

A Genetic Analysis Package with R

Jing Hua Zhao

Department of Public Health and Primary Care, University of Cambridge,
Cambridge, UK
<https://jinghuazhao.github.io/>

Contents

1	Introduction	1
2	Implementation	2
3	Independent programs	6
4	Demos	7
5	Examples	7
5.1	Pedigree drawing	7
5.2	Kinship calculation	7
5.3	Study design	9
5.4	Graphics examples	14
6	Polygenic modeling	27
7	Mendelian randomization	27
8	Known bugs	28
9	Summary	28
10	Bibliographic note	34

1 Introduction

This package was initiated to integrate some C/Fortran/SAS programs I have written or used over the years. As such, it would rather be a long-term project, but an immediate benefit would be something complementary to other packages currently available from CRAN, e.g. **genetics**, **hwde**,

etc. I hope eventually this will be part of a bigger effort to fulfill most of the requirements foreseen by many, e.g. Guo and Lange (2000), within the portable environment of R for data management, analysis, graphics and object-oriented programming. My view has been outlined more formally in Zhao and Tan (2006a) and Zhao and Tan (2006b) in relation to other package systems. Also reported are Zhao (2005) and Zhao (2006) on package **kinship**.

The number of functions are quite limited and experimental, but I already feel the enormous advantage by shifting to R and would like sooner rather than later to share my work with others. I will not claim this work as exclusively done by me, but would like to invite others to join me and enlarge the collections and improve them.

With my recent work on genomewide association studies (GWAS) especially protein GWAS, I have added many functions such as **METAL_forestplot** which handles data from software METAL and **sentinels** which extracts sentinels from GWAS summary statistics in a way that is very appealing to us compared to some other established software. At the meantime, the size of the package surpasses the limit as imposed by CRAN, thus the old good feature of **S** as with **R** that value both code and data alike has to suffer slightly in that **gap.datasets** and **gap.examples** are spun off as two separate packages; they do deserve a glimpse however for some general ideas.

2 Implementation

The following list shows the data and functions currently available.

* ANALYSIS *

AE3	AE model using nuclear family trios
bt	Bradley-Terry model for contingency table
ccsize	Power and sample size for case-cohort design
cs	Credibel set
fbsize	Sample size for family-based linkage and association design
gc.em	Gene counting for haplotype analysis
gcontrol	genomic control
gcontrol2	genomic control based on p values
gcp	Permutation tests using GENECOUNTING
gc.lambda	Estionmation of the genomic control inflation statistic (lambda)
genecounting	Gene counting for haplotype analysis
gif	Kinship coefficient and genetic index of familiality
grmMCMC	Mixed modeling with genetic relationship matrices
gsmr	Mendelian randomization analysis
hap	Haplotype reconstruction
hap.em	Gene counting for haplotype analysis
hap.score	Score statistics for association of traits with haplotypes
htr	Haplotype trend regression
hwe	Hardy-Weinberg equilibrium test for a multiallelic marker
hwe.cc	A likelihood ratio test of population Hardy-Weinberg equilibrium
hwe.hardy	Hardy-Weinberg equilibrium test using MCMC
invnormal	Inverse normal transformation
kin.morgan	kinship matrix for simple pedigree
LD22	LD statistics for two diallelic markers
LDkl	LD statistics for two multiallelic markers
lambda1000	A standardized estimate of the genomic inflation scaling to a study of 1,000 cases and 1,000 controls
log10p	log10(p) for a standard normal deviate
logp	log(p) for a normal deviate
masize	Sample size calculation for mediation analysis
mia	multiple imputation analysis for hap
mtdt	Transmission/disequilibrium test of a multiallelic marker
mtdt2	Transmission/disequilibrium test of a multiallelic marker by Bradley-Terry model
mvmeta	Multivariate meta-analysis based on generalized least squares
pbsize	Power for population-based association design
pbsize2	Power for case-control association design
pfc	Probability of familial clustering of disease
pfc.sim	Probability of familial clustering of disease
pgc	Preparing weight for GENECOUNTING
print.hap.score	Print a hap.score object
s2k	Statistics for 2 by K table
sentinels	Sentinel identification from GWAS summary statistics
tscc	Power calculation for two-stage case-control design

* GRAPHICS *

asplot	Regional association plot
ESplot	Effect-size plot
circos.cnvplot	circos plot of CNVs
circos.cis.vs.trans.plot	circos plot of cis/trans classification
circos.mhplot	circos Manhattan plot with gene annotation
cnvplot	genomewide plot of CNVs
METAL_forestplot	forest plot as R/meta's forest for METAL outputs
makeRLEplot	make relative log expression plot
mhplot	Manhattan plot
mhplot2	Manhattan plot with annotations
mhplot2d	2D Manhattan plot
mhplot3d	3D Manhattan plot
mhplot.trunc	truncated Manhattan plot
miamiplot	Miami plot
pedtodot	Converting pedigree(s) to dot file(s)
plot.hap.score	Plot haplotype frequencies versus haplotype score statistics
qqfun	Quantile-comparison plots
qqunif	Q-Q plot for uniformly distributed random variable

* UTILITIES *

SNP	Functions for single nucleotide polymorphisms (SNPs)
BFDP	Bayesian false-discovery probability
FPRP	False-positive report probability
ab	Test/Power calculation for mediating effect
b2r	Obtain correlation coefficients and their variance-covariances
chow.test	Chow's test for heterogeneity in two regressions
chr_pos_a1_a2	Form SNPID from chromosome, position and alleles
cis.vs.trans.classification	a cis/trans classifier
comp.score	score statistics for testing genetic linkage of quantitative trait
GRM functions	ReadGRM, ReadGRMBin, ReadGRMLINK, ReadGRMPCA, WriteGRM, WriteGRMBin, WriteGRMSAS
heritability functions	handle genomic relationship matrix involving other software h2G, VR, h2GC, h2l give point estimates as with their variances for continuous traits and binary traits under liability threshold model and case-control sampling
h2	Heritability estimation according to twin correlations for case-control studies
klem	Haplotype frequency estimation based on a genotype table of two multiallelic markers
makeped	A function to prepare pedigrees in post-MAKEPED format
metap	Meta-analysis of p values
metareg	Fixed and random effects model for meta-analysis
muvar	Means and variances under 1- and 2- locus (diallelic) QTL model
read.ms.output	A utility function to read ms output
snptest_sample	A utility to generate SNPTEST sample file
twinan90	Classic twin models
whscore	Whittemore-Halpern scores for allele-sharing
weighted.median	Weighted median with interpolation

Assuming proper installation, you will be able to obtain the list by typing
`library(help=gap)` or view the list within a web browser via `help.start()`.
See Appendix on how to obtain a full list of functions.

A PDF version of this file can be viewed with command `vignette("gap", package="gap")`.

You can cut and paste examples at end of each function's documentation.

Both *genecounting* and *hap* are able to handle SNPs and multiallelic markers, with the former being flexible enough to include features such as X-linked data and the latter being able to handle large number of SNPs. But they are unable to recode allele labels automatically, so functions *gc.em* and *hap.em*

are in *haplo.em* format and used by a modified function *hap.score* in association testing.

It is notable that multilocus data are handled differently from that in **hwde** and elegant definitions of basic genetic data can be found in the **genetics** package.

Incidentally, I found my C mixed-radix sorting routine as in Zhao and Sham (2003) is much faster than R's internal function.

With exceptions such as function *pfc* which is very computer-intensive, most functions in the package can easily be adapted for analysis of large datasets involving either SNPs or multiallelic markers. Some are utility functions, e.g. *muvar* and *whscore*, which will be part of the other analysis routines in the future.

The benefit with R compared to standalone programs is that for users, all functions have unified format. For developers, it is able to incorporate their C/C++ programs more easily and avoid repetitive work such as preparing own routines for matrix algebra and linear models. Further advantage can be taken from packages in **Bioconductor**, which are designed and written to deal with large number of genes.

3 Independent programs

To facilitate comparisons and individual preferences, The source codes for 2LD, EHPLUS, GENECOUNTING, HAP, now hosted at GitHub, have enjoyed great popularity ahead of the genomewide association studies (GWAS) therefore are likely to be more familiar than their R counterparts in **gap**. However, you need to follow their instructions to compile for a particular computer system.

I have included ms code (which is required by **read.ms.output**) and .xls files to accompany *read.ms.output* and *FPRP* and *BFDP* functions as with a classic twin example for ACE model in **OpenMx**. The package is now available from CRAN.

For these models it is actually simpler to use facilities as in package **mets**, which I now suggest.

A final category is *twinan90*, which is now dropped from the package function list due to difficulty to keep up with the requirements by the R environment but nevertheless you will still be able to compile and use otherwise.

4 Demos

You can also try several simple examples via *demos*:

```
library(gap)
demo(gap)
```

5 Examples

I would like to highlight *pedtodot*, *pbsize* and *ccsize* functions used for pedigree drawing and power/sample calculations in a genome-wide association study as reported in Zhao (2007).

5.1 Pedigree drawing

I have included the original file for the *R News* as well as put examples in separate vignettes. They can be accessed via `vignette("rnews", package="gap.examples")` and `vignette("pedtodot", package="gap.examples")`, respectively.

