

**GenABEL:  
an R package for Genome Wide  
Association Analysis**

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# Outline

- **R : conditional statements : if, else and for loop**
- **GeneABEL**
- **Genetic data QC**
- **GWA association analysis**

# Arithmetic operations

- Square roots, base-10 logarithm, and exponentiation can be done straightforwardly with R

```
> sqrt(5)
[1] 2.236068
> log10(2.24)
[1] 0.350248
> exp(0.35)
[1] 1.419068
```

- The arithmetic operations and functions can be nested:

```
> exp(log10(sqrt(2 + 3)))
[1] 1.418337
```

# Conditional execution : *if* statement

```
> x = 0.1
  if( x < 0.2)
{ x <- x + 1
cat("increment that number!\n")
}
Increment that number!
```

```
>x
[1] 1.1
```

# Conditional execution : *if* statement and the corresponding *else* statement

```
> x = 2.0
> if ( x < 0.2)
{
  x <- x + 1
  cat("increment that number!\n")
} else
{ x <- x - 1
  cat("nah, make it smaller.\n");
} nah,make it smaller.
```

```
> x
[1] 1
```

# Conditional execution : *for loop*

```
➤ for (list in seq(0,1,by=0.3))  
  { cat(list,"\n"); } 0 0.3 0.6 0.9
```

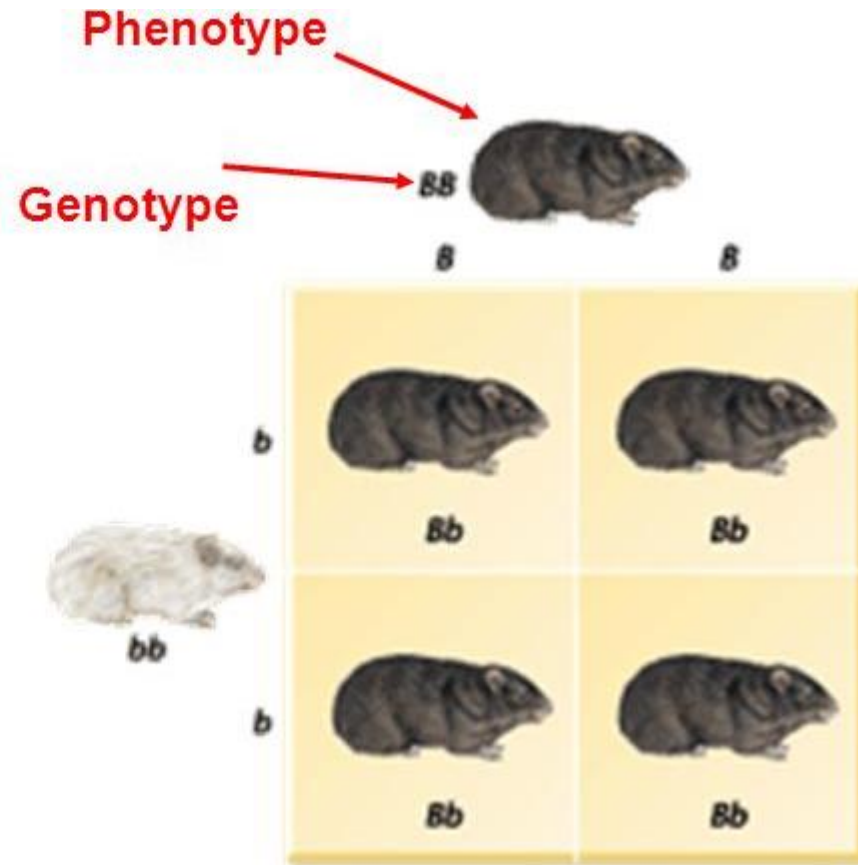
```
> x <- c(1,2,4,8,16)  
for (loop in x)  
{ cat("value of loop: ",loop,"\n");  
}  
value of loop: 1  
value of loop: 2  
value of loop: 4  
value of loop: 8  
value of loop: 16
```

# Introduction

- **GenABEL is an R library developed to facilitate Genome-Wide Association analysis of binary and quantitative traits.**
- **Features of GenABEL :**
  - **specific facilities for storage and manipulation of large data**
  - **QC**
  - **Maximum Likelihood estimation of linear, logistic and Cox regression on Genome-wide scale**
  - **Specific functions to analyze and display the results**

# Relationship between Genotypes and Phenotypes

- **Genotype**: Indicates the alleles that the organism has inherited regarding a particular trait.
- **Phenotype**: The actual visible trait of the organism.





# Importing data to GenABEL(1)

## ➤ Need a phenotypic and genotypic data

### ▪ Example of a phenotype file :

id	sex	age	bt1	qt	qt1
"cd289982"	0	30.33	NA	NA	3.93
"cd325285"	0	36.514	1	0.49	3.61
"cd357273"	1	37.811	0	1.65	5.30
"cd872422"	1	20.393	0	1.95	4.07
"cd1005389"	1	28.21	1	0.35	3.90

**Definition:** A phenotype is the composite of an organism's observable characteristics or traits, such as its morphology, development, biochemical or physiological properties, behavior, and products of behavior. For example : eyes color, height

# Importing data to GenABEL(2)

## ➤ Need a phenotypic and genotypic data

### ▪ Example of a genotypic data

1	rs1001	0	1235	A A	A G	A G	A A	G G	1	cd289982	0	0	1	0
9	rs6679	0	2344	G T	G G	G G	T G	G G	1	cd325285	0	0	1	0
22	rs2401	0	3455	A A	C C	C C	C C	A C	1	cd357273	0	0	1	0
X	rs123	0	32535	T T	G T	T T	T T	T T	1	cd872422	0	0	1	0
XY	rs6679	0	2344	G T	G G	G G	T G	G G	1	cd1005389	0	0	1	0
Y	rs876	0	23556	0 0	0 0	T T	G G	T T						
mt	mitoA1	0	24245	A A	C C	0 0	0 0	0 0						

# GWAS main philosophy

- **GWAS = Genome Wide Association Studies**
- **IDEA = GWAS involve scan for large number of genetic markers across the whole genome of many individuals to find specific genetic variations associated with the disease and/or other phenotype**
- **Find the genetic variation(s) that contribute(s) and explain(s) complex diseases**

# GWAS visually

- GWAS tries to uncover links between genetic basis of the disease
- Which set of SNPs explain the phenotype?

Genotype	Phenotype
ATGC <b>A</b> GTT	control
TTGC <b>A</b> GTT	control
CTGC <b>A</b> GTT	control
ATGC <b>G</b> GTT	case
TTGC <b>G</b> GTT	case
CTGC <b>C</b> GTT	case

SNP

# GWAS workflow

Large cohort (>1000) of cases and controls

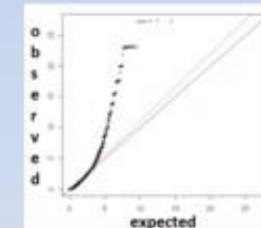
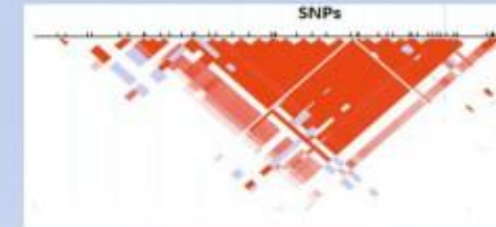
Get genome information with SNP arrays

Find deviating from expected haplotypes  
visualize SNP-SNP interactions using HapMap

Detection of potential association signals and their fine mapping (e.g. detection of LD, stratification effect)

Replication of detected association in new cohort /  
subset for validation purposes

