

A Tutorial for the R Package SNPRelate

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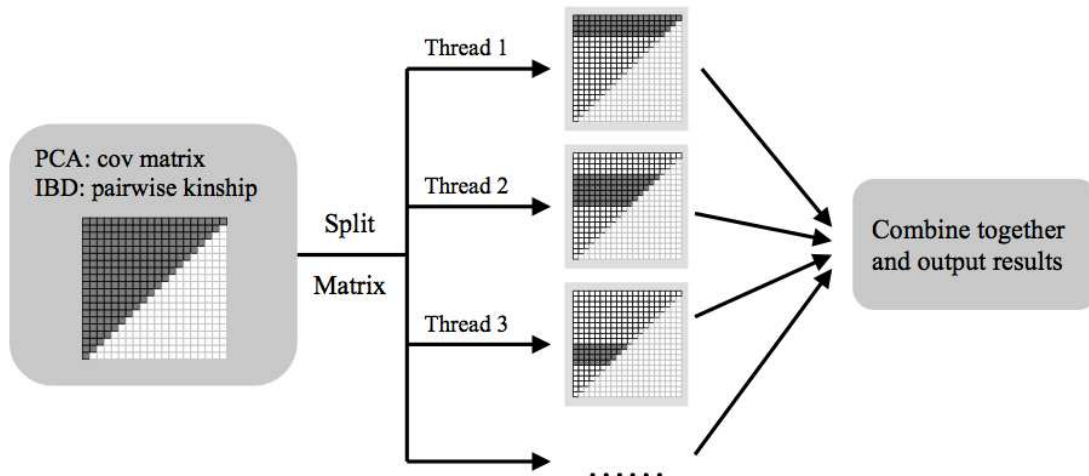


Figure 1: Flowchart of parallel computing for principal component analysis and identity-by-descent analysis.

1 Overview

Genome-wide association studies (GWAS) are widely used to help determine the genetic basis of diseases and traits, but they pose many computational challenges. We developed `gdsfmt` and `SNPRelate` (high-performance computing R packages for multi-core symmetric multiprocessing computer architectures) to accelerate two key computations in GWAS: principal component analysis (PCA) and relatedness analysis using identity-by-descent (IBD) measures¹. The kernels of our algorithms are written in C/C++ and have been highly optimized. The calculations of the genetic covariance matrix in PCA and pairwise IBD coefficients are split into non-overlapping parts and assigned to multiple cores for performance acceleration, as shown in Figure 1. Benchmarks show the uniprocessor implementations of PCA and IBD are ~ 8 to 50 times faster than the implementations provided in the popular `EIGENSTRAT` (v3.0) and `PLINK` (v1.07) programs respectively, and can be sped up to 30~300 folds by utilizing multiple cores.

GDS is also used by an R/Bioconductor package `GWASTools` as one of its data storage formats^{2,3}. `GWASTools` provides many functions for quality control and analysis of GWAS, including statistics by SNP or scan, batch quality, chromosome anomalies, association tests, etc.

R is the most popular statistical programming environment, but one not typically optimized for high performance or parallel computing which would ease the burden of large-scale GWAS calculations. To overcome these limitations we have developed a project named `CoreArray` (<http://corearray.sourceforge.net/>) that includes two R packages: `gdsfmt` to provide efficient, platform independent memory and file management for genome-wide numerical data, and `SNPRelate` to solve large-scale, numerically intensive GWAS calculations (i.e., PCA and IBD) on multi-core symmetric multiprocessing (SMP) computer architectures.

This vignette takes the user through the relatedness and principal component analysis used for genome wide association data. The methods in these vignettes have been introduced in the paper of Zheng *et al.* (2012)¹. For replication purposes the data used here are taken from the HapMap Phase II project. These data were kindly provided by the Center for Inherited Disease Research (CIDR) at Johns Hopkins University and the Broad Institute of MIT and Harvard University (Broad). The data supplied here should not be used for any purpose other than this tutorial.

2 Preparing Data

2.1 Data formats used in SNPRelate

To support efficient memory management for genome-wide numerical data, the `gdsfmt` package provides the genomic data structure (GDS) file format for array-oriented bioinformatic data, which is a container for storing annotation data and SNP genotypes. In this format each byte encodes up to four SNP genotypes thereby reducing file size and access time. The GDS format supports data blocking so that only the subset of data that is being processed needs to reside in memory. GDS formatted data is also designed for efficient random access to large data sets.

```
> # load the R packages: gdsfmt and SNPRelate
> library(gdsfmt)
> library(SNPRelate)
```

Here is a typical GDS file:

```
> snpgdsSummary(snpGdsExampleFileName())
```

```
The file name: /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYP0W/Rinst
```

```
The total number of samples: 279
```

```
The total number of SNPs: 9088
```

```
SNP genotypes are stored in individual-major mode.
```

`snpGdsExampleFileName()` returns the file name of a GDS file used as an example in `SNPRelate`, and it is a subset of data from the HapMap project and the samples were genotyped by the Center for Inherited Disease Research (CIDR) at Johns Hopkins University and the Broad Institute of MIT and Harvard University (Broad). `snpGdsSummary()` summarizes the genotypes stored in the GDS file. “Individual-major mode” indicates listing all SNPs for an individual before listing the SNPs for the next individual, etc. Conversely, “SNP-major mode” indicates listing all individuals for the first SNP before listing all individuals for the second SNP, etc. Sometimes “SNP-major mode” is more computationally efficient than “individual-major model”. For example, the calculation of genetic covariance matrix deals with genotypic data SNP by SNP, and then “SNP-major mode” should be more efficient.

```

> # open a GDS file
> (genofile <- openfn.gds(snpGdsExampleFileName()))

file name: /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYPOW/Rinst907d

+      [ ]
|--> sample.id      [ FStr8 279 ZIP(23.10%) ]
|--> snp.id        [ Int32 9088 ZIP(34.76%) ]
|--> snp.rs.id     [ FStr8 9088 ZIP(42.66%) ]
|--> snp.position  [ Int32 9088 ZIP(94.73%) ]
|--> snp.chromosome [ UInt8 9088 ZIP(0.94%) ] *
|--> snp.allele    [ FStr8 9088 ZIP(14.45%) ]
|--> genotype      [ Bit2 9088x279 ] *
|--> sample.annot  [ data.frame ] *
| |--> sample.id   [ FStr8 279 ZIP(23.10%) ]
| |--> family.id   [ FStr8 279 ZIP(28.37%) ]
| |--> geneva.id   [ Int32 279 ZIP(80.29%) ]
| |--> father.id   [ FStr8 279 ZIP(12.98%) ]
| |--> mother.id   [ FStr8 279 ZIP(12.86%) ]
| |--> plate.id    [ FStr8 279 ZIP(1.29%) ]
| |--> sex         [ FStr8 279 ZIP(28.32%) ]
| |--> pop.group   [ FStr8 279 ZIP(7.89%) ]

```

The output lists all variables stored in the GDS file. At the first level, it stores variables **sample.id**, **snp.id**, etc. The additional information are displayed in the square brackets indicating data type, size, compressed or not + compression ratio. The second-level variables **sex** and **pop.group** are both stored in the folder of **sample.annot**. All of the functions in **SNPRelate** require a minimum set of variables in the annotation data. The minimum required variables are

- **sample.id**, a unique identifier for each sample.
- **snp.id**, a unique identifier for each SNP.
- **snp.position**, the base position of each SNP on the chromosome, and 0 for unknown position; it does not allow NA.
- **snp.chromosome**, an integer mapping for each chromosome, with values 1-26, mapped in order from 1-22, 23=X,24=XY (the pseudoautosomal region), 25=Y, 26=M (the mitochondrial probes), and 0 for probes with unknown positions; it does not allow NA.
- **genotype**, a SNP genotypic matrix. SNP-major mode: $n_{sample} \times n_{snp}$, individual-major mode: $n_{snp} \times n_{sample}$.