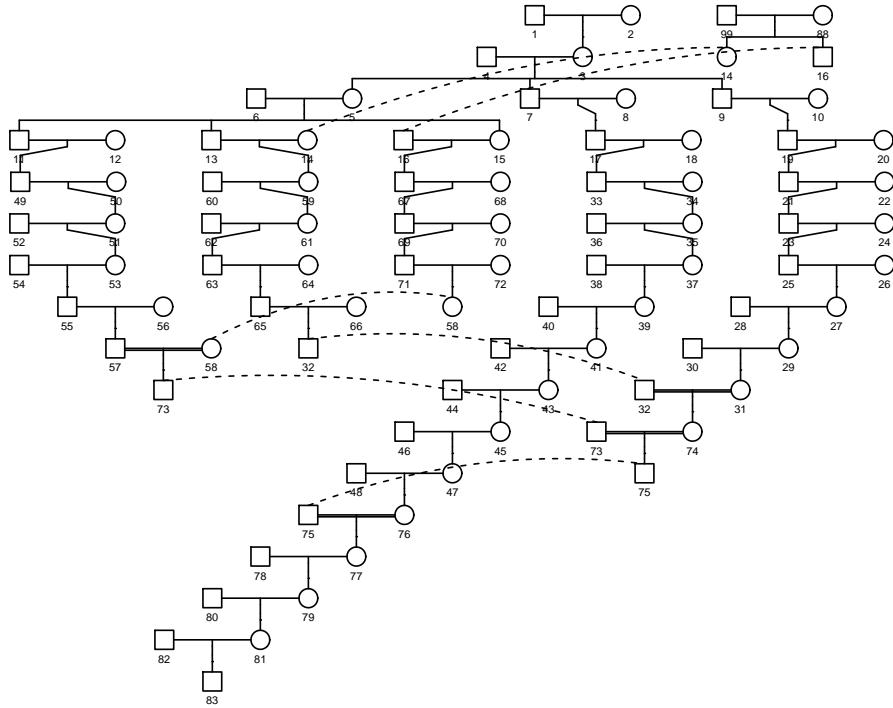
5.2 Kinship calculation

Next, I will provide an example for kinship calculation using *kin.morgan*. It is recommended that individuals in a pedigree are ordered so that parents always precede their children. In this regard, package **pedigree** can be used, and package **kinship2** can be used to produce pedigree diagram as with kinship matrix.

Pedigree diagram

The pedigree diagram is as follows,

```
> library(gap)
> # pedigree diagram
> data(lukas)
> library(kinship2)
> ped <- with(lukas, pedigree(id,father,mother,sex))
> plot(ped,cex=0.4)
```



Kinship calculation

We then turn to the kinship calculation.

```

> # unordered individuals
> library(gap)
> gk1 <- kin.morgan(lukas)
> write.table(gk1$kin.matrix, "results/gap_1.txt", quote=FALSE)
> library(kinship2)
> kk1 <- kinship(lukas[,1], lukas[,2], lukas[,3])
> write.table(kk1, "results/kinship_1.txt", quote=FALSE)
> d <- gk1$kin.matrix-kk1
> sum(abs(d))

[1] 2.443634

> # order individuals so that parents precede their children
> library(pedigree)

```

```

> op <- orderPed(lukas)
> olukas <- lukas[order(op),]
> gk2 <- kin.morgan(olukas)
> write.table(olukas,"olukas.csv",quote=FALSE)
> write.table(gk2$kin.matrix,"results/gap_2.txt",quote=FALSE)
> kk2 <- kinship(olukas[,1],olukas[,2],olukas[,3])
> write.table(kk2,"results/kinship_2.txt",quote=FALSE)
> z <- gk2$kin.matrix-kk2
> sum(abs(z))

[1] 0

```

We see that in the second case, the result agrees with **kinship2**.

5.3 Study design

Family-based design

The example involving family-based design is as follows,

```

> library(gap)
> models <- matrix(c(
+     4.0, 0.01,
+     4.0, 0.10,
+     4.0, 0.50,
+     4.0, 0.80,
+     2.0, 0.01,
+     2.0, 0.10,
+     2.0, 0.50,
+     2.0, 0.80,
+     1.5, 0.01,
+     1.5, 0.10,
+     1.5, 0.50,
+     1.5, 0.80), ncol=2, byrow=TRUE)
> outfile <- "fbsize.txt"
> cat("gamma","p","Y","N_asp","P_A","H1","N_tdt","H2","N_asp/tdt","L_o","L_s\n",
+     file=outfile,sep="\t")
> for(i in 1:12) {
+   g <- models[i,1]
+   p <- models[i,2]
+   z <- fbsize(g,p)
+   cat(z$gamma,z$p,z$y,z$n1,z$pA,z$h1,z$n2,z$h2,z$n3,z$\lambda_0,z$\lambda_{\beta},
+       file=outfile,append=TRUE,sep="\t")
+   cat("\n",file=outfile,append=TRUE)
+ }

```

```

> table1 <- read.table(outfile,header=TRUE,sep="\t")
> nc <- c(4,7,9)
> table1[,nc] <- ceiling(table1[,nc])
> dc <- c(3,5,6,8,10,11)
> table1[,dc] <- round(table1[,dc],2)
> unlink(outfile)
> # APOE-4, Scott WK, Pericak-Vance, MA & Haines JL
> # Genetic analysis of complex diseases 1327
> g <- 4.5
> p <- 0.15
> cat("\nAlzheimer's:\n\n")

```

Alzheimer's:

```

> fbsize(g,p)

$gamma
[1] 4.5

$p
[1] 0.15

$y
[1] 0.6256916

$n1
[1] 162.6246

$pA
[1] 0.8181818

$h1
[1] 0.4598361

$n2
[1] 108.994

$h2
[1] 0.6207625

$n3
[1] 39.97688

$lambda

```

```

[1] 1.671594

$lambda
[1] 1.784353

> table1

  gamma     p     Y   N_asp   P_A    H1  N_tdt    H2 N_asp.tdt  L_o  L_s
1  4.0 0.01 0.52    6402 0.80 0.05  1201 0.11      257 1.08 1.09
2  4.0 0.10 0.60     277 0.80 0.35   165 0.54      53 1.48 1.54
3  4.0 0.50 0.58     446 0.80 0.50   113 0.42      67 1.36 1.39
4  4.0 0.80 0.53    3024 0.80 0.24   244 0.16     177 1.12 1.13
5  2.0 0.01 0.50 445964 0.67 0.03  6371 0.04    2155 1.01 1.01
6  2.0 0.10 0.52    8087 0.67 0.25   761 0.32     290 1.07 1.08
7  2.0 0.50 0.53    3753 0.67 0.50   373 0.47     197 1.11 1.11
8  2.0 0.80 0.51   17909 0.67 0.27   701 0.22     431 1.05 1.05
9  1.5 0.01 0.50 6944779 0.60 0.02 21138 0.03    8508 1.00 1.00
10 1.5 0.10 0.51  101926 0.60 0.21  2427 0.25   1030 1.02 1.02
11 1.5 0.50 0.51   27048 0.60 0.50   1039 0.49     530 1.04 1.04
12 1.5 0.80 0.51  101926 0.60 0.29   1820 0.25   1030 1.02 1.02

```

Population-based design

The example involving population-based design is as follows,

```

> library(gap)
> kp <- c(0.01,0.05,0.10,0.2)
> models <- matrix(c(
+   4.0, 0.01,
+   4.0, 0.10,
+   4.0, 0.50,
+   4.0, 0.80,
+   2.0, 0.01,
+   2.0, 0.10,
+   2.0, 0.50,
+   2.0, 0.80,
+   1.5, 0.01,
+   1.5, 0.10,
+   1.5, 0.50,
+   1.5, 0.80), ncol=2, byrow=TRUE)
> outfile <- "pbsize.txt"
> cat("gamma", "p", "p1", "p5", "p10", "p20\n", sep="\t", file=outfile)
> for(i in 1:dim(models)[1])
+ {
+   g <- models[i,1]

```

```

+   p <- models[i,2]
+   n <- vector()
+   for(k in kp) n <- c(n,ceiling(pbsize(k,g,p)))
+   cat(models[i,1:2],n,sep="\t",file=outfile,append=TRUE)
+   cat("\n",file=outfile,append=TRUE)
+ }
> table5 <- read.table(outfile,header=TRUE,sep="\t")
> table5

  gamma    p      p1      p5     p10     p20
1 4.0 0.01 46681 8959 4244 1887
2 4.0 0.10 8180 1570 744 331
3 4.0 0.50 10891 2091 991 441
4 4.0 0.80 31473 6041 2862 1272
5 2.0 0.01 403970 77530 36725 16323
6 2.0 0.10 52709 10116 4792 2130
7 2.0 0.50 35285 6772 3208 1426
8 2.0 0.80 79391 15237 7218 3208
9 1.5 0.01 1599920 307056 145448 64644
10 1.5 0.10 192105 36869 17465 7762
11 1.5 0.50 98013 18811 8911 3961
12 1.5 0.80 192105 36869 17465 7762

```

Case-cohort design

For case-cohort design, we obtain results for ARIC and EPIC studies.

```

> library(gap)
> # ARIC study
> outfile <- "aric.txt"
> n <- 15792
> pD <- 0.03
> p1 <- 0.25
> alpha <- 0.05
> theta <- c(1.35,1.40,1.45)
> beta1 <- 0.8
> s_nb <- c(1463,722,468)
> cat("n","pD","p1","hr","q","power","ssize\n",file=outfile,sep="\t")
> for(i in 1:3)
+ {
+   q <- s_nb[i]/n
+   power <- ccsizer(n,q,pD,p1,alpha,log(theta[i]))
+   ssize <- ccsizer(n,q,pD,p1,alpha,log(theta[i]),beta1)
+   cat(n,"\t",pD,"\t",p1," \t",theta[i]," \t",q," \t",
+       signif(power,3)," \t",ssize," \n",

```

```

+           file=outfile,append=TRUE)
+ }
> read.table(outfile,header=TRUE,sep="\t")

      n   pD   p1    hr        q power ssize
1 15792 0.03 0.25 1.35 0.09264184    0.8 1463
2 15792 0.03 0.25 1.40 0.04571935    0.8   722
3 15792 0.03 0.25 1.45 0.02963526    0.8   468

> unlink(outfile)
> # EPIC study
> outfile <- "epic.txt"
> n <- 25000
> alpha <- 0.00000005
> power <- 0.8
> s_pD <- c(0.3,0.2,0.1,0.05)
> s_p1 <- seq(0.1,0.5,by=0.1)
> s_hr <- seq(1.1,1.4,by=0.1)
> cat("n","pD","p1","hr","alpha","ssize\n",file=outfile,sep="\t")
> # direct calculation
> for(pD in s_pD)
+ {
+   for(p1 in s_p1)
+   {
+     for(hr in s_hr)
+     {
+       ssize <- ccsize(n,q,pD,p1,alpha,log(hr),power)
+       if (ssize>0) cat(n,"\t",pD,"\t",p1,"\t",hr,"\t",alpha,"\t",
+                         ssize,
+                         file=outfile,append=TRUE)
+     }
+   }
+ }
> read.table(outfile,header=TRUE,sep="\t")

      n   pD   p1    hr alpha ssize
1 25000 0.3 0.1 1.3 5e-08 14391
2 25000 0.3 0.1 1.4 5e-08  5732
3 25000 0.3 0.2 1.2 5e-08 21529
4 25000 0.3 0.2 1.3 5e-08  5099
5 25000 0.3 0.2 1.4 5e-08  2613
6 25000 0.3 0.3 1.2 5e-08 11095
7 25000 0.3 0.3 1.3 5e-08  3490
8 25000 0.3 0.3 1.4 5e-08  1882