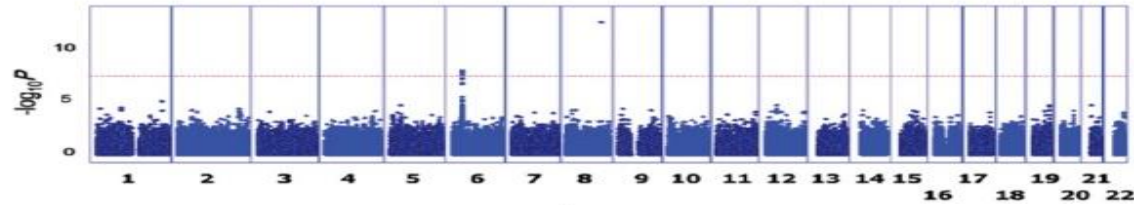
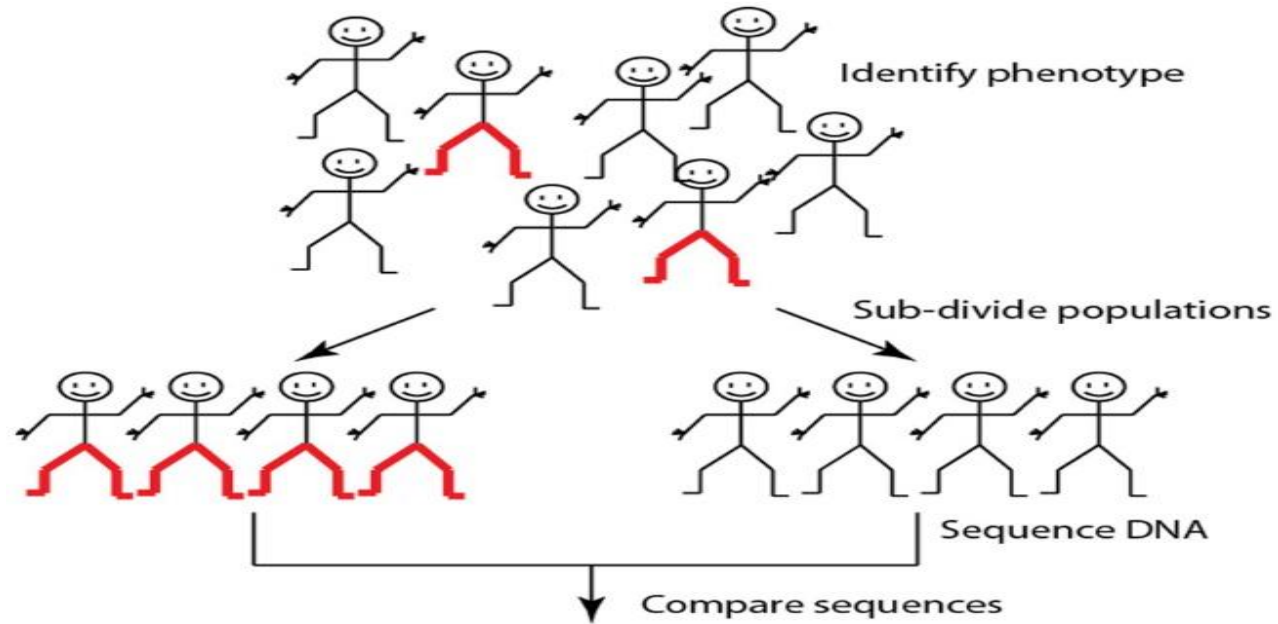
Biological / clinical validation



	AT	AG	Total
cases observed	35	65	100
controls observed	125	25	150
Totals	160	90	250



# GWAS workflow



Identify SNPs

	Chromosomal Region 1	Chromosomal Region 2	Chromosomal Region 3	
Person 1	ACTTA <b>C</b> GATCGA TGAAT <b>G</b> CTAGCT	GTACT <b>G</b> TGGGATA CATGA <b>C</b> ACCTAT	GCTAT <b>A</b> GAGGG CGATA <b>T</b> CTCCC	Person 1
Person 2	ACTTA <b>A</b> GATCGA TGAAT <b>T</b> CTAGCT	GTACT <b>A</b> TGGGATA CATGA <b>T</b> ACCTAT	GCTAT <b>T</b> GAGGG CGATA <b>A</b> CTCCC	Person 2
Person 3	ACTTA <b>C</b> GATCGA TGAAT <b>G</b> CTAGCT	GTACT <b>G</b> TGGGATA CATGA <b>C</b> ACCTAT	GCTAT <b>A</b> GAGGG CGATA <b>T</b> CTCCC	Person 3
	<b>SNP1</b>	<b>SNP2</b>	<b>SNP3</b>	

Verify GBIO0002

**Which tools to use to do  
GWAS workflows?**

**How to find SNP-Disease  
associations?**

# Common tools

- **Some of the popular tools**
  - **SVS Golden Helix (data filtering and normalization)**
    - Is commercial software providing ease of use compared to other free solutions requiring use of numerous libraries
    - Has unique feature on CNV Analysis
    - Manual: <http://doc.goldenhelix.com/SVS/latest/>
  - **Biofilter (pre-selection of SNPs using database info)**
  - **GenABEL library implemented in R (<http://www.genabel.org/>)**



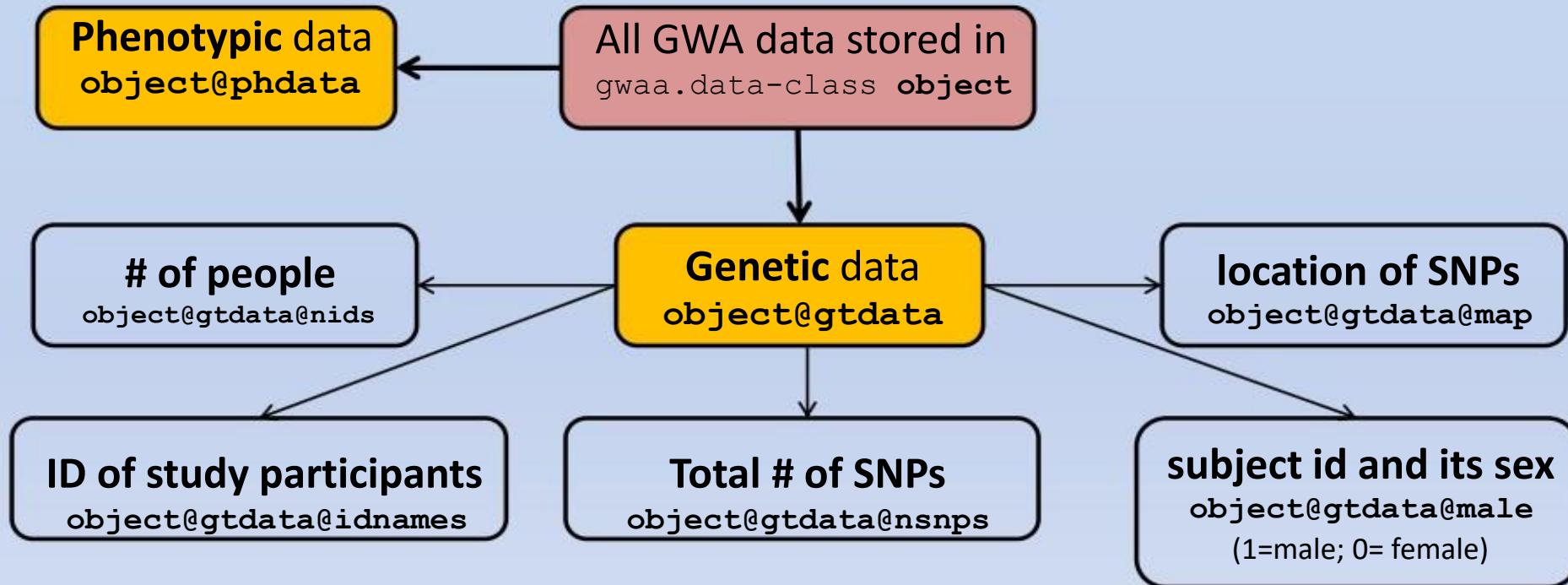
# Introduction to GenABEL (1/2)