Users can define the numeric chromosome codes which are stored with the variable **snp.chromosome** as attributes. For example, **snp.chromosome** has the attributes of chromosome coding:

```
> # get the attributes of chromosome coding
> get.attr.gdsn(index.gdsn(genofile, "snp.chromosome"))
```

```
$autosome.start
[1] 1
```

```
$autosome.end
[1] 22
```

```
$X
[1] 23
```

```
$XY
[1] 24
```

```
$Y
[1] 25
```

```
$M
[1] 26
```

```
$MT
[1] 26
```

autosome.start is the starting numeric code of autosomes, and **autosome.end** is the last numeric code of autosomes. **put.attr.gdsn** can be used to add a new attribute or modify an existing attribute.

There are four possible values stored in the variable **genotype**: 0, 1, 2 and 3. For bi-allelic SNP sites, “0” indicates two B alleles, “1” indicates one A allele and one B allele, “2” indicates two A alleles, and “3” is a missing genotype. For multi-allelic sites, it is a count of the reference allele (3 meaning no call). “Bit2” indicates that each byte encodes up to four SNP genotypes since one byte consists of eight bits.

```
> # Take out genotype data for the first 3 samples and the first 5 SNPs
> (g <- read.gdsn(index.gdsn(genofile, "genotype"), start=c(1,1), count=c(5,3)))
```

```
      [,1] [,2] [,3]
[1,]    2    1    2
[2,]    1    1    1
[3,]    0    0    1
```

```
[4,] 1 1 2
[5,] 2 2 2
```

```
> # Get the attribute of genotype
> get.attr.gdsn(index.gdsn(genofile, "genotype"))
```

```
$snp.order
NULL
```

The returned value could be either “snp.order” or “sample.order”, indicating individual-major mode (snp is the first dimension) and SNP-major mode (sample is the first dimension) respectively.

```
> # Take out snp.id
> head(read.gdsn(index.gdsn(genofile, "snp.id")))
```

```
[1] 1 2 3 4 5 6
```

```
> # Take out snp.rs.id
> head(read.gdsn(index.gdsn(genofile, "snp.rs.id")))
```

```
[1] "rs1695824" "rs13328662" "rs4654497" "rs10915489" "rs12132314"
[6] "rs12042555"
```

There are two additional variables:

- **snp.rs.id**, a character string for reference SNP ID that may not be unique.
- **snp.allele**, it is not necessary for the analysis, but it is necessary when merging genotypes from different platforms. The format of **snp.allele** is “A allele/B allele”, like “T/G” where T is A allele and G is B allele.

The information of sample annotation can be obtained by the same function **read.gdsn**. For example, population information. “FStr8” indicates a character-type variable.

```
> # Read population information
> pop <- read.gdsn(index.gdsn(genofile, path="sample.annot/pop.group"))
> table(pop)
```

```
pop
CEU HCB JPT YRI
 92 47 47 93
```

```
> # close the GDS file
> closefn.gds(genofile)
```

2.2 Create a GDS File of Your Own

2.2.1 snpgdsCreateGeno

The function `snpgdsCreateGeno` can be used to create a GDS file. The first argument should be a numeric matrix for SNP genotypes. There are possible values stored in the input genotype matrix: 0, 1, 2 and other values. “0” indicates two B alleles, “1” indicates one A allele and one B allele, “2” indicates two A alleles, and other values indicate a missing genotype. The SNP matrix can be either $n_{sample} \times n_{snp}$ (`snpfirstdim=FALSE`, the argument in `snpgdsCreateGeno`) or $n_{snp} \times n_{sample}$ (`snpfirstdim=TRUE`).

For example,

```
> # load data
> data(hapmap_geno)
> # create a gds file
> snpgdsCreateGeno("test.gds", genmat = hapmap_geno$genotype,
+   sample.id = hapmap_geno$sample.id, snp.id = hapmap_geno$snp.id,
+   snp.chromosome = hapmap_geno$snp.chromosome,
+   snp.position = hapmap_geno$snp.position,
+   snp.allele = hapmap_geno$snp.allele, snpfirstdim=TRUE)
> # open the gds file
> (genofile <- openfn.gds("test.gds"))
```

file name: /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYP0W/Rbuild907

```
+      [ ]
|---+ sample.id      [ VStr8 279 ZIP(29.89%) ]
|---+ snp.id         [ VStr8 1000 ZIP(42.42%) ]
|---+ snp.position   [ Float64 1000 ZIP(55.97%) ]
|---+ snp.chromosome [ Int32 1000 ZIP(2.00%) ]
|---+ snp.allele     [ VStr8 1000 ZIP(13.85%) ]
|---+ genotype      [ Bit2 1000x279 ] *
```

```
> # close the genotype file
> closefn.gds(genofile)
```

2.2.2 Uses of the Functions in the gdsfmt Package

In the following code, the functions `createfn.gds`, `add.gdsn`, `put.attr.gdsn`, `write.gdsn`, `index.gdsn`, `closefn.gds` are defined in the `gdsfmt` package:

```
# create a new GDS file
newfile <- createfn.gds("your_gds_file.gds")

# add variables
```

```

add.gdsn(newfile, "sample.id", sample.id)
add.gdsn(newfile, "snp.id", snp.id)
add.gdsn(newfile, "snp.position", snp.position)
add.gdsn(newfile, "snp.chromosome", snp.chromosome)
add.gdsn(newfile, "snp.allele", c("A/G", "T/C", ...))

#####
# create a snp-by-sample genotype matrix

# add genotypes
var.geno <- add.gdsn(newfile, "genotype",
  valdim=c(length(snp.id), length(sample.id)), storage="bit2")

# indicate the SNP matrix is snp-by-sample
put.attr.gdsn(var.geno, "snp.order")

# write SNPs into the file sample by sample
for (i in 1:length(sample.id))
{
  g <- ...
  write.gdsn(var.geno, g, start=c(1,i), count=c(-1,1))
}

#####
# OR, create a sample-by-snp genotype matrix

# add genotypes
var.geno <- add.gdsn(newfile, "genotype",
  valdim=c(length(sample.id), length(snp.id)), storage="bit2")

# indicate the SNP matrix is sample-by-snp
put.attr.gdsn(var.geno, "sample.order")

# write SNPs into the file sample by sample
for (i in 1:length(snp.id))
{
  g <- ...
  write.gdsn(var.geno, g, start=c(1,i), count=c(-1,1))
}

```



```

# get a description of chromosome codes
# allowing to define a new chromosome code, e.g., snpgdsOption(Z=27)
option <- snpgdsOption()
var.chr <- index.gdsn(newfile, "snp.chromosome")
put.attr.gdsn(var.chr, "autosome.start", option$autosome.start)
put.attr.gdsn(var.chr, "autosome.end", option$autosome.end)
for (i in 1:length(option$chromosome.code))
{
  put.attr.gdsn(var.chr, names(option$chromosome.code)[i],
    option$chromosome.code[[i]])
}

# add your sample annotation
samp.annot <- data.frame(sex = c("male", "male", "female", ...),
  pop.group = c("CEU", "CEU", "JPT", ...), ...)
add.gdsn(newfile, "sample.annot", samp.annot)

# close the GDS file
closefn.gds(newfile)