```

```

9 25000 0.3 0.4 1.2 5e-08 8596
10 25000 0.3 0.4 1.3 5e-08 2934
11 25000 0.3 0.4 1.4 5e-08 1611
12 25000 0.3 0.5 1.2 5e-08 7995
13 25000 0.3 0.5 1.3 5e-08 2786
14 25000 0.3 0.5 1.4 5e-08 1538
15 25000 0.2 0.1 1.4 5e-08 9277
16 25000 0.2 0.2 1.3 5e-08 7725
17 25000 0.2 0.2 1.4 5e-08 3164
18 25000 0.2 0.3 1.3 5e-08 4548
19 25000 0.2 0.3 1.4 5e-08 2152
20 25000 0.2 0.4 1.2 5e-08 20131
21 25000 0.2 0.4 1.3 5e-08 3648
22 25000 0.2 0.4 1.4 5e-08 1805
23 25000 0.2 0.5 1.2 5e-08 17120
24 25000 0.2 0.5 1.3 5e-08 3422
25 25000 0.2 0.5 1.4 5e-08 1713
26 25000 0.1 0.2 1.4 5e-08 8615
27 25000 0.1 0.3 1.4 5e-08 3776
28 25000 0.1 0.4 1.3 5e-08 13479
29 25000 0.1 0.4 1.4 5e-08 2824
30 25000 0.1 0.5 1.3 5e-08 10837
31 25000 0.1 0.5 1.4 5e-08 2606

```

```
> unlink(outfile)
```

5.4 Graphics examples

I now include some figures from the documentation that may be of interest.

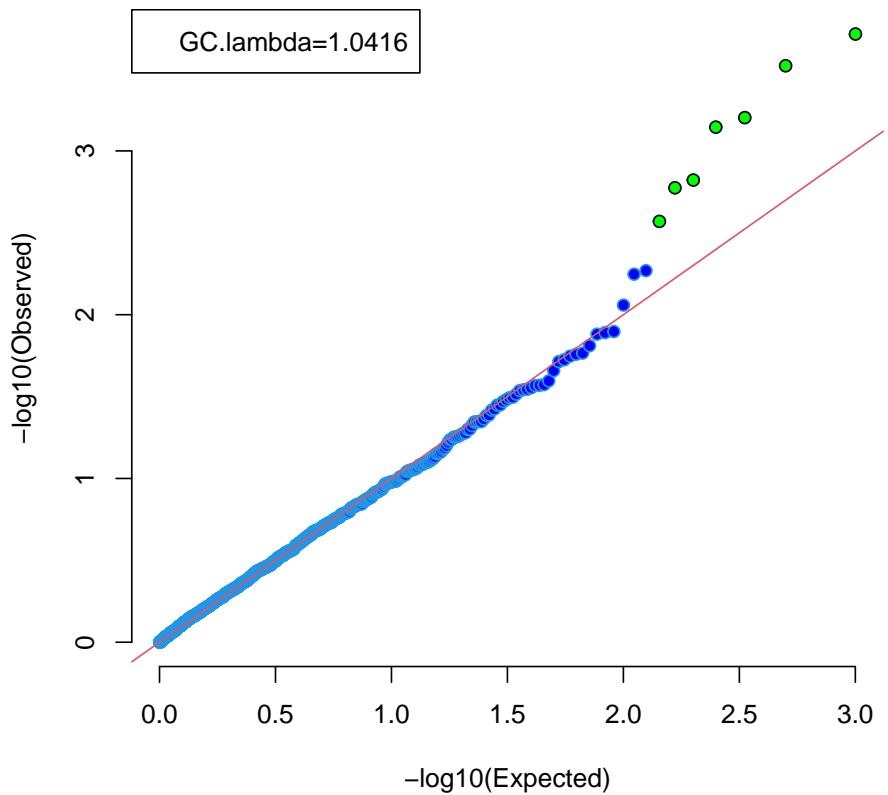
Genome-wide association

The following code is used to obtain a Q-Q plot via *qqunif* function,

```

> library(gap)
> u_obs <- runif(1000)
> r <- qqunif(u_obs,pch=21,bg="blue",bty="n")
> u_exp <- r$y
> hits <- u_exp >= 2.30103
> points(r$x[hits],u_exp[hits],pch=21,bg="green")
> legend("topleft",sprintf("GC.lambda=% .4f",gc.lambda(u_obs)))

```



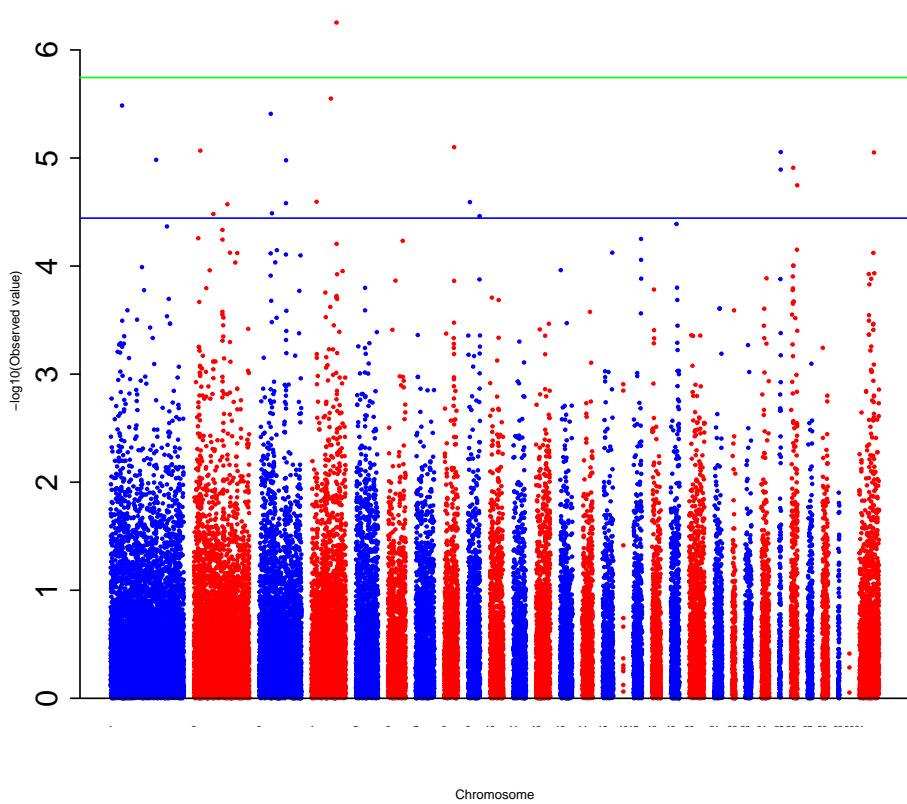
Based on a chicken genome scan data, the code below generates a Manhattan plot, demonstrating the use of gaps to separate chromosomes.

```
> library(gap.datasets)
> ord <- with(w4,order(chr,pos))
> w4 <- w4[ord,]
> oldpar <- par()
> par(cex=0.6)
> colors <- c(rep(c("blue","red"),15),"red")
> mhtplot(w4,control=mht.control(colors=colors,gap=1000),pch=19,srt=0)

Plotting points  1 - 7244
Plotting points  7245 - 12710
Plotting points  12711 - 16875
Plotting points  16876 - 20271
Plotting points  20272 - 22463
Plotting points  22464 - 24192
Plotting points  24193 - 26021
```

```
Plotting points 26022 - 27371
Plotting points 27372 - 28558
Plotting points 28559 - 29860
Plotting points 29861 - 31101
Plotting points 31102 - 32504
Plotting points 32505 - 33690
Plotting points 33691 - 34708
Plotting points 34709 - 35737
Plotting points 35738 - 35748
Plotting points 35749 - 36594
Plotting points 36595 - 37451
Plotting points 37452 - 38281
Plotting points 38282 - 39765
Plotting points 39766 - 40531
Plotting points 40532 - 40831
Plotting points 40832 - 41432
Plotting points 41433 - 42175
Plotting points 42176 - 42343
Plotting points 42344 - 42983
Plotting points 42984 - 43462
Plotting points 43463 - 44022
Plotting points 44023 - 44131
Plotting points 44132 - 44134
Plotting points 44135 - 46059

> axis(2,cex.axis=2)
> suggestiveline <- -log10(3.60036E-05)
> genomewideline <- -log10(1.8E-06)
> abline(h=suggestiveline, col="blue")
> abline(h=genomewideline, col="green")
> abline(h=0)
```