- This library allows to do complete GWAS workflow
- GWAS data and corresponding attributes (SNPs, phenotype, sex, etc.) are stored in data object `gwas.data-class`
- The object attributes could be accessed with `@`
  - phenotype data: `gwaa_object@phdata`
  - number of people in study: `gwaa_object@gtdata@nids`

# Introduction to GenABEL(2/2)

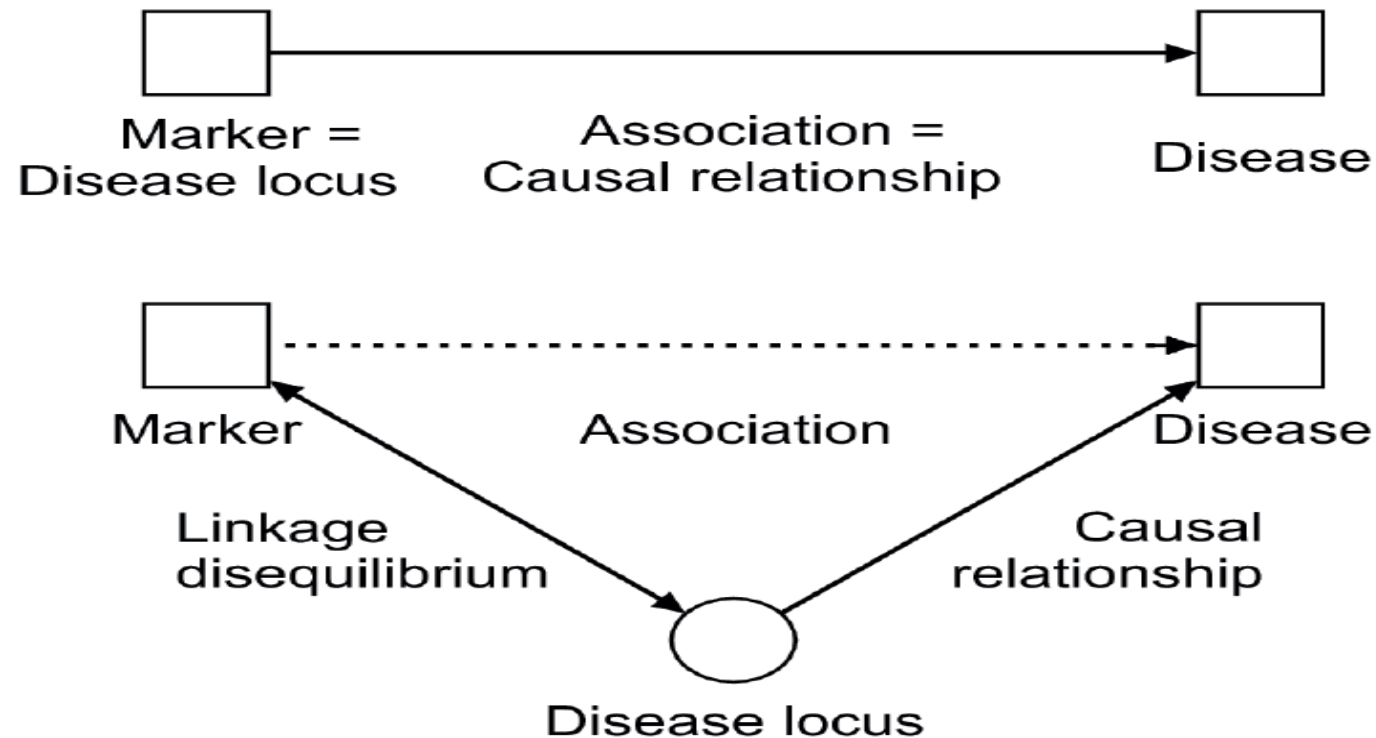
- number of SNPs: `gwaa_object@gtdata@nsnps`
- SNP names: `gwaa_object@gtdata@snpnames`
- Chromosome labels: `gwaa_object@gtdata@chromosome`
- SNPs map positions: `gwaa_object@gtdata@map`

# GeneABEL object structure



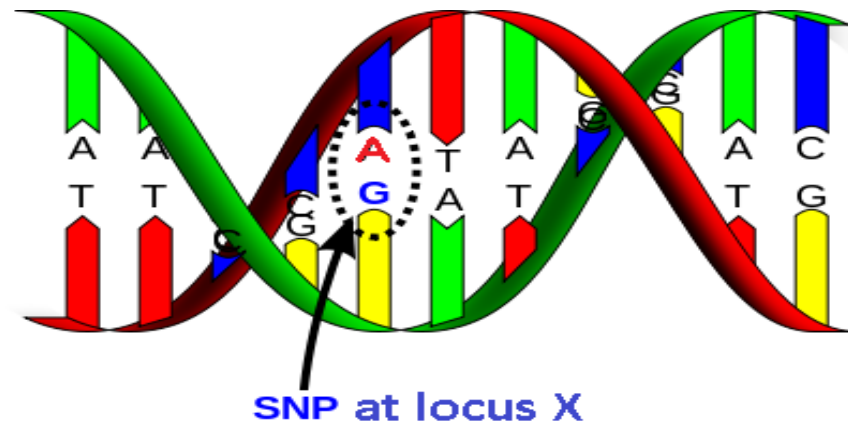
# The main question of GWA studies

- What is the **causal model** underlying genetic association?



# Important genetic terms

- Given position in the genome (i.e. locus) has several associated alleles (**A** and **G**) which produce genotypes  $r_A/r_G$



- Haplotypes
  - Combination of alleles at different loci

# Genotype coding

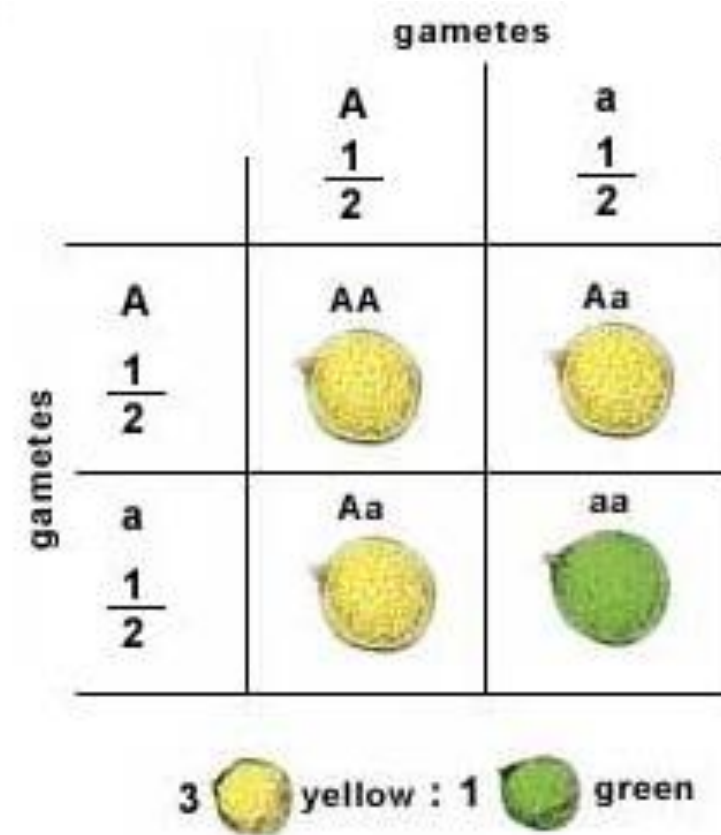
- For given bi-allelic marker/SNP/loci there could be total of **3 possible genotypes** given alleles **A** and **a**

Genotype	Coding
AA	0
Aa	1
aa	2

**Note: A is major allele and a is minor**

# Genetic allelic dominance

- Dominance describes relationship of two alleles (A and a) in relation to final phenotype
  - if one allele (e.g. A) “masks” the effect of other (e.g. a) it is said to be dominant and masked allele recessive
  - Here the dominant allele A gives pea a yellow color



Source: [http://nissemann.blogspot.be/2009\\_04\\_01\\_archive.html](http://nissemann.blogspot.be/2009_04_01_archive.html)