```

2.3 Format conversion from PLINK binary files

The SNPRelate package provides a function `snpgdsBED2GDS` for converting a PLINK binary file to a GDS file:

```

> # the PLINK BED file, using the example in the SNPRelate package
> bed.fn <- system.file("extdata", "plinkhapmap.bed", package="SNPRelate")
> bim.fn <- system.file("extdata", "plinkhapmap.bim", package="SNPRelate")
> fam.fn <- system.file("extdata", "plinkhapmap.fam", package="SNPRelate")

```

Or, uses your own PLINK files:

```

> bed.fn <- "C:/your_folder/your_plink_file.bed"
> bim.fn <- "C:/your_folder/your_plink_file.bim"
> fam.fn <- "C:/your_folder/your_plink_file.fam"

> # convert
> snpgdsBED2GDS(bed.fn, fam.fn, bim.fn, "test.gds")

```

Start `snpgdsBED2GDS` ...

```

open /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYP0W/Rinst90
open /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYP0W/Rinst90

```

```

      open /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYP0W/Rinst9
Wed Sep  4 17:50:48 2013          store sample id, snp id, position, and chromosome.
      start writing: 279 samples, 5000 SNPs ...
      Wed Sep  4 17:50:48 2013          0%
      Wed Sep  4 17:50:48 2013          100%
Wed Sep  4 17:50:48 2013          Done.

```

```

> # summary
> snpgdsSummary("test.gds")

```

```

The file name: test.gds
The total number of samples: 279
The total number of SNPs: 5000
SNP genotypes are stored in individual-major mode.

```

2.4 Format conversion from VCF files

The SNPRelate package provides a function `snpgdsVCF2GDS` to reformat a VCF file. There are two options for extracting markers from a VCF file for downstream analyses: (1) to extract and store dosage of the reference allele only for biallelic SNPs and (2) to extract and store dosage of the reference allele for all variant sites, including bi-allelic SNPs, multi-allelic SNPs, indels and structural variants.

```

> # the VCF file, using the example in the SNPRelate package
> vcf.fn <- system.file("extdata", "sequence.vcf", package="SNPRelate")

```

Or, uses your own VCF file:

```

> vcf.fn <- "C:/your_folder/your_vcf_file.vcf"

> # reformat
> snpgdsVCF2GDS(vcf.fn, "test.gds", method="biallelic.only")

```

```

Start snpgdsVCF2GDS ...
      Extracting bi-allelic and polymorphic SNPs.
      Scanning ...
      file: /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYP0W/Rinst9
      content: 5 rows x 12 columns
Wed Sep  4 17:50:48 2013          store sample id, snp id, position, and chromosome.
      start writing: 3 samples, 2 SNPs ...
      file: /private/var/folders/m3/hrfnm36n27x3ppdl3hk4czfr0000gn/T/RtmpUQYP0W/Rinst9
[1] 1
Wed Sep  4 17:50:48 2013          Done.

```

```
> # summary
> snpgdsSummary("test.gds")
```

```
The file name: test.gds
The total number of samples: 3
The total number of SNPs: 2
SNP genotypes are stored in SNP-major mode.
```

3 Data Analysis

We developed `gdsfmt` and `SNPRelate` (high-performance computing R packages for multi-core symmetric multiprocessing computer architectures) to accelerate two key computations in GWAS: principal component analysis (PCA) and relatedness analysis using identity-by-descent (IBD) measures.

```
> # open the GDS file
> genofile <- openfn.gds(snpGdsExampleFileName())

> # get population information
> #   or pop_code <- scan("pop.txt", what=character()), if it is stored in a text file
> pop_code <- read.gdsn(index.gdsn(genofile, path="sample.annot/pop.group"))
> # display the first six values
> head(pop_code)
```

```
[1] "YRI" "YRI" "YRI" "YRI" "CEU" "CEU"
```

3.1 LD-based SNP pruning

It is suggested to use a pruned set of SNPs which are in approximate linkage equilibrium with each other to avoid the strong influence of SNP clusters in principal component analysis and relatedness analysis.

```
> set.seed(1000)
> # try different LD thresholds for sensitivity analysis
> snpset <- snpgdsLDpruning(genofile, ld.threshold=0.2)
```

SNP pruning based on LD:

Sliding window: 500000 basepairs, Inf SNPs

|LD| threshold: 0.2

Removing 365 non-autosomal SNPs

Removing 1 SNPs (monomorphic, < MAF, or > missing rate)

Working space: 279 samples, 8722 SNPs

Chromosome 1: 75.42%, 540/716

```
Chromosome 2: 72.24%, 536/742
Chromosome 3: 74.71%, 455/609
Chromosome 4: 73.31%, 412/562
Chromosome 5: 77.03%, 436/566
Chromosome 6: 75.58%, 427/565
Chromosome 7: 75.42%, 356/472
Chromosome 8: 71.31%, 348/488
Chromosome 9: 77.88%, 324/416
Chromosome 10: 74.33%, 359/483
Chromosome 11: 77.40%, 346/447
Chromosome 12: 76.81%, 328/427
Chromosome 13: 75.58%, 260/344
Chromosome 14: 76.95%, 217/282
Chromosome 15: 76.34%, 200/262
Chromosome 16: 72.66%, 202/278
Chromosome 17: 74.40%, 154/207
Chromosome 18: 73.68%, 196/266
Chromosome 19: 85.00%, 102/120
Chromosome 20: 71.62%, 164/229
Chromosome 21: 76.98%, 97/126
Chromosome 22: 75.86%, 88/116
6547 SNPs are selected in total.
```

```
> names(snpset)
```

```
[1] "chr1" "chr2" "chr3" "chr4" "chr5" "chr6" "chr7" "chr8" "chr9"
[10] "chr10" "chr11" "chr12" "chr13" "chr14" "chr15" "chr16" "chr17" "chr18"
[19] "chr19" "chr20" "chr21" "chr22"
```

```
> head(snpset$chr1) # snp.id
```

```
[1] 1 2 4 5 7 10
```

```
> # get all selected snp id
> snpset.id <- unlist(snpset)
```

3.2 Principal Component Analysis

The functions in SNPRelate for PCA include calculating the genetic covariance matrix from genotypes, computing the correlation coefficients between sample loadings and genotypes for each SNP, calculating SNP eigenvectors (loadings), and estimating the sample loadings of a new dataset from specified SNP eigenvectors.

```

> # get sample id
> sample.id <- read.gdsn(index.gdsn(genofile, "sample.id"))
> # get population information
> # or pop_code <- scan("pop.txt", what=character()), if it is stored in a text file
> pop_code <- read.gdsn(index.gdsn(genofile, "sample.annot/pop.group"))

> # run PCA
> pca <- snpgdsPCA(genofile)

```

Principal Component Analysis (PCA) on SNP genotypes:

Removing 365 non-autosomal SNPs.