The code below obtains a Manhattan plot with gene annotation,

```

> data <- with(mhtdata, cbind(chr, pos, p))
> glist <- c("IRS1", "SPRY2", "FTO", "GRIK3", "SNED1", "HTR1A", "MARCH3", "WISP3",
+           "PPP1R3B", "RP1L1", "FDFT1", "SLC39A14", "GFRA1", "MC4R")
> hdata <- subset(mhtdata, gene %in% glist)[c("chr", "pos", "p", "gene")]
> color <- rep(c("lightgray", "gray"), 11)
> glen <- length(glist)
> hcolor <- rep("red", glen)
> par(las=2, xpd=TRUE, cex.axis=1.8, cex=0.4)
> ops <- mht.control(colors=color, yline=1.5, xline=3)
> hops <- hmht.control(data=hdata, colors=hcolor)
> mhtplot(data, ops, hops, pch=19)

Plotting points  1 - 12123
Plotting points  12124 - 26444
Plotting points  26445 - 37326
Plotting points  37327 - 47549

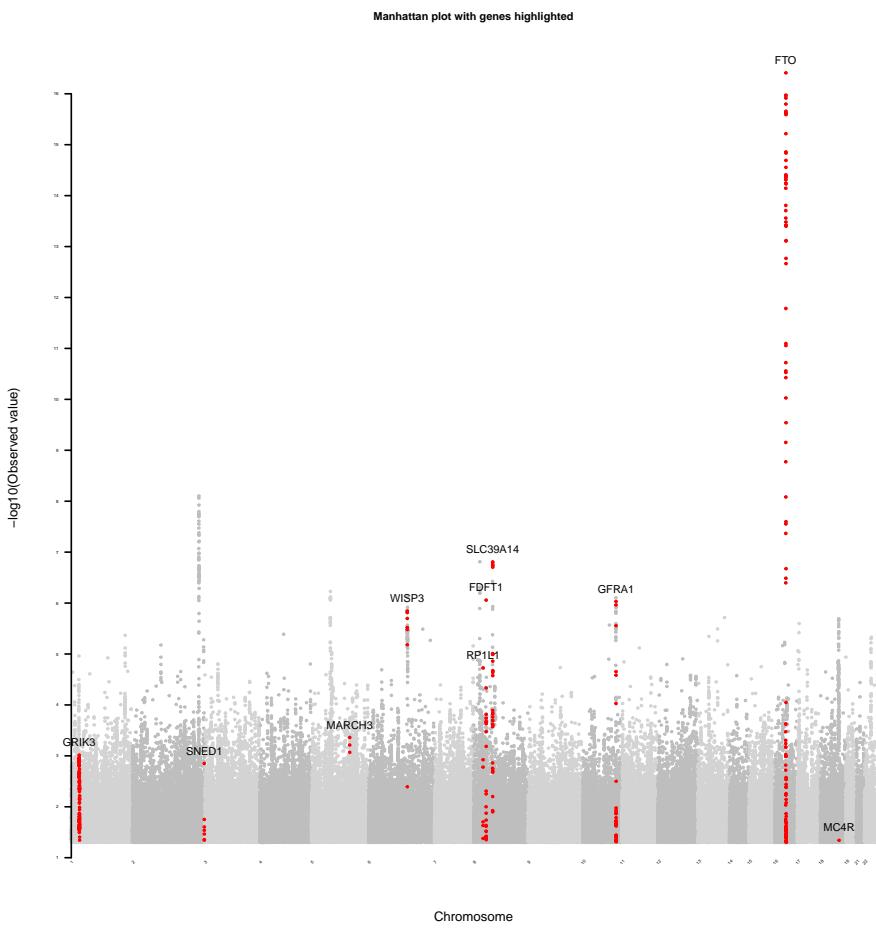
```

```

Plotting points 47550 - 58877
Plotting points 58878 - 71908
Plotting points 71909 - 79690
Plotting points 79691 - 90464
Plotting points 90465 - 101267
Plotting points 101268 - 109000
Plotting points 109001 - 116159
Plotting points 116160 - 124094
Plotting points 124095 - 130329
Plotting points 130330 - 134176
Plotting points 134177 - 139300
Plotting points 139301 - 143751
Plotting points 143752 - 148345
Plotting points 148346 - 153379
Plotting points 153380 - 155466
Plotting points 155467 - 157052
Plotting points 157053 - 159312
... highlighting 1559 - 1657 GRIK3
... highlighting 26343 - 26349 SNED1
... highlighting 55142 - 55144 MARCH3
... highlighting 66533 - 66539 WISP3
... highlighting 81546 - 81551 RP1L1
... highlighting 82146 - 82168 FDFT1
... highlighting 83425 - 83458 SLC39A14
... highlighting 107866 - 107894 GFRA1
... highlighting 141457 - 141576 FTO
... highlighting 152037 - 152037 MC4R

> axis(2, pos=2, at=1:16, cex.axis=0.5)
> title("Manhattan plot with genes highlighted", cex.main=1)

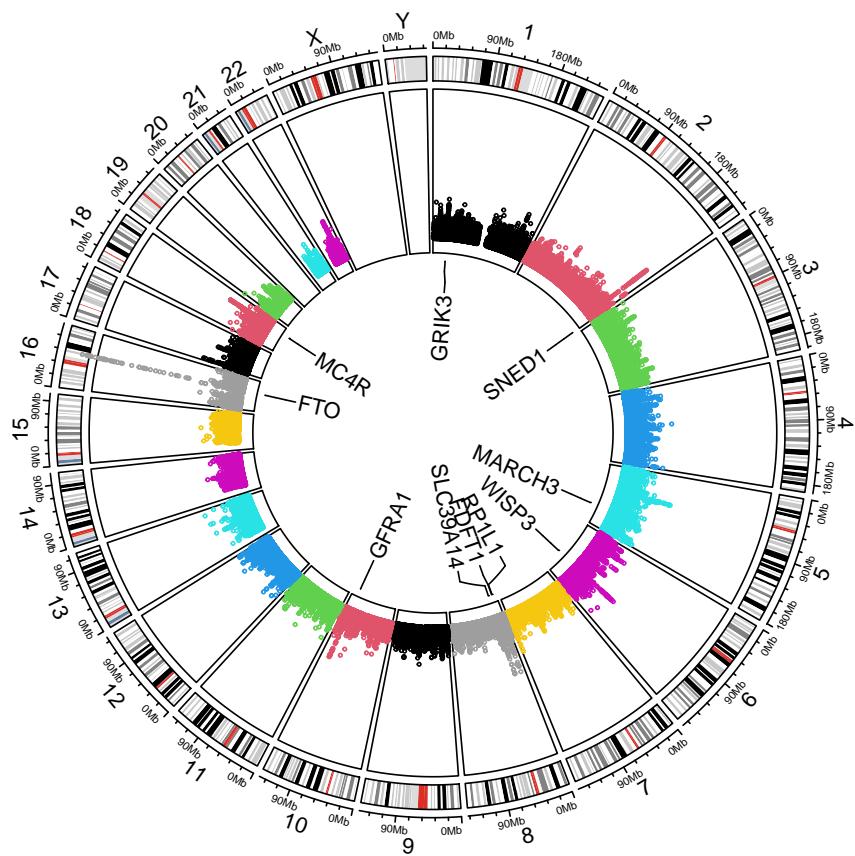
```



All these look familiar, so revised form of the function called **mhtplot2** was created for additional features such as centering the chromosome ticks, allowing for more sophisticated coloring schemes, using prespecified fonts, etc. Please refer to the function's documentation example.

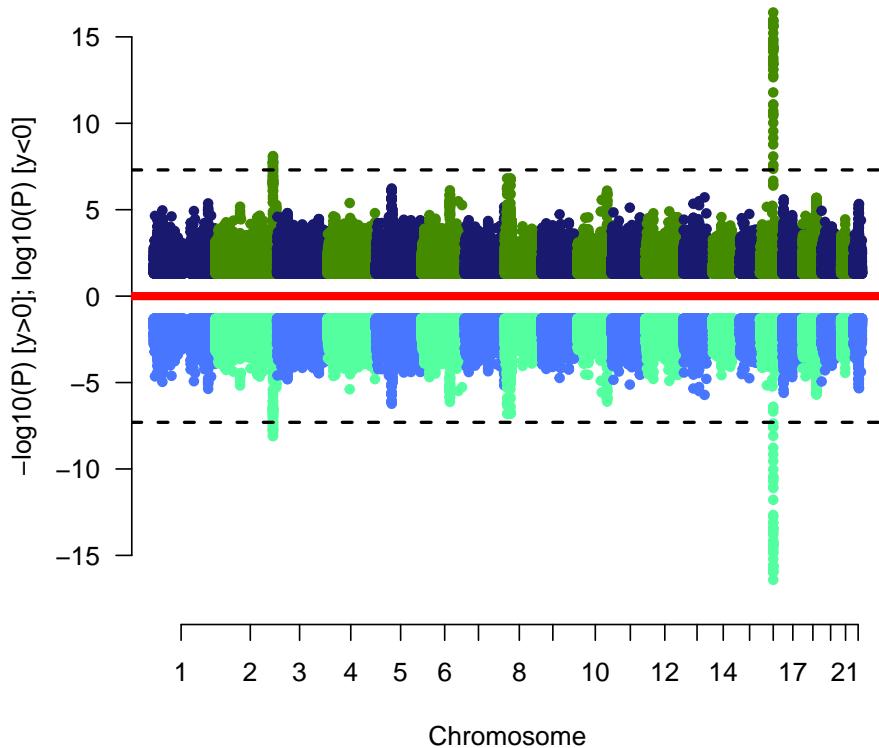
We could also go further with a circos Manhattan plot,

```
> circos.mhtplot(mhtdata, glist)
```



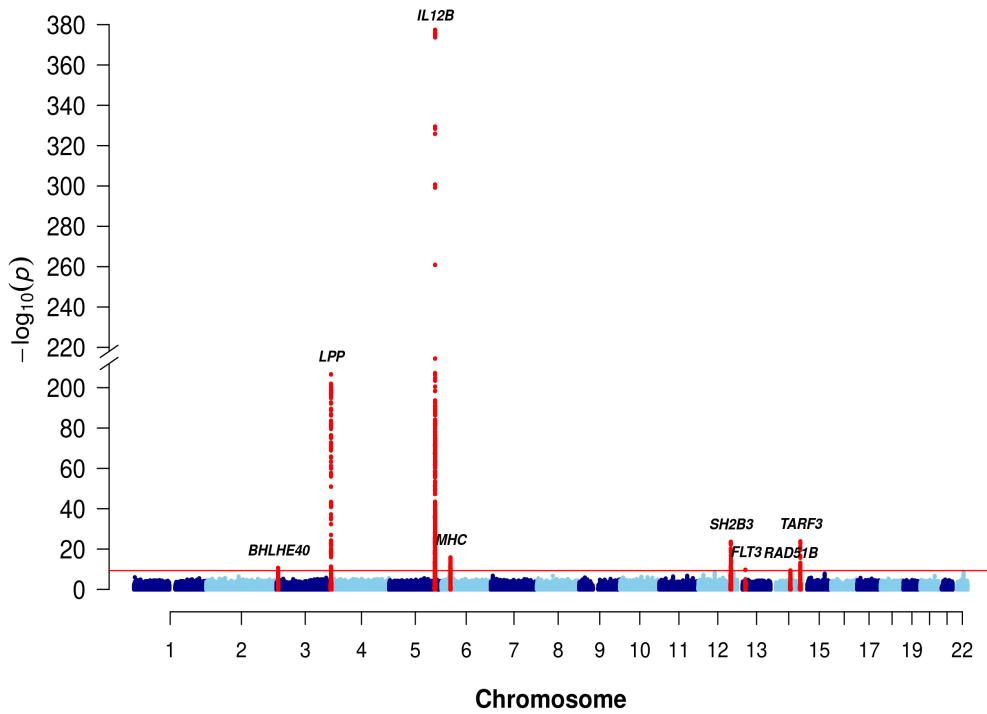
We now experiment with Miami plot,

```
> mhtdata <- within(mhtdata, {pr=p})
> miamiplot(mhtdata, chr="chr", bp="pos", p="p", pr="pr",.snp="rsn")
```