Homozygote dominant:	AA
Heterozygote:	Aa
Homozygote recessive:	aa

# Genotype genetic based models

- Hypothesis ( $H_0$ ): the genetic effects of AA and Aa are the same (A is dominant allele)
- Hypothesis ( $H_0$ ): the genetic effects of aa and AA are the same
- Hypothesis ( $H_0$ ): the genetic effects of aa and Aa are the same (a is recessive allele)

	Dominant (A)		Heterozygote		Recessive (a)	
	aa	aA or AA	aa or AA	aA	aa or aA	AA
Cases	$r_0$	$r_1 + r_2$	$r_0 + r_2$	$r_1$	$r_0 + r_1$	$r_2$
Controls	$s_0$	$s_1 + s_2$	$s_0 + s_2$	$s_1$	$s_0 + s_1$	$s_2$
Total	$n_0$	$n_2$	$n_0 + n_2$	$n_1$	$n_0 + n_1$	$n_2$

$$\bullet \chi_{dom}^2 = n \cdot \frac{(r_0(s_1 + s_2) - (r_1 + r_2)s_0)^2}{r \cdot s \cdot n_0 \cdot (n_1 + n_2)} \quad \text{Dominant}$$

$$\bullet \chi_{het}^2 = n \cdot \frac{(r_1(s_0 + s_2) - (r_0 + r_2)s_1)^2}{r \cdot s \cdot n_1 \cdot (n_0 + n_2)} \quad \text{Heterozygous}$$

$$\bullet \chi_{rec}^2 = n \cdot \frac{((r_0 + r_1)s_2 - r_2(s_0 + s_1))^2}{r \cdot s \cdot (n_0 + n_1) \cdot n_2} \quad \text{Recessive}$$



# Working on Linux? : GenABEL Installation (1/2)

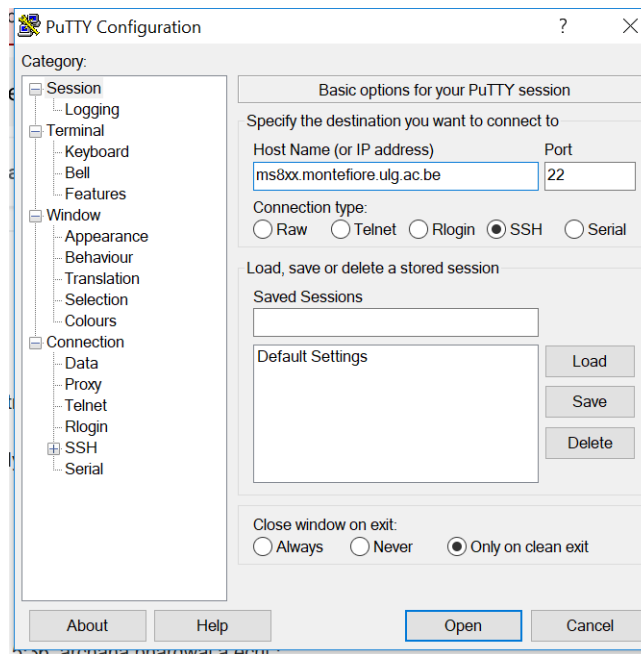
- Download source code from website <https://cran.r-project.org/src/contrib/Archive/GenABEL/>
- Download most updated version 1.8
- Go to link and download dependent packages  
<https://mran.microsoft.com/snapshot/2016-10-02/web/packages/GenABEL.data/index.html>

# GenABEL Installation (2/2)

- **First install the dependency packages**
  - > `install.packages('genetics')`
  - > `install.packages('haplo.stats')`
  
- **Do installation by running following command**
  - > `install.packages("/dirpath/GenABEL.data_1.0.0.tar.gz", repos=NULL, type="source")`
  - > `install.packages('dirpath/GenABEL_1.8-0.tar.gz', repos=NULL, type="source')`

# Working on Windows?

- Download Putty from <https://putty.org/>
- Step 1 : Login into `ms8xx.montefiore.ulg.ac.be` ( $01 \leq xx \leq 18$ )



- [Step 2 : Enter the username and password into ms801.montefiore.ulg.ac.be](https://ms801.montefiore.ulg.ac.be) (01 <= xx <= 18)



The image shows a PuTTY terminal window titled "ms801.montefiore.ulg.ac.be - PuTTY". The terminal output is as follows:

```
login as: bhardwaj
bhardwaj@ms801.montefiore.ulg.ac.be's password:
login as: bhardwaj
bhardwaj@ms801.montefiore.ulg.ac.be's password:
Welcome to Ubuntu 16.04.3 LTS (GNU/Linux 4.4.0-137-generic x86_64)

 * Documentation:  https://help.ubuntu.com
 * Management:    https://landscape.canonical.com
 * Support:       https://ubuntu.com/advantage

317 packages can be updated.
0 updates are security updates.

Last login: Tue Oct  9 00:01:55 2018 from 10.38.4.207
bhardwaj@ms801:~$
```

**Connected !!**

# Hands on GenABEL

## ➤ Load package

```
> library("GenABEL")
```

```
> data(ge03d2ex) #loads data(i.e. from GWAS) on type 2 diabetes
```

```
> summary(ge03d2ex)[1:5,] #view first 5 SNP data (genotypic data)
```

	Chromosome	Position	Strand	A1	A2	NoMeasured	CallRate	Q.2	P.11	P.12	P.22	Pexact	Fmax	Plrt
rs1646456	1	653	+	C	G	135	0.9926471	0.33333333	57	66	12	0.3323747	-0.10000000	0.2404314
rs4435802	1	5291	+	C	A	134	0.9852941	0.07462687	114	20	0	1.0000000	-0.08064516	0.2038385
rs946364	1	8533	-	T	C	134	0.9852941	0.27611940	68	58	8	0.3949055	-0.08275286	0.3302839
rs299251	1	10737	+	A	G	135	0.9926471	0.04444444	123	12	0	1.0000000	-0.04651163	0.4549295
rs2456488	1	11779	+	G	C	135	0.9926471	0.34814815	59	58	18	0.5698988	0.05343327	0.5360019

**>= 0,98 means good genotyping**

```
> summary(ge03d2ex@phdata) #view phenotypic data
```

id	sex	age	dm2	height	weight	diet	bmi
<b>Length:136</b>	Min. :0.0000	Min. :23.84	Min. :0.0000	Min. :150.2	Min. : 46.63	Min. :0.00000	Min. :17.30
Class :character	1st Qu.:0.0000	1st Qu.:38.33	1st Qu.:0.0000	1st Qu.:161.5	1st Qu.: 69.02	1st Qu.:0.00000	1st Qu.:24.56
Mode :character	Median :1.0000	Median :48.71	Median :1.0000	Median :169.4	Median : 81.15	Median :0.00000	Median :28.35
	Mean :0.5294	Mean :49.07	Mean :0.6324	Mean :169.4	Mean : 87.40	Mean :0.05882	Mean :30.30
	3rd Qu.:1.0000	3rd Qu.:58.57	3rd Qu.:1.0000	3rd Qu.:175.9	3rd Qu.:102.79	3rd Qu.:0.00000	3rd Qu.:35.69
	Max. :1.0000	Max. :81.57	Max. :1.0000	Max. :191.8	Max. :161.24	Max. :1.00000	Max. :59.83
				NA's :1	NA's :1		NA's :1

**A1 A2** = allele 1 and 2

**Strand** = DNA strand + or -

**NoMeasured** = # of times the genotype was observed

**Pexact** = P-value of the exact test for HWE

**Fmax** = estimate of deviation from HWE, allowing meta-analysis

**Position** = genomic position (bp)

**CallRate** = allelic frequency expressed as a ratio

# Exploring phenotypic data

## ➤ See aging phenotype data in compressed form

```
> descriptives.trait(ge03d2ex)
```

	No	Mean	SD
id	136	NA	NA
sex	136	0.529	0.501
age	136	49.069	12.926
dm2	136	0.632	0.484
height	135	169.440	9.814
weight	135	87.397	25.510
diet	136	0.059	0.236
bmi	135	30.301	8.082