Removing 1 SNPs (monomorphic, < MAF, or > missing rate)

Working space: 279 samples, 8722 SNPs

Using 1 CPU core.

```

PCA:      the sum of all working genotypes (0, 1 and 2) = 2446510
PCA:      Wed Sep  4 17:50:48 2013      0%
PCA:      Wed Sep  4 17:50:49 2013      100%
PCA:      Wed Sep  4 17:50:49 2013      Begin (eigenvalues and eigenvectors)
PCA:      Wed Sep  4 17:50:49 2013      End (eigenvalues and eigenvectors)

```

```

> # make a data.frame
> tab <- data.frame(sample.id = pca$sample.id,
+   pop = factor(pop_code)[match(pca$sample.id, sample.id)],
+   EV1 = pca$eigenvect[,1],      # the first eigenvector
+   EV2 = pca$eigenvect[,2],      # the second eigenvector
+   stringsAsFactors = FALSE)
> head(tab)

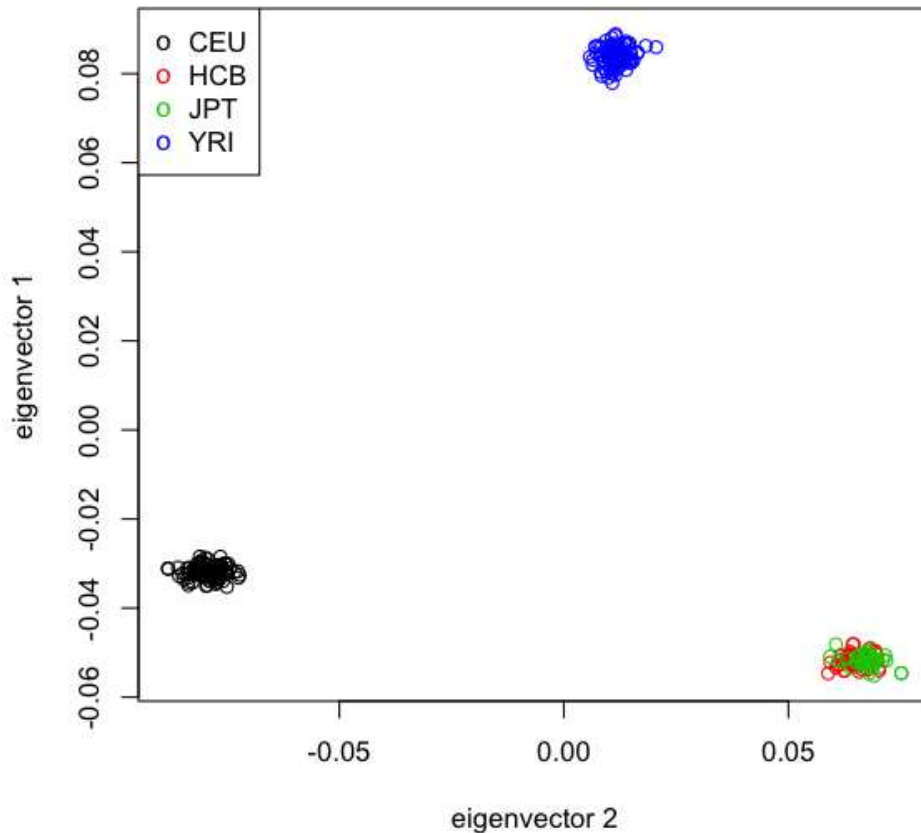
```

	sample.id	pop	EV1	EV2
1	NA19152	YRI	0.08405438	0.01243429
2	NA19139	YRI	0.08363225	0.01099277
3	NA18912	YRI	0.08104325	0.01196670
4	NA19160	YRI	0.08682153	0.01465503
5	NA07034	CEU	-0.03096588	-0.07717809
6	NA07055	CEU	-0.03212054	-0.08159248

```

> # draw
> plot(tab$EV2, tab$EV1, col=as.integer(tab$pop),
+   xlab="eigenvector 2", ylab="eigenvector 1")
> legend("topleft", legend=levels(tab$pop), pch="o", col=1:nlevels(tab$pop))

```



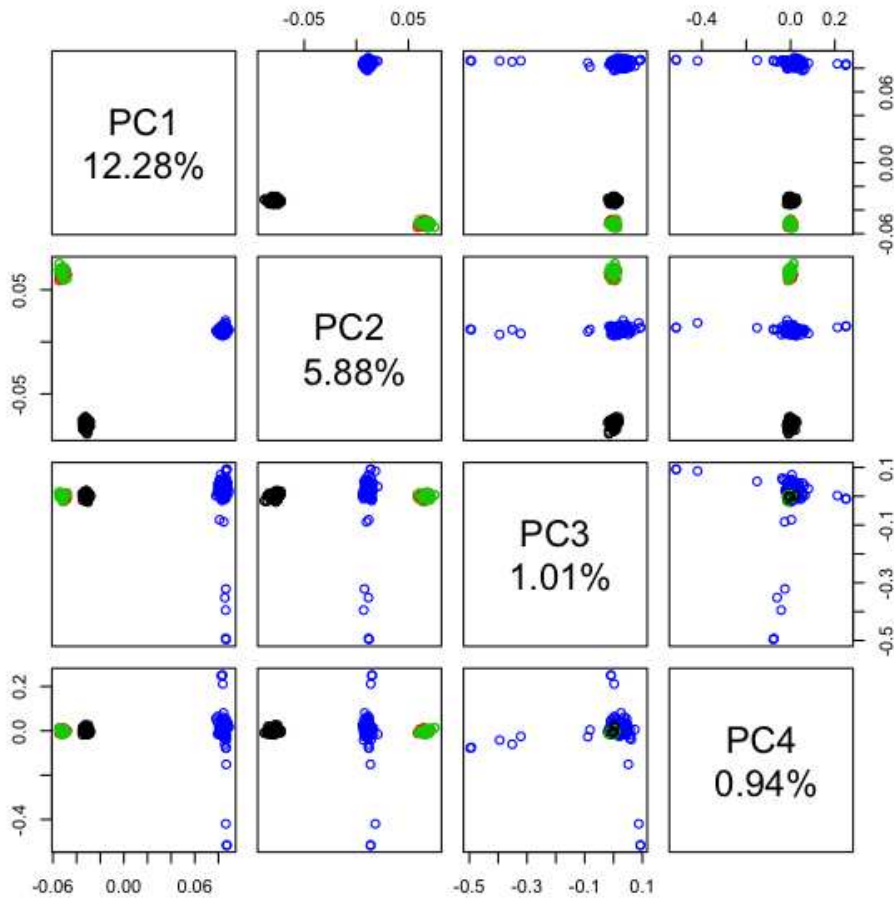
The code below shows how to calculate the percent of variation is accounted for by the principal component for the first 16 PCs. It is clear to see the first two eigenvectors hold the largest percentage of variance among the population, although the total variance accounted for is still less the one-quarter of the total.

```
> pc.percent <- 100 * pca$eigenval[1:16]/sum(pca$eigenval)
> pc.percent

[1] 12.2763042  5.8776373  1.0073833  0.9404113  0.8397200  0.7333046
[7]  0.7313332  0.7215112  0.7144956  0.7015307  0.6989026  0.6911611
[13] 0.6805916  0.6735051  0.6681554  0.6656673
```

Plot the principal component pairs for the first four PCs:

```
> lbls <- paste("PC", 1:4, "\n", format(pc.percent[1:4], digits=2), "%", sep="")
> pairs(pca$eigenvect[,1:4], col=tab$pop, labels=lbls)
```



To calculate the SNP correlations between eigenvectors and SNP genotypes:

```
> # get chromosome index
> chr <- read.gdsn(index.gdsn(genofile, "snp.chromosome"))
> CORR <- snpgdsPCACorr(pca, genofile, eig.which=1:4)
```

SNP correlations:

Working space: 279 samples, 9088 SNPs

Using 1 CPU core.

Using the top 32 eigenvectors.