We now illustrate with a truncated Manhattan plot,

```
> par(oma=c(0,0,0,0), mar=c(5,6.5,1,1))
> mhtplot.trunc(IL.12B, chr="Chromosome", bp="Position", z="Z",
+  .snp="MarkerName",
+   suggestiveline=FALSE, genomewideline=-log10(5e-10),
+   cex.mtext=1.2, cex.text=0.7,
+   annotatelog10P=-log10(5e-10), annotateTop = FALSE,
+   highlight=with(genes,gene),
+   mtext.line=3, y.brk1=115, y.brk2=200, delta=0.01,
+   cex.axis=1.2, cex.y=1.2, cex=0.5, font=2, font.axis=1,
+   y.ax.space=20,
+   col = c("blue4", "skyblue"))
+ )
```

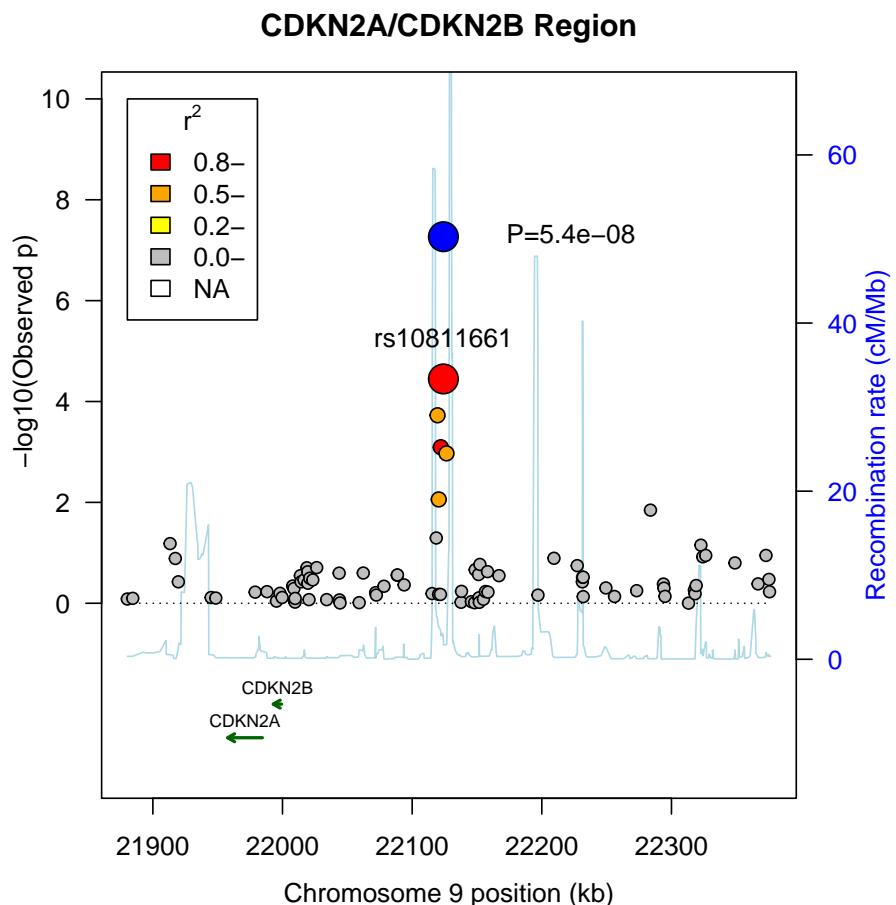


The code below obtains a regional association plot with the *asplot* function,

```
> asplot(CDKN1locus, CDKNmap, CDKNgenes, best.pval=5.4e-8, sf=c(3,6))

- CDKN2A
- CDKN2B

> title("CDKN2A/CDKN2B Region")
```

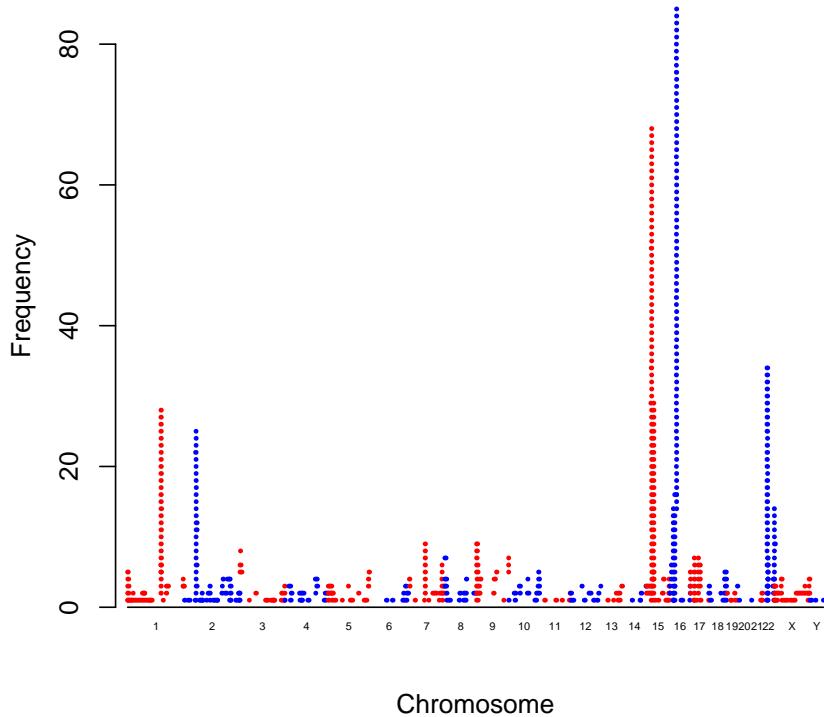


The function predates the currently popular **locuszoom** software but leaves the option open for generating such plots on the fly and locally.
 Note that all these can serve as templates to customize features of your own.

Copy number variation

A plot of copy number variation (CNV) is shown here,

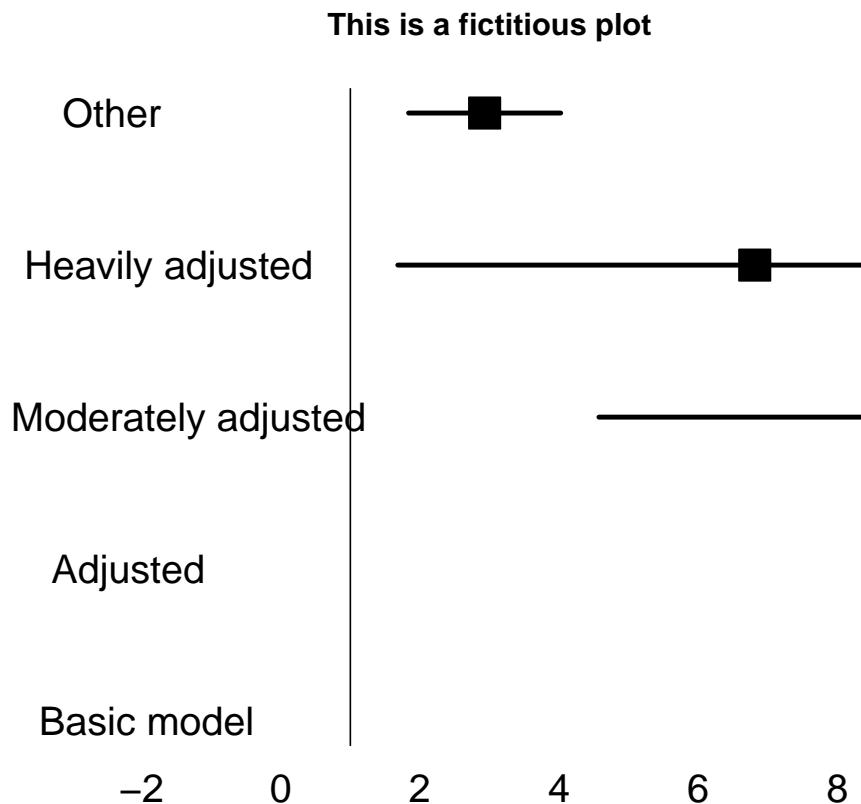
```
> cnvplot(cnv)
```



Effect size plot

The code below obtains an effect size plot via the ESplot function.

```
> library(gap)
> options(stringsAsFactors=FALSE)
> testdata <- data.frame(models=c("Basic model", "Adjusted",
+                               "Moderately adjusted",
+                               "Heavily adjusted", "Other"),
+ + OR = c(4.5, 3.5, 2.5, 1.5, 1),
+ + SElogOR = c(0.2, 0.1, 0.5, 0.5, 0.2))
> ESplot(testdata, v=1)
> title("This is a fictitious plot")
```