## ➤ Extract all sexes of all individuals

```
> ge03d2ex@phdata$sex # accessing sex column of the data frame with $
```

```
1 0 1 0 0 1 1 0 0 1 0 0 1 1 0 0 0 1 1 1 1 1 1 1 1 1 1 0 1 0 1 0 1 0 1 1 0 0 0 1 1 1 1 1 0 1 1  
1 0 1 1 1 1 0 1 1 1 1 0 1 0 1 0 0 1 0 1 1 0 1 0 0 1 0 1 1 1 1 1 1 0 1 0 0 1 0 1 0 0 0 0  
0 0 0 1 0 0 0 1 1 0 1 1 0 1 0 1 0 1 1 0 0 0 0 1 0 1 0 0 0 1 0 0 1 0 0 1 1 0 1 1 1 0 1 0  
0 1 1 0
```

## ➤ Sorting data by binary attribute (e.g. sex)

```
> descriptives.trait(ge03d2ex, by=ge03d2ex@phdata$sex)
```

	No (by.var=0)	Mean	SD	No (by.var=1)	Mean	SD	Ptt	Pkw	Pexact
id	64	NA	NA	72	NA	NA	NA	NA	NA
sex	64	NA	NA	72	NA	NA	NA	NA	NA
age	64	46.942	12.479	72	50.959	13.107	0.070	0.081	NA
dm2	64	0.547	0.502	72	0.708	0.458	0.053	0.052	0.074
height	64	162.680	6.819	71	175.534	7.943	0.000	0.000	NA
weight	64	78.605	26.908	71	95.322	21.441	0.000	0.000	NA
diet	64	0.109	0.315	72	0.014	0.118	0.025	0.019	0.026
bmi	64	29.604	9.506	71	30.930	6.547	0.352	0.040	NA

➤ **How many people are included in the study?**

```
> nids(ge03d2ex)
```

➤ **How many of these are males?**

```
> sum(male(ge03d2ex))
```

➤ **How many are females?**

```
> nids(ge03d2ex) - sum(male(ge03d2ex) )
```

➤ **What is male proportion?**

```
> sum(male(ge03d2ex)) / nids(ge03d2ex)
```



# Exploring genotypic data / statistics

>descriptives.marker (ge03d2ex)

```
$`Minor allele frequency distribution`
      X<=0.01 0.01<X<=0.05 0.05<X<=0.1 0.1<X<=0.2   X>0.2
No    146.000      684.000      711.000      904.000 1555.000
Prop   0.036        0.171        0.178        0.226   0.389
```

*Number of copies minor/rare alleles out of total number (i.e. 4000)*

```
$`Cumulative distr. of number of SNPs out of HWE, at different alpha`
      X<=1e-04 X<=0.001 X<=0.01 X<=0.05 all X
No      46.000   71.000 125.000 275.000 4000
Prop    0.012   0.018  0.031  0.069   1
```

*Total number of SNPs*

```
$`Distribution of proportion of successful genotypes (per person)`
      X<=0.9 0.9<X<=0.95 0.95<X<=0.98 0.98<X<=0.99 X>0.99
No     1.000           0           0          135.000      0
Prop  0.007           0           0           0.993      0
```

*Proportion of missing values (subject id9049 has missing info on "sex" "age" "dm2" "height" "weight" "diet" "bmi" )*

```
$`Distribution of proportion of successful genotypes (per SNP)`
      X<=0.9 0.9<X<=0.95 0.95<X<=0.98 0.98<X<=0.99 X>0.99
No     37.000      6.000      996.000      1177.000 1784.000
Prop  0.009      0.002      0.249      0.294   0.446
```

*Number of SNPs that successfully were able to identify sample genotype (i.e. call rate). E.g. in this case*

```
$`Mean heterozygosity for a SNP`
[1] 0.2582298
```

*Only 25% SNPs are heterozygous (i.e. have different types of alleles)*

*98% SNPs were able to identify / explain more than 96% genotypes*

```
$`Standard deviation of the mean heterozygosity for a SNP`
[1] 0.1592255
```

```
$`Mean heterozygosity for a person`
[1] 0.2476507
```

```
$`Standard deviation of mean heterozygosity for a person`
[1] 0.04291038
```

# Assessing quality of the raw data (1)

- Test for Hardy-Weinberg equilibrium given set of SNPs
  - in controls (i.e.  $dm2 = 0$ )

```
> dim(ge03d2ex@gtdata)
[1] 136 4000
> ge03d2ex@phdata$dm2
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
> summary(ge03d2ex@gtdata[(ge03d2ex@phdata$dm2 == 0),])
          Chromosome Position Strand A1 A2 NoMeasured CallRate    Q.2 P.11 P.12 P.22    Pexact     Fmax     Plrt
rs1646456             1       653      + C G          50      1.00 0.34000000    23  20   7  0.5275140  0.10873440  0.4448755
rs4435802             1      5291      + C A          48      0.96 0.04166667    44   4   0  1.0000000 -0.04347826  0.6766092
rs946364              1      8533      - T C          50      1.00 0.33000000    22  23   5  1.0000000 -0.04025328  0.7750907
rs299251              1     10737      + A G          50      1.00 0.06000000    44   6   0  1.0000000 -0.06382979  0.5358747
rs2456488             1     11779      + G C          50      1.00 0.37000000    21  21   8  0.5450202  0.09909910  0.4849983
#extract the exact HWE test P-values into separate vector "Pexact"
> Pexact0<-summary(ge03d2ex@gtdata[(ge03d2ex@phdata$dm2 == 0),])[, "Pexact"]
# perform chi square test on the Pexact values and calculate λ (inflation factor).
# If λ=1.0 no inflation or diflation of test statistic (i.e. no stratification effect)
> estlambda(Pexact0, plot=TRUE)
$estimate
[1] 1.029817
Inflation of test statistic (Pexact) is seen, see stratification effect
$se
[1] 0.002185684
```

# Assessing quality of the raw data (2)

## 1. Test for Hardy-Weinberg equilibrium on given set of SNPs

- in cases (i.e.  $dm2 = 1$ )

```
Pexact1<-summary(ge03d2ex@gtdata[(ge03d2ex@phdata$dm2 == 1),])[, "Pexact"]  
estlambda(Pexact1, plot=TRUE)
```

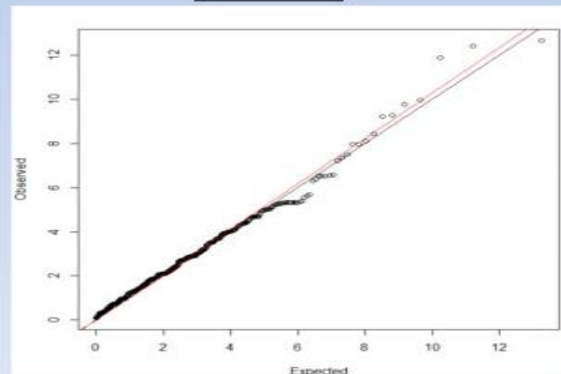
```
$estimate
```

```
[1] 2.304846
```

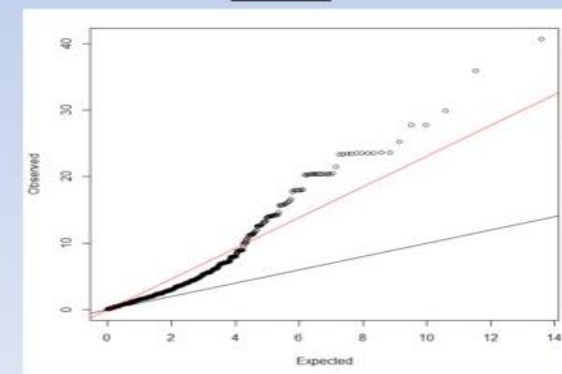
```
$se
```

```
[1] 0.01319398
```

**Controls (raw data)**



**Cases (raw data)**



Q-Q plots:

# Save the Plots

## ➤ Save plots on system

```
> pdf('filename')
```

```
> plot(qTest, df="Pc1df")
```

```
> dev.off()
```

## ➤ Check the output

## ➤ Draw QQ plot for (srdata) for cases and controls and check the output

# Loci Association Analysis

- Let's apply a simple method that uses both *mixed model* and *regression* to find statistically significant associations between trait (**presence/absence** of diabetes type 2) and loci (SNPs)

```
> qTest = qtscore(dm2, ge03d2ex, trait="binomial")
```

```
> descriptives.scan(qTest, sort="Pc1df")
```

	Chromosome	Position	Strand	A1	A2	N	effB	se_effB	chi2.1df	P1df	effAB	effBB	chi2.2df	P2df	Pc1df
rs1719133	1	4495479	+	T	A	136	0.33729339	0.09282784	13.202591	0.0002795623	0.40042370	0.000000	14.729116	0.0006333052	<b>0.0003504258</b>
rs2975760	3	10518480	+	A	T	134	3.80380024	1.05172986	13.080580	0.0002983731	3.4545455	10.000000	13.547345	0.0011434877	<b>0.0003732694</b>
rs7418878	1	2808520	+	A	T	136	3.08123060	0.93431795	10.875745	0.0009743183	3.6051282	4.871795	12.181064	0.0022642036	<b>0.0011762545</b>
rs5308595	3	10543128	-	C	G	133	3.98254950	1.21582875	10.729452	0.0010544366	3.3171429	Inf	10.766439	0.0045930101	<b>0.0012699705</b>
rs4804634	1	2807417	+	C	G	132	0.43411456	0.13400290	10.494949	0.0011970132	0.5240642	0.173913	11.200767	0.0036964462	<b>0.0014362332</b>

**effAB / effBB** = odds ratio of each possible genotype combination

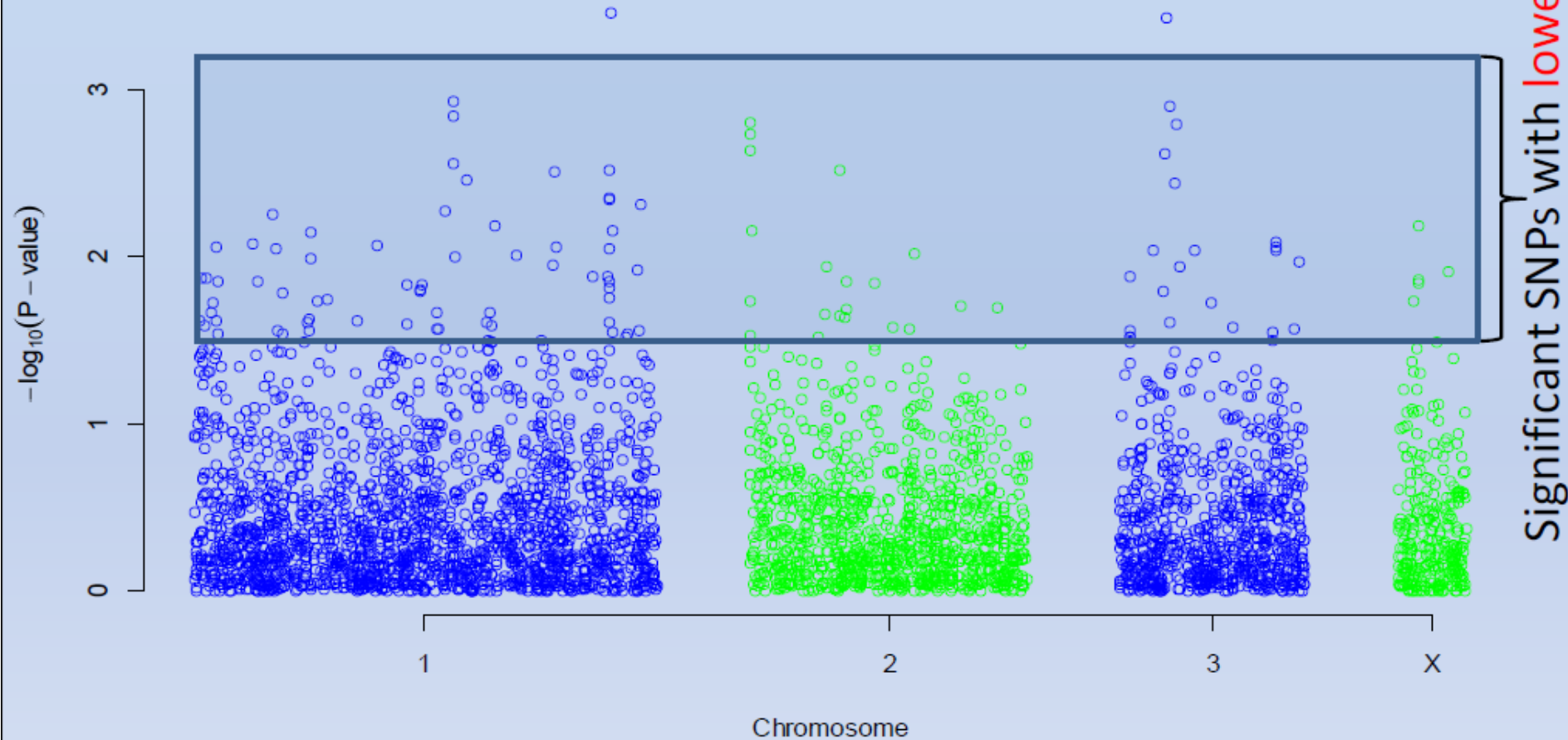
**P1df / P2df** = probability values from GWA analysis

**Pc1df** = probability values corrected for inflation factor (stratification effects) at 1 degree of freedom

```
# plot the lambda corrected values and visualize the Manhattan plot
```

```
plot(qTest, df="Pc1df")
```

# Manhattan plot of raw data



➤ To visualize to SNPs associated to the trait use

> `descriptives.scan(qTest)`

To see all the results covering all SNPs

> `results(qTest)`

- load the (srdta) in R
- Find statistically significant associations between “sex” trait and loci (SNPs) one by one in srdta
- plot the lambda corrected values and visualize the Manhattan plot

# Empirical resembling with qtscore

- The previous GWA ran only once
- Lets re-run 500 times the same test with random resembling of the data

- This method is more rigorous
- Empirical distribution of P-values are obtained

```
> qTest.E <- qtscore(dm2, ge03d2ex, times=500)
```

```
> descriptives.scan(qTest.E, sort="Pc1df")
```

	Chromosome	Position	Strand	A1	A2	N	effB	se_effB	chi2.1df	P1df	Pc1df	effAB	effBB	chi2.2df	P2df
rs1719133	1	4495479	+	T	A	136	-0.2652064	0.07298850	13.202591	0.458	0.540	-0.2080882	-0.7375000	14.729116	NA
rs2975760	3	10518480	+	A	T	134	0.2340655	0.06471782	13.080580	0.478	0.558	0.2755102	0.4090909	13.547345	NA
rs7418878	1	2808520	+	A	T	136	0.2089098	0.06334746	10.875745	0.862	0.912	0.2807405	0.3268398	12.181064	NA
rs5308595	3	10543128	-	C	G	133	0.2445516	0.07465893	10.729452	0.890	0.924	0.2564832	0.4623656	10.766439	NA

- None of the top SNPs hits the  $P < 0.05$  significance!
- None of the "P2df" values pass threshold (i.e. all = NA)



# Quality Control (QC) of GWA data

➤ Since we suspect irregularities in our data we will do

- Simple QC assessment without HWE threshold

- Clean data

➤ Will run `check.marker()` QC function

```
> QCresults <- check.marker(ge03d2ex,p.level=0)
> summary(QCresults)
```

```
$`Per-SNP fails statistics`
```