SNP Correlations: the sum of all working genotypes (0, 1 and 2) = 2553065

SNP Correlations: Wed Sep 4 17:50:49 2013 0%

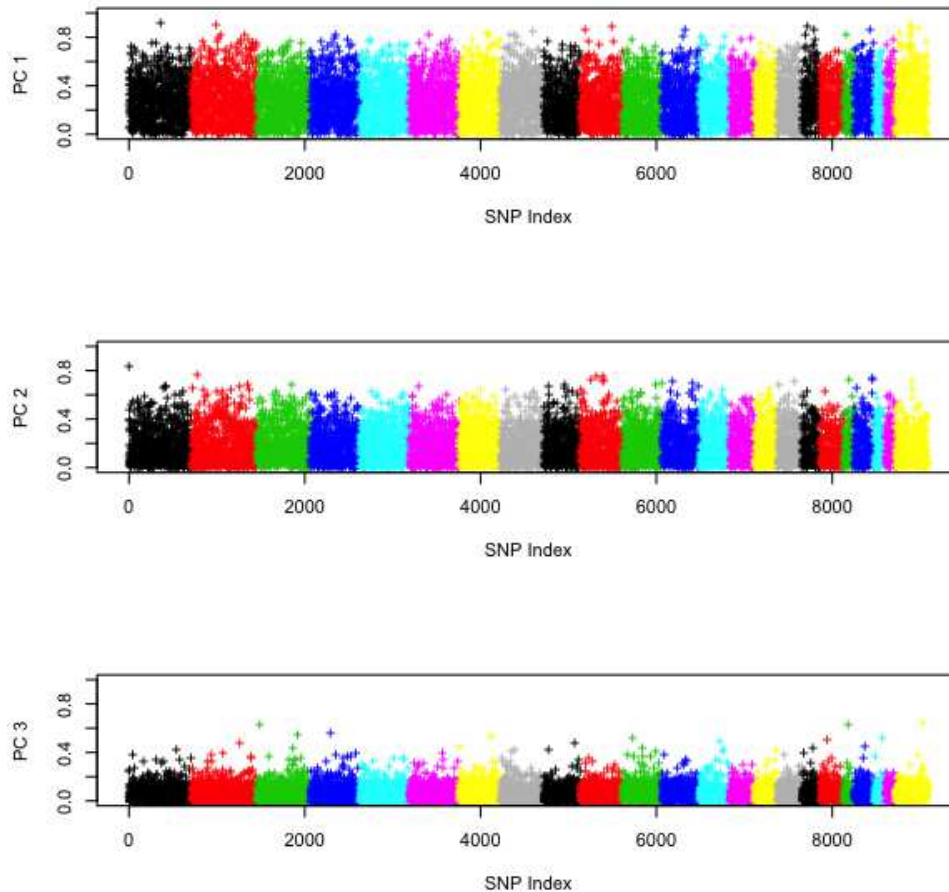
SNP Correlations: Wed Sep 4 17:50:49 2013 100%

```
> par( mfrow=c(3,1))
> for (i in 1:3)
+ {
```

```

+   plot(abs(CORR$snpcorr[i,]), ylim=c(0,1), xlab="SNP Index",
+         ylab=paste("PC", i), col=chr, pch="+")
+ }

```



3.3 Relatedness Analysis

For relatedness analysis, identity-by-descent (IBD) estimation in SNPRelate can be done by either the method of moments (MoM) (Purcell et al., 2007) or maximum likelihood estimation (MLE) (Milligan, 2003; Choi et al., 2009). Although MLE estimates are more reliable than MoM, MLE is significantly more computationally intensive. For both of these methods it is preferred to use a LD pruned SNP set.

```

> # YRI samples
> sample.id <- read.gdsn(index.gdsn(genofile, "sample.id"))
> YRI.id <- sample.id[pop_code == "YRI"]

```


3.3.1 Estimating IBD Using PLINK method of moments (MoM)

```
> # estimate IBD coefficients
> ibd <- snpgdsIBDMoM(genofile, sample.id=YRI.id, snp.id=snpset.id,
+   maf=0.05, missing.rate=0.05)
```

Identity-By-Descent analysis (PLINK method of moment) on SNP genotypes:
Removing 1285 SNPs (monomorphic, < MAF, or > missing rate)
Working space: 93 samples, 5262 SNPs
Using 1 CPU core.

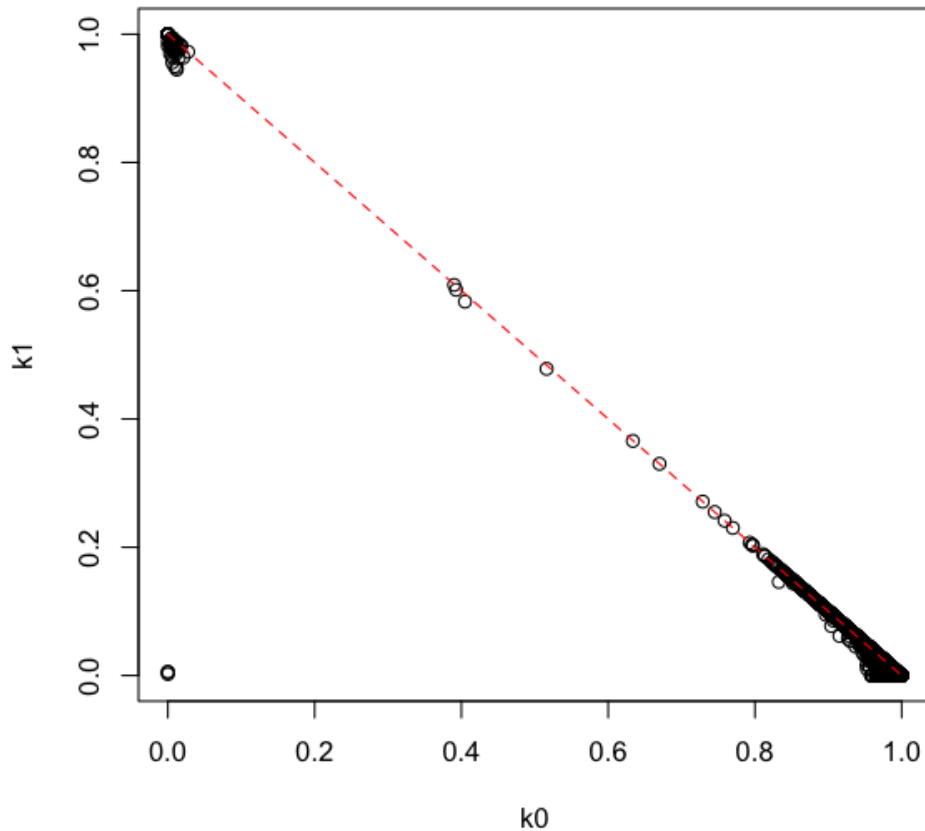
```
PLINK IBD:      the sum of all working genotypes (0, 1 and 2) = 484520
PLINK IBD:      Wed Sep  4 17:51:21 2013          0%
PLINK IBD:      Wed Sep  4 17:51:21 2013          100%
```

```
> # make a data.frame
> ibd.coeff <- snpgdsIBDSelection(ibd)
> head(ibd.coeff)
```

	ID1	ID2	k0	k1	kinship
1	NA19152	NA19139	0.9548539	0.04514610	0.011286524
2	NA19152	NA18912	1.0000000	0.00000000	0.000000000
3	NA19152	NA19160	1.0000000	0.00000000	0.000000000
4	NA19152	NA18515	0.9234541	0.07654590	0.019136475
5	NA19152	NA19222	1.0000000	0.00000000	0.000000000
6	NA19152	NA18508	0.9833803	0.01661969	0.004154922

```
> plot(ibd.coeff$k0, ibd.coeff$k1, xlim=c(0,1), ylim=c(0,1),
+   xlab="k0", ylab="k1", main="YRI samples (MoM)")
> lines(c(0,1), c(1,0), col="red", lty=2)
```