Forest plot

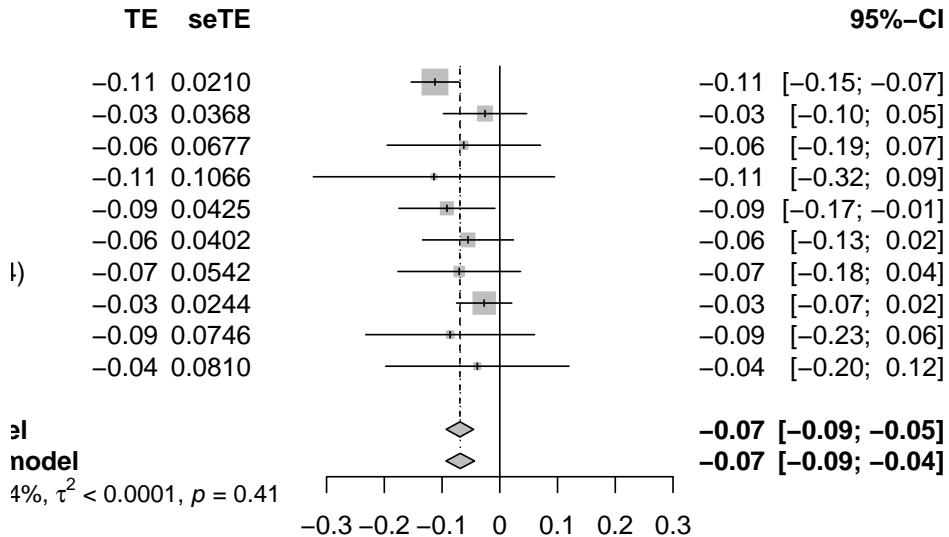
It is possible to draw many forest plots given a list of variants; an example is given (only the first one here) here

```
> data(OPG)
> METAL_forestplot(OPGtbl[1,],OPGall,OPGrsid,width=8.75,height=5)

[1] "1-OPG:chr8:119440018_C_G"
    CHR      POS STRAND      N EFFECT_ALLELE REFERENCE_ALLELE CODE_ALL_FQ
3102   8 119440018    <NA>  4896          G             C  0.6544730
3103   8 119440018    <NA>  1496          C             G  0.3963900
3104   8 119440018        +   487          G             C  0.6292000
3105   8 119440018        +   185          G             C  0.6567570
3106   8 119440018    <NA> 1064          G             C  0.6318490
3107   8 119440018    <NA>   866          C             G  0.3350000
3108   8 119440018        +   444          C             G  0.3446000
```

3109	8	119440018	+	2951	G		C	0.6231345			
3110	8	119440018	<NA>	344	C		G	0.3676000			
3111	8	119440018	<NA>	300	C		G	0.3631000			
		BETA	SE	PVAL	RSQ	RSQ_IMP	IMP	prot	study		
3102	0.11223700	0.02103850	9.994910e-08		NA	0.989189	NA	OPG	INTERVAL		
3103	-0.02561350	0.03679860	4.865080e-01		NA	NA	NA	OPG	BioFinder		
3104	0.06230000	0.06770000	3.582000e-01		NA	0.959100	1	OPG	EGCUT		
3105	0.11400000	0.10660000	2.864000e-01	0.006207	0.976000	1	OPG	MadCam			
3106	0.09158860	0.04245590	3.121030e-02		NA	0.957157	NA	OPG	KORA		
3107	-0.05505878	0.04021724	1.709886e-01		NA	NA	NA	OPG	NSPHS		
3108	-0.07024000	0.05416000	1.954000e-01		NA	0.968610	1	OPG	RECOMBINE		
3109	0.02705780	0.02440500	2.675600e-01		NA	0.989080	1	OPG	STABILITY		
3110	-0.08600000	0.07460000	2.500000e-01		NA	1.045800	NA	OPG	STANLEY		
3111	-0.03890000	0.08100000	6.310000e-01		NA	0.984500	NA	OPG	STANLEY		
		MarkerName									
3102	chr8:119440018_C_G										
3103	chr8:119440018_C_G										
3104	chr8:119440018_C_G										
3105	chr8:119440018_C_G										
3106	chr8:119440018_C_G										
3107	chr8:119440018_C_G										
3108	chr8:119440018_C_G										
3109	chr8:119440018_C_G										
3110	chr8:119440018_C_G										
3111	chr8:119440018_C_G										
		A1	A2	EFFECT_ALLELE	REFERENCE_ALLELE	a1	a2				
[1,]	"C"	"G"	"G"		"C"		"C"	"G"	"0.1122"	"-0.1122"	
[2,]	"C"	"G"	"C"		"G"		"C"	"G"	"-0.0256"	"-0.0256"	
[3,]	"C"	"G"	"G"		"C"		"C"	"G"	"0.0623"	"-0.0623"	
[4,]	"C"	"G"	"G"		"C"		"C"	"G"	"0.1140"	"-0.1140"	
[5,]	"C"	"G"	"G"		"C"		"C"	"G"	"0.0916"	"-0.0916"	
[6,]	"C"	"G"	"C"		"G"		"C"	"G"	"-0.0551"	"-0.0551"	
[7,]	"C"	"G"	"C"		"G"		"C"	"G"	"-0.0702"	"-0.0702"	
[8,]	"C"	"G"	"G"		"C"		"C"	"G"	"0.0271"	"-0.0271"	
[9,]	"C"	"G"	"C"		"G"		"C"	"G"	"-0.0860"	"-0.0860"	
[10,]	"C"	"G"	"C"		"G"		"C"	"G"	"-0.0389"	"-0.0389"	
prot = OPG	MarkerName = chr8:119440018_C_G	Q = 9.348983	df = 9	p = 0.4057033	I2 = 0						

OPG [chr8:119440018_C_G (rs10955879) (C/G) N=13033]



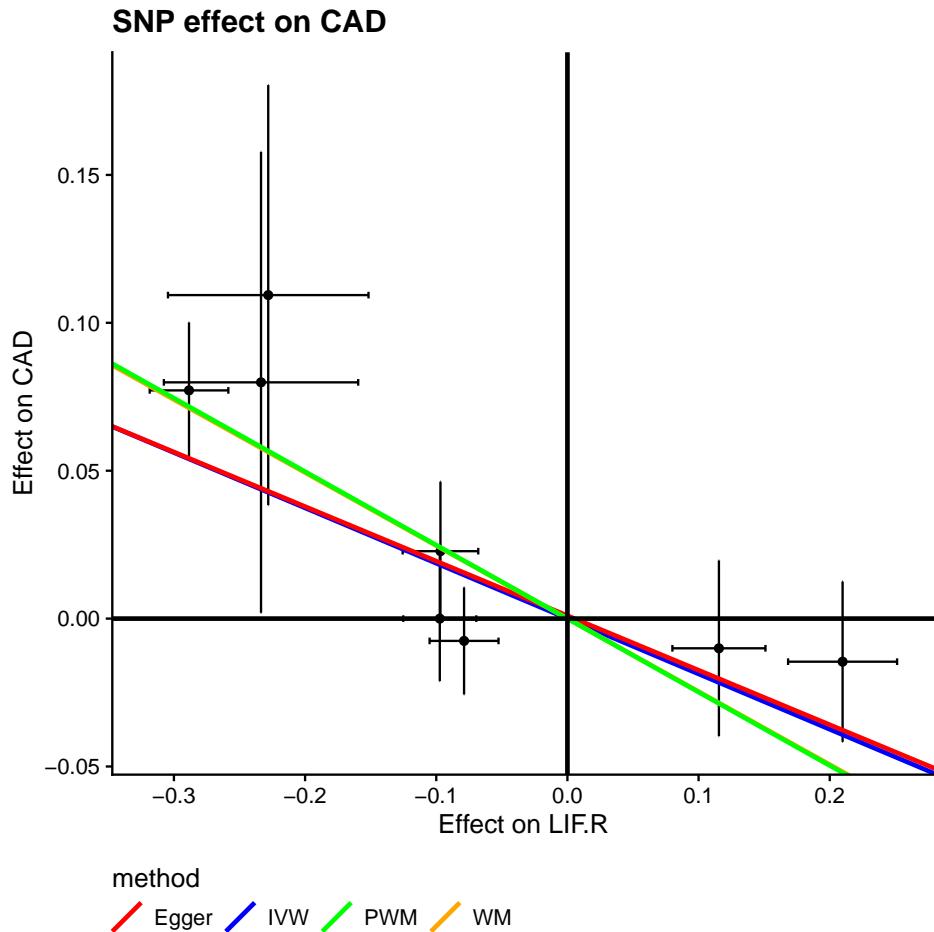
6 Polygenic modeling

In line with the recent surge of interest in the polygenic models, a separate vignette is available through `vignette("h2", package="gap.examples")` demonstrating aspect of the models on heritability.

7 Mendelian randomization

The function `gsmr()` implements several methods and gives effect size plots.

```
> library(cowplot)
> library(ggplot2)
> library(gap)
> r <- gsmr(mr, "LIF.R", c("CAD", "FEV1"))
```



8 Known bugs

Unaware of any bug. However, better memory management is expected.

9 Summary

I believe by now the package should have given you a flavour of initiatives I have made so far in relation to how the project was envisaged. More importantly, it is clear that availability of the package will serve as a platform on which future work can be accumulated and collaboration can be built.

