.9999906 0.9065390
y2_y1 0.999526684 0.002189889 0.9986352 0.9978101
y2_y3 0.978836716 0.736115878 0.9814397 0.2638841
y3_y1 0.990096585 0.205271925 0.9999713 0.7947281
y3_y2 0.719507792 0.977326933 0.9809198 0.2804922

```

\$pvals.np.AIC

```

      pval.1      pval.2      pval.3      pval.4
y1_y2 6.289575e-06 9.999977e-01 1.0000000 0.99999765
y1_y3 3.318560e-03 9.999084e-01 1.0000000 0.99824118
y2_y1 9.999977e-01 6.289575e-06 1.0000000 0.99999765
y2_y3 9.823999e-01 9.895106e-01 0.9997956 0.02844397
y3_y1 9.991050e-01 4.431304e-02 1.0000000 0.97155603
y3_y2 9.823999e-01 9.895106e-01 0.9997956 0.02844397

```

\$pvals.cit

```

      pval.1      pval.2
y2 1.641765e-06 7.741579e-01
y3 1.770222e-06 6.029575e-01
y1 7.741579e-01 1.641765e-06
y3 2.692473e-02 8.015192e-04
y1 4.219075e-01 4.617830e-06
y2 1.351854e-04 3.160420e-02

```

\$phenos

```

      [,1] [,2]
[1,] "y1" "y2"
[2,] "y1" "y3"
[3,] "y2" "y1"
[4,] "y2" "y3"
[5,] "y3" "y1"
[6,] "y3" "y2"

```

Finally, we compare the inferred causal relationships to the known **targets** to assess precision, true positive rate and false positive rate.

```
> PrecTpFpMatrix(alpha = seq(0.01, 0.10, by = 0.01),
+   val.targets = targets, all.orfs = CMSThigh$names, tests = tests,
+   cand.reg = cand.reg, cis.cand.reg = cis.cand.reg)
```

```
$Prec1
```

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
aic	1.00	1.00	1.00	1	1	1	1	1	1	1
bic	1.00	1.00	1.00	1	1	1	1	1	1	1
j.bic	1.00	1.00	1.00	1	1	1	1	1	1	1
p.bic	1.00	1.00	1.00	1	1	1	1	1	1	1
np.bic	1.00	1.00	1.00	1	1	1	1	1	1	1
j.aic	1.00	1.00	1.00	1	1	1	1	1	1	1
p.aic	1.00	1.00	1.00	1	1	1	1	1	1	1
np.aic	1.00	1.00	1.00	1	1	1	1	1	1	1
cit	0.67	0.67	0.67	1	1	1	1	1	1	1

```
$Prec2
```

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
aic	1	1	1	1	1	1	1	1	1	1
bic	1	1	1	1	1	1	1	1	1	1
j.bic	1	1	1	1	1	1	1	1	1	1
p.bic	1	1	1	1	1	1	1	1	1	1
np.bic	1	1	1	1	1	1	1	1	1	1
j.aic	1	1	1	1	1	1	1	1	1	1
p.aic	1	1	1	1	1	1	1	1	1	1
np.aic	1	1	1	1	1	1	1	1	1	1
cit	1	1	1	1	1	1	1	1	1	1

```
$Tp1
```

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
aic	2	2	2	2	2	2	2	2	2	2
bic	2	2	2	2	2	2	2	2	2	2
j.bic	1	1	2	2	2	2	2	2	2	2
p.bic	2	2	2	2	2	2	2	2	2	2
np.bic	2	2	2	2	2	2	2	2	2	2
j.aic	1	1	1	1	1	1	1	1	1	1
p.aic	1	1	1	1	1	1	1	1	1	2
np.aic	2	2	2	2	2	2	2	2	2	2
cit	2	2	2	2	2	2	2	2	2	2

```
$Tp2
```

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
aic	2	2	2	2	2	2	2	2	2	2
bic	2	2	2	2	2	2	2	2	2	2

j.bic	1	1	2	2	2	2	2	2	2	2
p.bic	2	2	2	2	2	2	2	2	2	2
np.bic	2	2	2	2	2	2	2	2	2	2
j.aic	1	1	1	1	1	1	1	1	1	1
p.aic	1	1	1	1	1	1	1	1	1	2
np.aic	2	2	2	2	2	2	2	2	2	2
cit	2	2	2	2	2	2	2	2	2	2

\$Fp1

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
aic	0	0	0	0	0	0	0	0	0	0
bic	0	0	0	0	0	0	0	0	0	0
j.bic	0	0	0	0	0	0	0	0	0	0
p.bic	0	0	0	0	0	0	0	0	0	0
np.bic	0	0	0	0	0	0	0	0	0	0
j.aic	0	0	0	0	0	0	0	0	0	0
p.aic	0	0	0	0	0	0	0	0	0	0
np.aic	0	0	0	0	0	0	0	0	0	0
cit	1	1	1	0	0	0	0	0	0	0

\$Fp2

	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
aic	0	0	0	0	0	0	0	0	0	0
bic	0	0	0	0	0	0	0	0	0	0
j.bic	0	0	0	0	0	0	0	0	0	0
p.bic	0	0	0	0	0	0	0	0	0	0
np.bic	0	0	0	0	0	0	0	0	0	0
j.aic	0	0	0	0	0	0	0	0	0	0
p.aic	0	0	0	0	0	0	0	0	0	0
np.aic	0	0	0	0	0	0	0	0	0	0
cit	0	0	0	0	0	0	0	0	0	0

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