YRI samples (MoM)



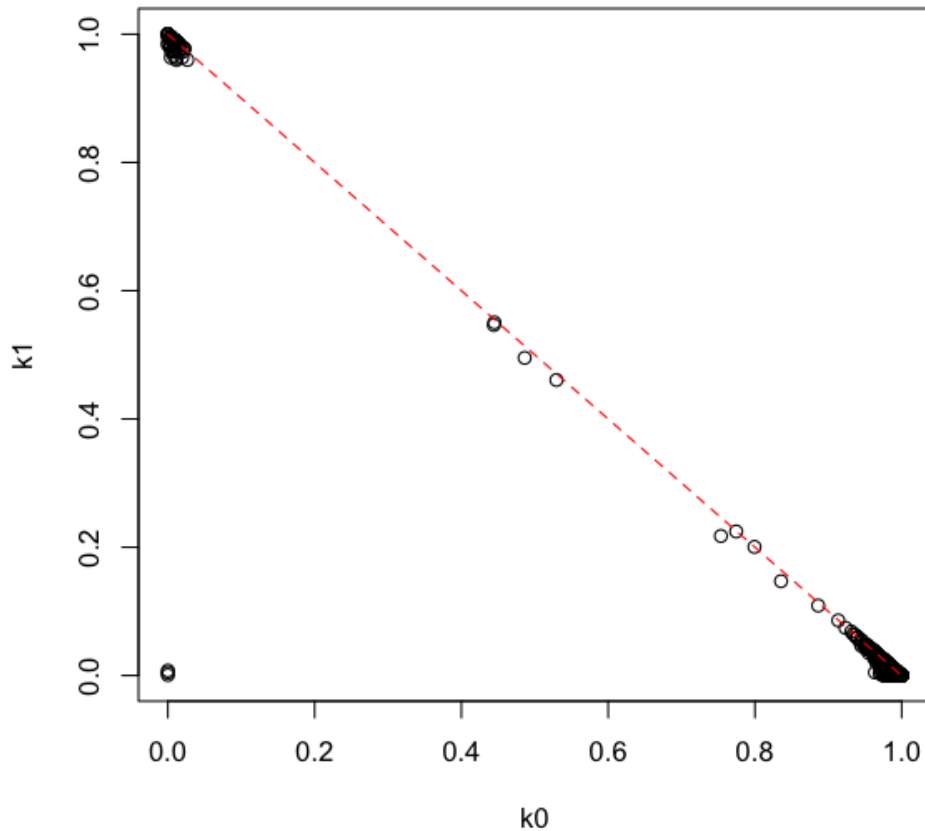
3.3.2 Estimating IBD Using Maximum Likelihood Estimation (MLE)

```
> # estimate IBD coefficients
> set.seed(1000)
> snp.id <- sample(snpset.id, 5000) # random 5000 SNPs
> ibd <- snpgdsIBDMLE(genofile, sample.id=YRI.id, snp.id=snp.id,
+   maf=0.05, missing.rate=0.05)

> # make a data.frame
> ibd.coeff <- snpgdsIBDSelection(ibd)

> plot(ibd.coeff$k0, ibd.coeff$k1, xlim=c(0,1), ylim=c(0,1),
+   xlab="k0", ylab="k1", main="YRI samples (MLE)")
> lines(c(0,1), c(1,0), col="red", lty=2)
```

YRI samples (MLE)



3.3.3 Relationship inference Using KING method of moments

Within- and between-family relationship could be inferred by [the KING-robust method](#) in the presence of population stratification.

```
> # incorporate with pedigree information
> family.id <- read.gdsn(index.gdsn(genofile, "sample.annot/family.id"))
> family.id <- family.id[match(YRI.id, sample.id)]
> table(family.id)
```

```
family.id
101 105 112 117 12 13 16 17 18 23 24 28 4 40 42 43 45 47 48 5
 3 3 3 4 4 3 3 3 3 3 4 3 3 3 3 3 3 3 3 3
50 51 56 58 60 71 72 74 77 9
 3 3 3 3 3 3 3 3 3 3
```

```
> ibd.robust <- snpgdsIBDKING(genofile, sample.id=YRI.id, family.id=family.id)
```

```

Identity-By-Descent analysis (KING method of moment) on SNP genotypes:
# of families: 30, and within- and between-family relationship are estimated differently
Removing 365 non-autosomal SNPs
Removing 563 SNPs (monomorphic, < MAF, or > missing rate)
Working space: 93 samples, 8160 SNPs
    Using 1 CPU core.
Relationship inference in the presence of population stratification.
KING IBD:      the sum of all working genotypes (0, 1 and 2) = 755648
KING IBD:      Wed Sep  4 17:51:21 2013      0%
KING IBD:      Wed Sep  4 17:51:21 2013      100%

> names(ibd.robust)

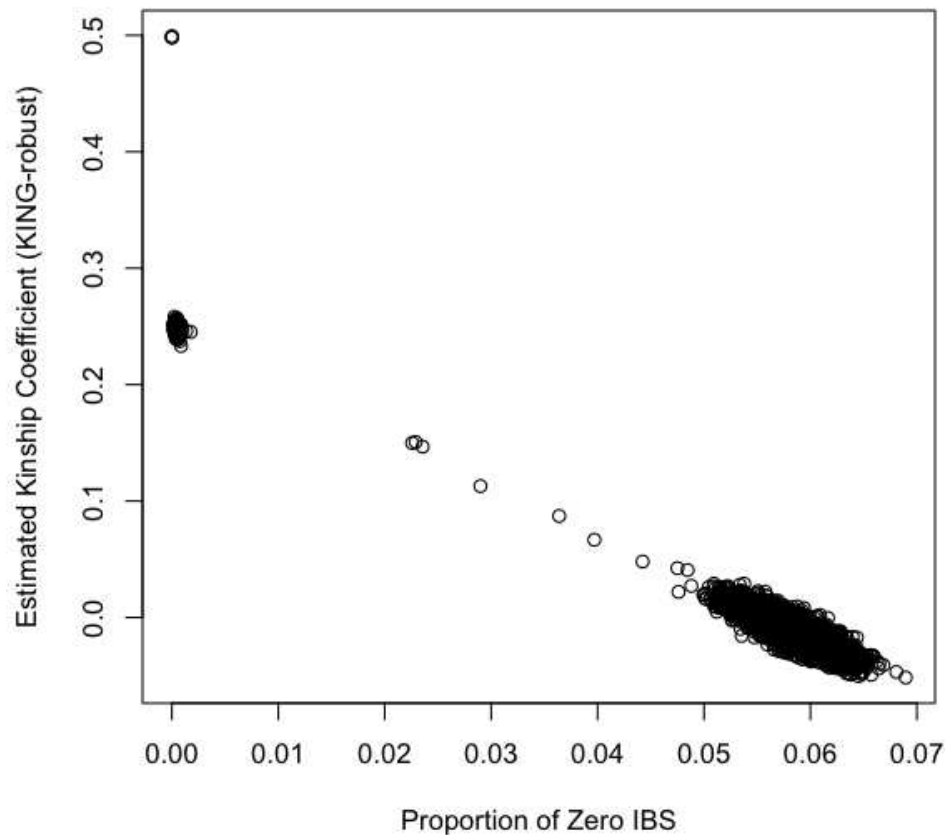
[1] "sample.id" "snp.id"      "afreq"      "IBS0"      "kinship"

> # pairs of individuals
> dat <- snpgdsIBDSelection(ibd.robust)
> head(dat)

      ID1      ID2      IBS0      kinship
1 NA19152 NA19139 0.05504926 -0.005516960
2 NA19152 NA18912 0.05738916 -0.003658537
3 NA19152 NA19160 0.06230760 -0.034086156
4 NA19152 NA18515 0.05602758  0.007874016
5 NA19152 NA19222 0.05923645 -0.012668574
6 NA19152 NA18508 0.05561722  0.002216848

> plot(dat$IBS0, dat$kinship, xlab="Proportion of Zero IBS",
+       ylab="Estimated Kinship Coefficient (KING-robust)")