	NoCall	NoMAF	NoHWE	Redundant	Xsnpfail
NoCall	42	0	0	0	0
NoMAF	NA	384	0	0	0
NoHWE	NA	NA	0	0	0
Redundant	NA	NA	NA	0	0
Xsnpfail	NA	NA	NA	NA	1

*Number of SNPs with call rate lower than of 0.95*

*# of SNPs with MAF < 5/(2\* # of SNPs)*

```
$`Per-person fails statistics`
```

	IDnoCall	HetFail	IBSFail	isfemale	ismale	isXXY	otherSexErr
IDnoCall	1	0	0	0	0	0	0
HetFail	NA	3	0	0	0	0	0
IBSFail	NA	NA	2	0	0	0	0
isfemale	NA	NA	NA	2	0	0	0
ismale	NA	NA	NA	NA	0	0	0
isXXY	NA	NA	NA	NA	NA	0	0
otherSexErr	NA	NA	NA	NA	NA	NA	0

# Checking QC results

## ➤ Check how many subjects **PASSED** the QC test

```
> names(QCresults)
```

```
"nofreq"      "nocall"      "nohwe"      "Xmrkfail"   "hetfail"    "idnocall"   "ibsfail"  
"isfemale"   "ismale"     "otherSexErr" "snpok"     "idok"       "call"
```

```
> QCresults$idok
```

```
"id199" "id300" "id403" "id415" "id666" "id689" "id765" "id830" "id908" "id980"  
"id994" "id1193" "id1423" "id1505" "id1737" "id1827" "id1841" "id2068" "id2094" "id2097"  
"id2151" "id2317" "id2618" "id2842" "id2894" "id2985" ... "id6934"
```

```
> length(QCresults$idok)
```

```
[1] 128
```

## ➤ Check how many SNPs **PASSED** the QC test

```
> length(QCresults$snpok)
```

```
[1] 3573
```

```
#see the SNP ids that passed the QC test
```

```
QCresults$idok
```

# Select “cleaned” data

## ➤ Selection of data from original object **BOTH**:

\*by particular individual                      \*by set of SNPs

```
> ge03d2ex["id199", "rs1646456"]
```

```
      id  sex  age dm2  height  weight diet  bmi
id199  1 59.22872  1 163.9123 80.40746  0 29.92768
@nids = 1
@nsnps = 1
@nbytes = 1
@idnames = id199
@snpnames = rs1646456
@chromosome = 1
@coding = 11
@strand = 01
@map = 653
@male = 1
@gtps = 80
```

## ➤ Give vectors of QC passed SNPs and individuals

```
>Cdata <- ge03d2ex[QCresults$idok, QCresults$snpok]
```

# Check the quality of overall QC data

## >descriptives.marker(Cdata)

```
$`Minor allele frequency distribution`
```

	X<=0.01	0.01<X<=0.05	0.05<X<=0.1	0.1<X<=0.2	X>0.2
No	0	508.000	677.000	873.000	1515.000
Prop	0	0.142	0.189	0.244	0.424

```
$`Cumulative distr. of number of SNPs out of HWE, at different alpha`
```

	X<=1e-04	X<=0.001	X<=0.01	X<=0.05	all X
No	44.000	66.000	117.000	239.000	3573
Prop	0.012	0.018	0.033	0.067	1

```
$`Distribution of proportion of successful genotypes (per person)`
```

	X<=0.9	0.9<X<=0.95	0.95<X<=0.98	0.98<X<=0.99	X>0.99
No	0	0	0	65.000	63.000
Prop	0	0	0	0.508	0.492

```
$`Distribution of proportion of successful genotypes (per SNP)`
```

	X<=0.9	0.9<X<=0.95	0.95<X<=0.98	0.98<X<=0.99	X>0.99
No	0	0	458.000	814.000	2301.000
Prop	0	0	0.128	0.228	0.644

```
$`Mean heterozygosity for a SNP`
```

```
[1] 0.2787418
```

```
$`Standard deviation of the mean heterozygosity for a SNP`
```

```
[1] 0.1497257
```

```
$`Mean heterozygosity for a person`
```

```
[1] 0.26521
```

```
$`Standard deviation of mean heterozygosity for a person`
```

```
[1] 0.01888496
```

```
GBIO0002
```

Better but still lots of HWE outliers. Population structure not accounted for?

The **lambda** did not improved significantly also indicating that the QC data still has factors not accounted for

```
estlambda(summary(Cdata)[,"Pexact"])
```

```
$estimate
```

```
[1] 2.150531
```

The genotype data has much higher call rates since individuals with NA values eliminated in the range of > 99%

# Which sub-group causing deviation from HWE?

```
> descriptives.marker(Cdata[Cdata@phdata$dm2==0,]) [2]
```

```
$`Cumulative distr. of number of SNPs out of HWE, at  
different alpha`
```

	X<=1e-04	X<=0.001	X<=0.01	X<=0.05	all	X	<b>controls</b>
No	0	0	7.000	91.000	3573		
Prop	0	0	0.002	0.025	1		

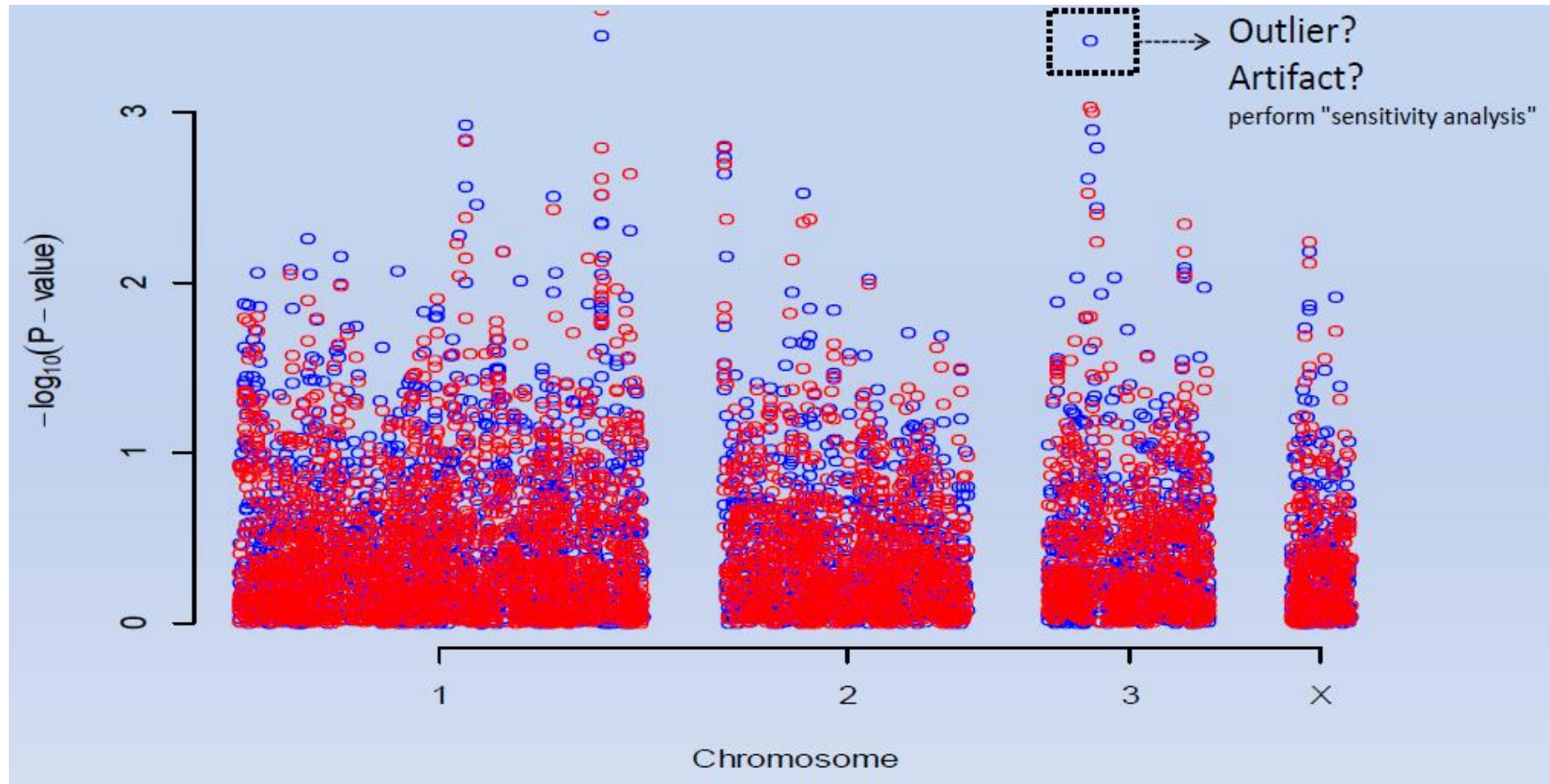
```
> descriptives.marker(Cdata[Cdata@phdata$dm2==1,]) [2]
```

```
$`Cumulative distr. of number of SNPs out of HWE, at  
different alpha`
```