Appendix

Assuming that you have already loaded the package via `library(gap)`, you can use `lsf.str("package:gap")` and `data(package="gap")` to generate

a list of functions and a list of datasets, respectively. If this looks odd to you, you might try `search()` within R to examine what is available in your environment before issuing the `lsf.str` command.

```
[1] ".GlobalEnv"           "package:ggplot2"      "package:cowplot"
[4] "package:gap.datasets" "package:pedigree"     "package:reshape"
[7] "package:HaploSim"     "package:kinship2"    "package:quadprog"
[10] "package:Matrix"       "package:gap"        "package:stats"
[13] "package:graphics"     "package:grDevices"   "package:utils"
[16] "package:datasets"     "package:methods"    "Autoloads"
[19] "package:base"

AE3 : function (model, random, data, seed = 1234, n.sim = 50000, verbose = TRUE)
BFDP : function (a, b, pi1, W, logscale = FALSE)
Cox.T : function (parms, case, control, k)
Cox.est : function (case, ctl, k0, initial)
DevH0dominant : function (parms, case, control, k)
DevH0dominant.est : function (case, ctl, k0, initial)
DevH0recessive : function (parms, case, control, k)
DevH0recessive.est : function (case, ctl, k0, initial)
DevHaGdominant : function (parms, case, control, k)
DevHaGdominant.est : function (case, ctl, k0, initial)
DevHaGrecessive : function (parms, case, control, k)
DevHaGrecessive.est : function (case, ctl, k0, initial)
ESplot : function (ESdat, SE = TRUE, logscale = TRUE, alpha = 0.05, xlim = c(-2,
8), v = 1, ...)
FPRP : function (a, b, pi0, ORlist, logscale = FALSE)
HapDesign : function (HaploEM)
HapFreqSE : function (HaploEM)
KCC : function (model, GRR, p1, K)
LD22 : function (h, n)
LDkl : function (n1 = 2, n2 = 2, h, n, optrho = 2, verbose = FALSE)
MCMCgrm : function (model, prior, data, GRM, eps = 0, n.thin = 10, n.burnin = 3000,
n.iter = 13000, ...)
METAL_forestplot : function (tbl, all, rsid, package = "meta", ...)
PARn : function (p, RRlist)
ReadGRM : function (prefix = 51)
ReadGRMBin : function (prefix, AllN = FALSE, size = 4)
ReadGRMPCA : function (prefix)
ReadGRMLINK : function (prefix, diag = 1)
VR : function (v1, vv1, v2, vv2, c12)
WriteGRM : function (prefix = 51, id, N, GRM)
WriteGRMBin : function (prefix, grm, N, id, size = 4)
WriteGRMSAS : function (grmlist, outfile = "gwas")
```

```

a2g : function (a1, a2)
ab : function (type = "power", n = 25000, a = 0.15, sa = 0.01, b = log(1.19),
             sb = 0.01, alpha = 0.05, fold = 1)
allele.recode : function (a1, a2, miss.val = NA)
asplot : function (locus, map, genes, flanking = 1000, best.pval = NULL, sf = c(4,
                           4), logpmax = 10, pch = 21)
b2r : function (b, s, rho, n)
bt : function (x)
ccsize : function (n, q, pD, p1, alpha, theta, power = NULL, verbose = FALSE)
chow.test : function (y1, x1, y2, x2, x = NULL)
chr_pos_a1_a2 : function (chr, pos, a1, a2, prefix = "chr", seps = c(":", "_", "_"))
circos.cis.vs.trans.plot : function (hits, panel, id, radius = 1e+06)
circos.cnvplot : function (data)
circos.mhtplot : function (data, glist)
cis.vs.trans.classification : function (hits, panel, id, radius = 1e+06)
cnvplot : function (data)
comp.score : function (ibddata = "ibd_dist.out", phenotype = "pheno.dat", mean = 0,
                      var = 1, h2 = 0.3)
cov.invlogit : function (logit.p1, logit.p2, cov.logit)
cs : function (tbl, b = "Effect", se = "StdErr", log_p = NULL, cutoff = 0.95)
fbsize : function (gamma, p, alpha = c(1e-04, 1e-08, 1e-08), beta = 0.2, debug = 0,
                  error = 0)
g2a : function (g)
g2a.c : function (g)
gc.control : function (xdata = FALSE, convl1 = 1, handle.miss = 0, eps = 1e-06, tol
                      maxit = 50, pl = 0.001, assignment = "assign.dat", verbose = T)
gc.em : function (data, locus.label = NA, converge.eps = 1e-06, maxiter = 500,
                  handle.miss = 0, miss.val = 0, control = gc.control())
gc.lambda : function (p)
gcode : function (a1, a2)
gcontrol : function (data, zeta = 1000, kappa = 4, tau2 = 1, epsilon = 0.01, ngib =
                  burn = 50, idum = 2348)
gcontrol2 : function (p, col = palette()[4], lcol = palette()[2], ...)
gcp : function (y, cc, g, handle.miss = 1, miss.val = 0, n.sim = 0, locus.label = NU
                 quietly = FALSE)
genecounting : function (data, weight = NULL, loci = NULL, control = gc.control())
geno.recode : function (geno, miss.val = 0)
getPTE : function (b1, b2, rho, sdx1 = 1, sdx2 = 1)
getb1star : function (b1, b2, rho, sdx1 = 1, sdx2 = 1)
gif : function (data, gifset)
grec2g : function (h, n, t)
gsmr : function (data, X, Y, alpha = 0.05, other_plots = FALSE)
h2 : function (mzDat = NULL, dzDat = NULL, rmz = NULL, rdz = NULL, nmz = NULL,
              ndz = NULL, selV = NULL)

```

```

h2.jags : function (y, x, G, eps = 1e-04, sigma.p = 0, sigma.r = 1, parms = c("b",
  "p", "r", "h2"), ...)
h2G : function (V, VCOV, verbose = TRUE)
h2GE : function (V, VCOV, verbose = TRUE)
h2l : function (K = 0.05, P = 0.5, h2, se, verbose = TRUE)
hap : function (id, data, nloci, loci = rep(2, nloci), names = paste("loci",
  1:nloci, sep = ""), control = hap.control())
hap.control : function (mb = 0, pr = 0, po = 0.001, to = 0.001, th = 1, maxit = 100,
  n = 0, ss = 0, rs = 0, rp = 0, ro = 0, rv = 0, sd = 0, mm = 0, mi = 0,
  mc = 50, ds = 0.1, de = 0, q = 0, hapfile = "hap.out", assignfile = "assign.out")
hap.em : function (id, data, locus.label = NA, converge.eps = 1e-06, maxiter = 500,
  miss.val = 0)
hap.score : function (y, geno, trait.type = "gaussian", offset = NA, x.adj = NA, skip =
  locus.label = NA, miss.val = 0, n.sim = 0, method = "gc", id = NA,
  handle.miss = 0, mloci = NA, sexid = NA)
hmht.control : function (data = NULL, colors = NULL, yoffset = 0.25, cex = 1.5, boxe
htr : function (y, x, n.sim = 0)
hwe : function (data, data.type = "allele", yates.correct = FALSE, miss.val = 0)
hwe.cc : function (model, case, ctrl, k0, initial1, initial2)
hwe.hardy : function (a, alleles = 3, seed = 3000, sample = c(1000, 1000, 5000))
hwe.jags : function (k, n, delta = rep(1/k, k), lambda = 0, lambdamu = -1, lambdasd
  parms = c("p", "f", "q", "theta", "lambda"), ...)
inv_chr_pos_a1_a2 : function (chr_pos_a1_a2, prefix = "chr", seps = c(":", "_", "_"))
invlogit : function (x = 0)
invnormal : function (x)
k : function (r, N, adjust = TRUE)
kin.morgan : function (ped, verbose = FALSE)
klem : function (obs, k = 2, l = 2)
lambda1000 : function (lambda, ncases, ncontrols)
log10p : function (z)
log10pvalue : function (p = NULL, base = NULL, exponent = NULL)
logit : function (p = 0.5)
logp : function (z)
m2plem : function (a1, a2)
makeRLEplot : function (E, log2.data = TRUE, groups = NULL, col.group = NULL, showTi
  title = "Relative log expression (RLE) plot", ...)
makeped : function (pifile = "pedfile.pre", pofile = "pedfile.ped", auto.select = 1,
  with.loop = 0, loop.file = NA, auto.proband = 1, proband.file = NA)
masize : function (model, opts, alpha = 0.025, gamma = 0.2)
metap : function (data, N, verbose = "Y", prefixp = "p", prefixn = "n")
metareg : function (data, N, verbose = "Y", prefixb = "b", prefixse = "se")
mht.control : function (type = "p", usepos = FALSE, logscale = TRUE, base = 10, cuto
  colors = NULL, labels = NULL, srt = 45, gap = NULL, cex = 0.4, yline = 3,
  xline = 3)

```

```

mhtplot : function (data, control = mht.control(), hcontrol = hmht.control(), ...)
mhtplot.trunc : function (x, chr = "CHR", bp = "BP", p = NULL, log10p = NULL, z = NULL,
  snp = "SNP", col = c("gray10", "gray60"), chrlabs = NULL, suggestiveline = -log10(5e-08),
  genomewideline = -log10(5e-08), highlight = NULL, annotatelog10P = NULL,
  annotateTop = FALSE, cex.mtext = 1.5, cex.text = 0.7, mtext.line = 2,
  cex.y = 1, y.ax.space = 5, y.brk1, y.brk2, delta = 0.05, ...)
mhtplot2 : function (data, control = mht.control(), hcontrol = hmht.control(), ...)
mhtplot2d : function (data, plot = TRUE, cex = 0.6)
mhtplot3d : function (xyz = "INF1.merge.cis.vs.trans", cols = c("id", "chr1", "pos1",
  "chr2", "pos2", "gene", "target", "log10p", "x", "y", "col"), xy.scale = c(1.3e+08),
  marker.size = 4, log10p.max = 400, prefix = c("Sentinel",
  "CHR", "POS", "CHR", "POS", "Gene", "Target", "-log10(p)"), postfix = "</br>",
  json.file = "d3.json", pretty = TRUE)
mia : function (hapfile = "hap.out", assfile = "assign.out", miafile = "mia.out",
  so = 0, ns = 0, mi = 0, allsnp = 0, sas = 0)
miamiplot : function (x, chr = "CHR", bp = "BP", p = "P", pr = "PR", snp = "SNP", co =
  "chartreuse4"), col2 = c("royalblue1", "seagreen1"), ymax = NULL, highlight = NULL,
  highlight.add = NULL, pch = 19, cex = 0.75, cex.lab = 1, xlab = "Chromosome",
  ylab = "-log10(P) [y>0]; log10(P) [y<0]", lcols = c("red", "black"),
  lwds = c(5, 2), ltys = c(1, 2), main = "", ...)
micombine : function (est, std.err, confidence = 0.95)
mr.boot : function (bXG, sebXG, bYG, sebYG, w, n.boot = 1000, method = "median")
mtdt : function (x, n.sim = 0)
mtdt2 : function (x, verbose = TRUE, n.sim = NULL, ...)
muvar : function (n.loci = 1, y1 = c(0, 1, 1), y12 = c(1, 1, 1, 1, 1, 0, 0, 0,
  0), p1 = 0.99, p2 = 0.9)
mvmeta : function (b, V)
pbsize : function (kp, gamma = 4.5, p = 0.15, alpha = 5e-08, beta = 0.2)
pbsize2 : function (N, fc = 0.5, alpha = 0.05, gamma = 4.5, p = 0.15, kp = 0.1, mode =
  "min")
pedtodot : function (pedfile, makeped = FALSE, sink = TRUE, page = "B5", url = "http://
  www.sph.umich.edu/~abecasis/mh/mht.html", height = 0.5, width = 0.75, rotate = 0, dir = "none")
pfc : function (famdata, enum = 0)
pfc.sim : function (famdata, n.sim = 1e+06, n.loop = 1)
pgc : function (data, handle.miss = 1, is.genotype = 0, with.id = 0)
plem2m : function (a)
plot.hap.score : function (x, ...)
print.hap.score : function (x, ...)
pvalue : function (z, decimals = 2)
qqfun : function (x, distribution = "norm", ylab = deparse(substitute(x)), xlab = pa
  "quantiles"), main = NULL, las = par("las"), envelope = 0.95, labels = FALSE,
  col = palette()[4], lcol = palette()[2], xlim = NULL, ylim = NULL,
  lwd = 1, pch = 1, bg = palette()[4], cex = 0.4, line = c("quartiles",
  "robust", "none"), ...)
qqunif : function (u, type = "unif", logscale = TRUE, base = 10, col = palette()[4],
  lcol = palette()[2], lwd = 1, pch = 1, bg = palette()[4], cex = 0.4, line = c("quartiles",
  "robust", "none"), ...)