```



3.4 Identity-By-State Analysis

For the n individuals in a sample, `snpGdsIBS` can be used to create a $n \times n$ matrix of genome-wide average IBS pairwise identities:

```
> ibs <- snpGdsIBS(genofile, num.thread=2)
```

Identity-By-State (IBS) analysis on SNP genotypes:

Removing 365 non-autosomal SNPs

Removing 1 SNPs (monomorphic, < MAF, or > missing rate)

Working space: 279 samples, 8722 SNPs

Using 2 CPU cores.

IBS: the sum of all working genotypes (0, 1 and 2) = 2446510

IBS: Wed Sep 4 17:51:22 2013 0%

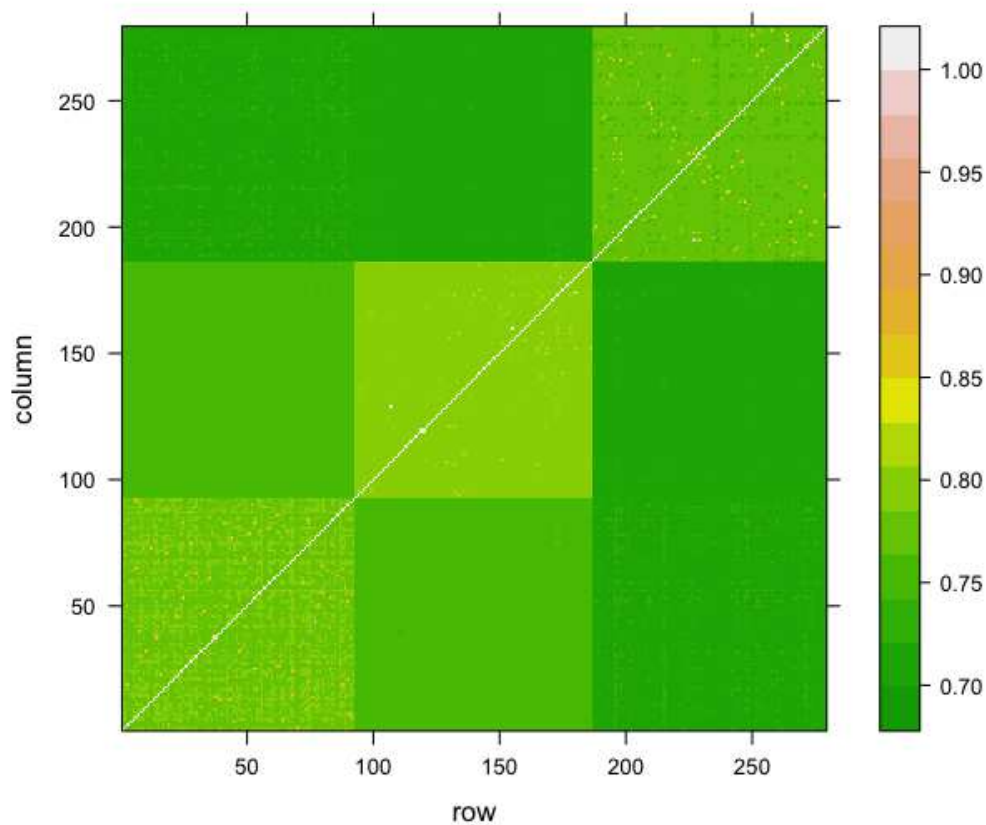
IBS: Wed Sep 4 17:51:22 2013 100%

The heat map is shown:

```

> library(lattice)
> L <- order(pop_code)
> levelplot(ibs$ibs[L, L], col.regions = terrain.colors)

```



To perform multidimensional scaling analysis on the $n \times n$ matrix of genome-wide IBS pairwise distances:

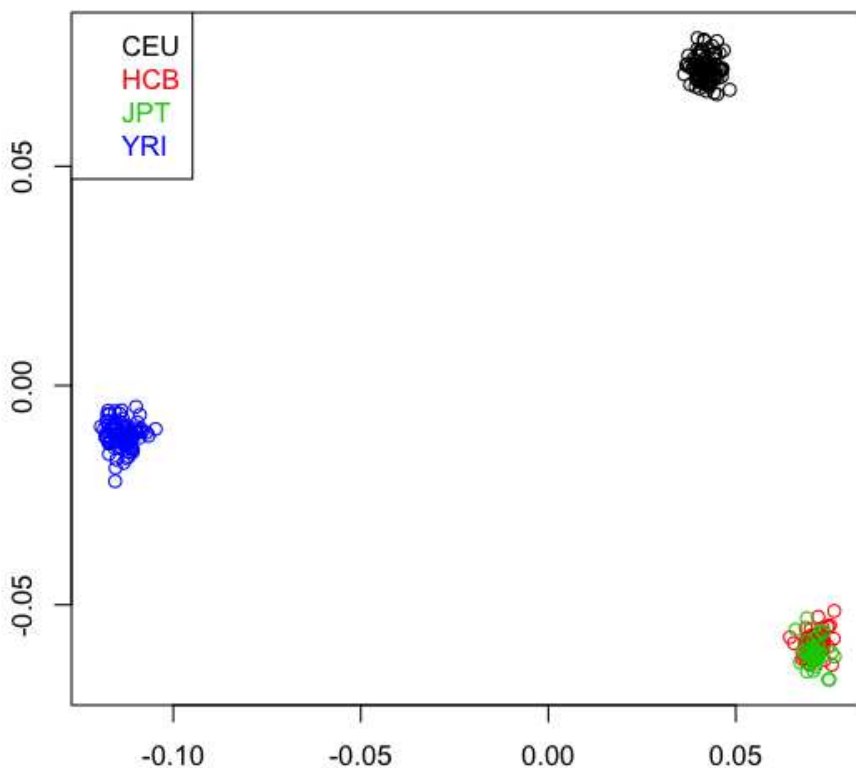
```

> loc <- cmdscale(1 - ibs$ibs, k = 2)
> x <- loc[, 1]; y <- loc[, 2]
> race <- as.factor(pop_code)

> plot(x, y, col=race, xlab = "", ylab = "",
+      main = "Multidimensional Scaling Analysis (IBS Distance)")
> legend("topleft", legend=levels(race), text.col=1:nlevels(race))

```

Multidimensional Scaling Analysis (IBS Distance)



To perform cluster analysis on the $n \times n$ matrix of genome-wide IBS pairwise distances, and determine the groups by a permutation score:

```
> set.seed(100)
> ibs.hc <- snpgdsHCluster(snpgdsIBS(genofile, num.thread=2))
```

Identity-By-State (IBS) analysis on SNP genotypes:

Removing 365 non-autosomal SNPs

Removing 1 SNPs (monomorphic, < MAF, or > missing rate)

Working space: 279 samples, 8722 SNPs

Using 2 CPU cores.