```

```

lcol = palette()[2], ci = FALSE, alpha = 0.05, ...)
read.ms.output : function (msout, is.file = TRUE, xpose = TRUE, verbose = TRUE, outif
    outfileonly = FALSE)
revhap : function (loci, hapid)
revhap.i : function (loci, hapid)
s2k : function (y1, y2)
se.exp : function (p, se.p)
se.invlogit : function (logit.p, se.logit)
sentinels : function (p, pid, st, debug = FALSE, flanking = 1e+06, chr = "Chrom", po
    b = "Effect", se = "StdErr", log_p = NULL, snp = "MarkerName", sep = ",")
snp.ES : function (beta, SE, N)
snp.HWE : function (g)
snp.PAR : function (RR, MAF, unit = 2)
snptest_sample : function (data, sample_file = "snptest.sample", ID_1 = "ID_1", ID_2
    missing = "missing", C = NULL, D = NULL, P = NULL)
solve_skol : function (rootfun, target, lo, hi, e)
toETDT : function (a)
tscc : function (model, GRR, p1, n1, n2, M, alpha.genome, pi.samples, pi.markers,
    K)
ungcode : function (g)
weighted.median : function (x, w)
whscore : function (allele, type)
x2 : function (p1, p2, n1, n2)
z : function (p1, p2, n1, n2, r)

```

	Package	LibPath	Item
[1,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"OPGall (OPG)"
[2,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"OPGrsid (OPG)"
[3,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"OPGtbl (OPG)"
[4,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"PD"
[5,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"aldh2"
[6,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"apoeapoc"
[7,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"cf"
[8,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"cnv"
[9,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"crohn"
[10,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"fa"
[11,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"fsnps"
[12,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"hla"
[13,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"inf1"
[14,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"jma.cojo"
[15,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"151"
[16,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"lukas"
[17,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"mao"
[18,]	"gap"	"/tmp/RtmpwSPqF9/Rinst3774f50e84212"	"meyer"

```

[19,] "gap"    "/tmp/RtmpwSPqF9/Rinst3774f50e84212" "mfblong"
[20,] "gap"    "/tmp/RtmpwSPqF9/Rinst3774f50e84212" "mr"
[21,] "gap"    "/tmp/RtmpwSPqF9/Rinst3774f50e84212" "nep499"
  Title
[1,] "Internal functions for gap"
[2,] "Internal functions for gap"
[3,] "Internal functions for gap"
[4,] "Internal functions for gap"
[5,] "Internal functions for gap"
[6,] "Internal functions for gap"
[7,] "Internal functions for gap"
[8,] "Internal functions for gap"
[9,] "Internal functions for gap"
[10,] "Internal functions for gap"
[11,] "Internal functions for gap"
[12,] "Internal functions for gap"
[13,] "Internal functions for gap"
[14,] "Internal functions for gap"
[15,] "Internal functions for gap"
[16,] "Internal functions for gap"
[17,] "Internal functions for gap"
[18,] "Internal functions for gap"
[19,] "Internal functions for gap"
[20,] "Internal functions for gap"
[21,] "Internal functions for gap"

```

10 Bibliographic note

The main references are Chow (1960); Guo and Thompson (1992); Williams et al. (1992); Gholamic and Thomas (1994); Hartung et al. (2008); Risch and Merikangas (1996); Spielman and Ewens (1996); Risch and Merikangas (1997); Miller (1997); Sham (1997); Elston (1975); Sham (1998); Devlin and Roeder (1999); Zhao et al. (1999); Guo and Lange (2000); Hirotsu et al. (2001); Zhao et al. (2002); Zaykin et al. (2002); Zhao (2004); Wacholder et al. (2004); Wang (2005); Skol et al. (2006); Wakefield (2007).

References

- G. C. Chow. Tests of equality between sets of coefficients in two linear regression. *Econometrica*, 28:591–605, 1960.
- B. Devlin and K. Roeder. Genomic control for association studies. *Biometrics*, 55(4):997–1004, 1999.

- R. C. Elston. On the correlation between correlations. *Biometrika*, 62:133–140, 1975.
- K. Gholamian and A. Thomas. A linear time algorithm for calculation of multiple pairwise kinship coefficients and genetic index of familiality. *Comp Biomed Res*, 27:342–350, 1994.
- S. W. Guo and K. Lange. Genetic mapping of complex traits: promises, problems, and prospects. *Theor Popul Biol*, 57:1–11, 2000.
- S. W. Guo and E. A. Thompson. Performing the exact test of hardy-weinberg proportion for multiple alleles. *Biometrics*, 48:361–372, 1992.
- J. Hartung, G. Knapp, and B. K. Sinha. *Statistical Meta-analysis with Applications*. Wiley, 2008.
- C. Hirotsu, S. Aoki, T. Inada, and Y. Kitao. An exact test for the association between the disease and alleles at highly polymorphic loci with particular interest in the haplotype analysis. *Biometrics*, 57:769–778, 2001.
- M. B. Miller. Genomic scanning and the transmission/disequilibrium test: analysis of error rates. *Genet Epidemiol*, 14:851–856, 1997.
- N. Risch and K. Merikangas. The future of genetic studies of complex human diseases. *Science*, 273(September):1516–1517, 1996.
- N. Risch and K. Merikangas. Reply to Scott et al. *Science*, 275:1329–1330., 1997.
- P. C. Sham. Transmission/disequilibrium tests for multiallelic loci. *Am J Hum Genet*, 61:774–778, 1997.
- P. C. Sham. *Statistics in Human Genetics*. Arnold Applications of Statistics Series. Edward Arnold, London, 1998. 11-1-1999.
- A. D. Skol, L. J. Scott, G. R. Abecasis, and M. Boehnke. Joint analysis is more efficient than replication-based analysis for two-stage genome-wide association studies. *Nat Genet*, 38(2):209–13, 2006.
- R. S. Spielman and W. J. Ewens. The TDT and other family-based tests for linkage disequilibrium and association. *Am J Hum Genet*, 59(5):983–9, 1996.
- S. Wacholder, S. Chanock, M. Garcia-Closas, L. El Ghormli, and N. Rothman. Assessing the probability that a positive report is false: an approach for molecular epidemiology studies. *J Natl Cancer Inst*, 96(6):434–42, 2004.

- J. Wakefield. A bayesian measure of the probability of false discovery in genetic epidemiology studies. *Am J Hum Genet*, 81:208–226, 2007.
- K. Wang. A likelihood approach for quantitative-trait-locus mapping with selected pedigrees. *Biometrics*, 61:465–473, 2005.
- C. J. Williams, J. C. Christian, and J.A. Jr. Norton. Twinan90: A fortran programfor conducting anova-based and likelihood-based analyses of twin data. *Comp Meth Prog Biomed*, 38(2-3):167–76, 1992.
- D. V. Zaykin, P. H. Westfall, S. S. Young, M. A. Karnoub, M. J. Wagner, and M. G. Ehm. Testing association of statistically inferred haplotypes with discrete and continuous traits in samples of unrelated individuals. *Hum Hered*, 53(2):79–91, 2002.
- J. H. Zhao. 2LD. GENECOUNTING and HAP: computer programs for linkage disequilibrium analysis. *Bioinformatics*, 20:1325–6, 2004.
- J. H. Zhao. Mixed-effects Cox models of alcohol dependence in extended families. *BMC Genet*, 6(Suppl):S127, 2005.
- J. H. Zhao. Pedigree-drawing with R and graphviz. *Bioinformatics*, 22(8):1013–4, 2006.
- J. H. Zhao. gap: genetic analysis package. *Journal of Statistical Software*, 23(8):1–18, 2007.
- J. H. Zhao and P. C. Sham. Generic number systems and haplotype analysis. *Comp Meth Prog Biomed*, 70:1–9, 2003.
- J. H. Zhao and Q. Tan. Integrated analysis of genetic data with R. *Hum Genomics*, 2(4):258–65, 2006a.
- J. H. Zhao and Q. Tan. Genetic dissection of complex traits in silico: approaches, problems and soluations. *Current Bioinformatics*, 1(3):359–369, 2006b.
- J. H. Zhao, P. C. Sham, and D. Curtis. A program for the Monte Carlo evaluation of significance of the extended transmission/disequilibrium test. *Am J Hum Genet*, 64:1484–1485, 1999.
- J. H. Zhao, S. Lissarrague, L. Essioux, and P. C. Sham. GENECOUNTING: haplotype analysis with missing genotypes. *Bioinformatics*, 18(12):1694–5, 2002.