IBS: the sum of all working genotypes (0, 1 and 2) = 2446510

IBS: Wed Sep 4 17:51:25 2013 0%

IBS: Wed Sep 4 17:51:25 2013 100%

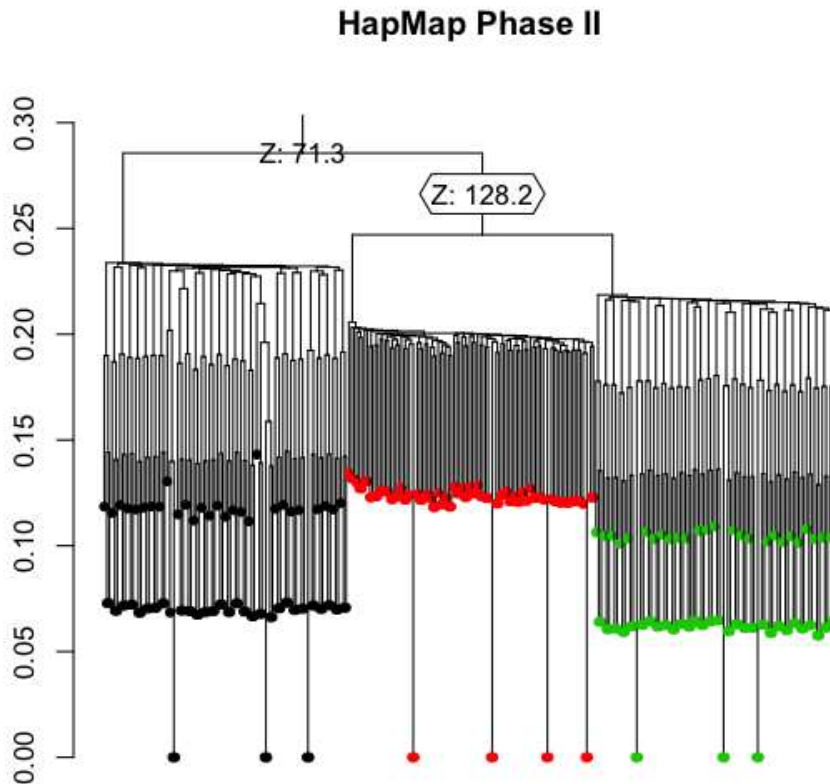
```
> # to determine groups of individuals automatically
```

```
> rv <- snpgdsCutTree(ibs.hc)
```

Determine groups by permutation (Z threshold: 15, outlier threshold: 5):
Create 3 groups.

```
> plot(rv$dendrogram, leaflab="none", main="HapMap Phase II")  
> table(rv$samp.group)
```

```
G001 G002 G003  
93 94 92
```

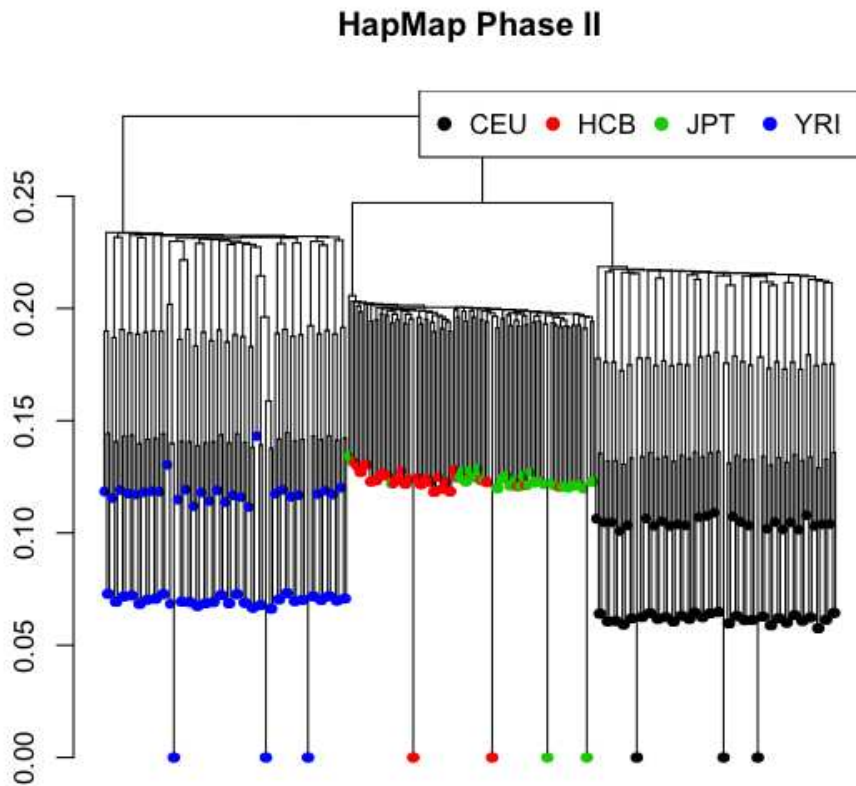


Here is the population information we have known:

```
> # to determine groups of individuals by population information  
> rv2 <- snpgdsCutTree(ibs.hc, samp.group=as.factor(pop_code))
```

Create 4 groups.

```
> plot(rv2$dendrogram, leaflab="none", main="HapMap Phase II")  
> legend("topright", legend=levels(race), col=1:nlevels(race), pch=19, ncol=4)
```

```
> # close the GDS file
> closefn.gds(genofile)
```

4 Resources

1. CoreArray project: <http://corearray.sourceforge.net/>
2. gdsfmt R package: <http://cran.r-project.org/web/packages/gdsfmt/index.html>
3. SNPRelate R package: <http://cran.r-project.org/web/packages/SNPRelate/index.html>
4. GENEVA R package: <https://www.genevastudy.org/Accomplishments/software>
5. GWASTools: an R/Bioconductor package for quality control and analysis of Genome-Wide Association Studies <http://www.bioconductor.org/packages/2.11/bioc/html/GWASTools.html>

5 References

1. **A High-performance Computing Toolset for Relatedness and Principal Component Analysis of SNP Data.** Xiuwen Zheng; David Levine; Jess Shen; Stephanie M. Gogarten; Cathy Laurie; Bruce S. Weir. *Bioinformatics* 2012; doi: 10.1093/bioinformatics/bts606.
2. **GWASTools: an R/Bioconductor package for quality control and analysis of Genome-Wide Association Studies.** Stephanie M. Gogarten, Tushar Bhangale, Matthew P. Conomos, Cecelia A. Laurie, Caitlin P. McHugh, Ian Painter, Xiuwen Zheng, David R. Crosslin, David Levine, Thomas Lumley, Sarah C. Nelson, Kenneth Rice, Jess Shen, Rohit Swarnkar, Bruce S. Weir, and Cathy C. Laurie. *Bioinformatics* 2012; doi:10.1093/bioinformatics/bts610.
3. **Quality control and quality assurance in genotypic data for genome-wide association studies.** Laurie CC, Doheny KF, Mirel DB, Pugh EW, Bierut LJ, Bhangale T, Boehm F, Caporaso NE, Cornelis MC, Edenberg HJ, Gabriel SB, Harris EL, Hu FB, Jacobs KB, Kraft P, Landi MT, Lumley T, Manolio TA, McHugh C, Painter I, Paschall J, Rice JP, Rice KM, Zheng X, Weir BS; GENEVA Investigators. *Genet Epidemiol.* 2010 Sep;34(6):591-602.

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