	X<=1e-04	X<=0.001	X<=0.01	X<=0.05	all	X	<b>cases</b>
No	46.000	70.00127.000	228.000	3573			
Prop	0.013	0.02	0.036	0.064	1		

**As expected, the cases display the greatest deviation from HWE**

# Compare raw and cleaned data



```
> plot(qTest, df="Pc1df", col="blue")  
> qTest_QC = qtscore(dm2,Cdata,trait="binomial")  
> add.plot(qTest_QC , df="Pc1df", col="red")
```

Note that the cleaned data values are all lower this is due to lower  $\lambda$  value

# Finding population structure (1)

- The data seems to have clear population substructure that we should account for in order to do sensible data analysis
- Need to detect individuals that are “genetic outliers” compared to the rest using SNP data

- compute matrix of genetic kinship between subjects of this study

```
Cdata.gkin <- ibs(Cdata[,autosomal(Cdata)],weight="freq")
```

```
Cdata.gkin[1:5,1:5]
```

	id199	id300	id403	id415	id666
id199	<b>0.494427766</b>	3255.00000000	3253.00000000	3241.00000000	3257.00000000
id300	-0.011754266	<b>0.49360296</b>	3261.00000000	3250.00000000	3264.00000000
id403	-0.012253378	-0.01262949	<b>0.50541775</b>	3247.00000000	3262.00000000
id415	-0.001812109	0.01388179	-0.02515438	<b>0.53008236</b>	3251.00000000
id666	-0.018745051	-0.02127344	0.02083723	-0.02014175	<b>0.5306584</b>

- The numbers below the diagonal show the genomic estimate of kinship ('genome-wide IBD'),
- The numbers on the diagonal correspond to 0.5 plus the genomic homozygosity
- The numbers above the diagonal tell how many SNPs were typed successfully for both subjects

GBIO0002

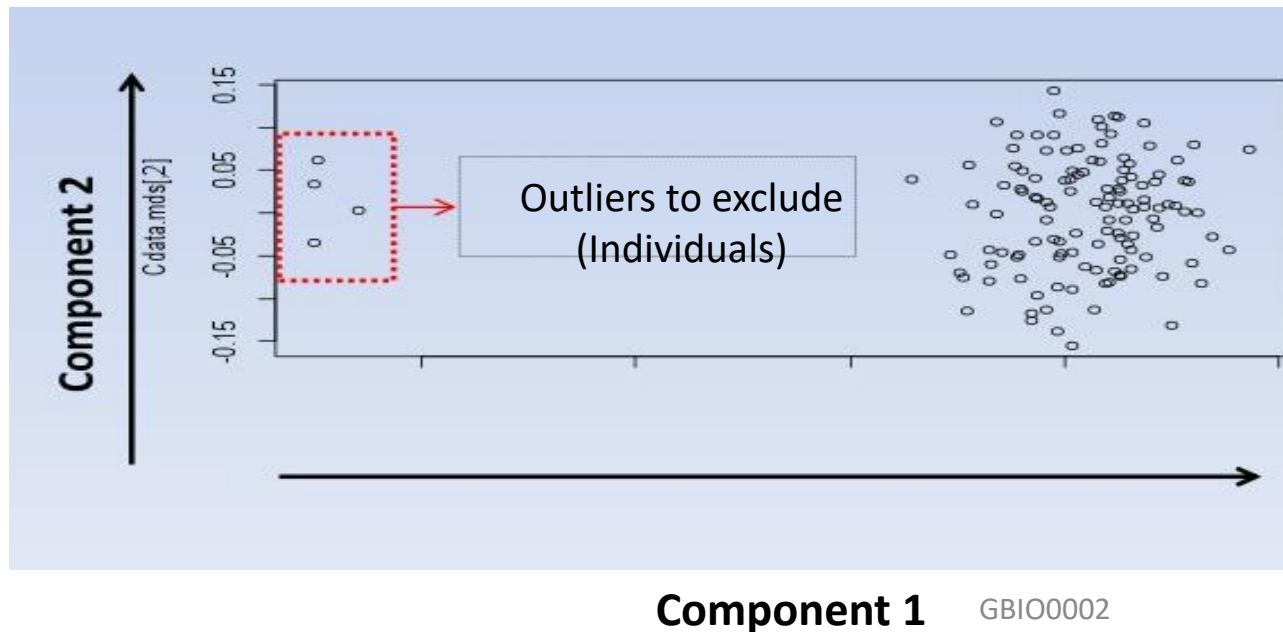
# Finding population structure (2)

## 2. Compute distance matrix from previous

```
Cdata.dist <- as.dist(0.5-Cdata.gkin)
```

## 3. Do Classical Multidimensional Scaling (PCA) and visualize results

```
Cdata.mds <- cmdscale(Cdata.dist)  
plot(Cdata.mds)
```



- The PCA fitted the genetic distances along the 2 components
- Points are individuals
- There are clearly two clusters
- Need to select all individuals from biggest cluster



# Second round of QC

## ➤ Select the ids of individuals from each cluster

- Can use k-means since clusters are well defined

```
> kmeans.res <- kmeans(Cdata.mds, centers=2, nstart=1000)
> cluster1 <- names(which(kmeans.res$cluster==1))
> cluster2 <- names(which(kmeans.res$cluster==2))
```

## ➤ Select another clean dataset using data for individuals in cluster #2 (the largest)

```
> Cdata2 <- Cdata[cluster1,]
```

## ➤ Perform QC on new data

```
> QCdata2 <- check.marker(Cdata2, hweids=(phdata(Cdata2)$dm == 0), fdr = 0.2)
```

# Second round QC results

## ➤ Visualize the QC results and make conclusions

```
> summary(QCdata2)
```

```
$`Per-SNP fails statistics`
```

	NoCall	NoMAF	NoHWE	Redundant	Xsnpfail
NoCall	0	0	0	0	0
NoMAF	NA	40	0	0	0
NoHWE	NA	NA	0	0	0
Redundant	NA	NA	NA	0	0
Xsnpfail	NA	NA	NA	NA	0

- All markers passed the HWE test
- 40 markers did not pass the MAF QC test and need to be removed
- No phenotypic errors

```
$`Per-person fails statistics`
```

	IDnoCall	HetFail	IBSFail	isfemale	ismale	isXXY	otherSexErr
IDnoCall	0	0	0	0	0	0	0
HetFail	NA	0	0	0	0	0	0
IBSFail	NA	NA	0	0	0	0	0
isfemale	NA	NA	NA	0	0	0	0
ismale	NA	NA	NA	NA	0	0	0
isXXY	NA	NA	NA	NA	NA	0	0
otherSexErr	NA	NA	NA	NA	NA	NA	0

## ➤ Clean the dataset again excluding those SNPs

```
Cdata2 <- Cdata2[QCdata2$idok, QCdata2$snpok]
```

# Final QC test before GWA

## ➤ Final check on cases and controls QC data

```
> descriptives.marker(Cdata2[phdata(Cdata2)$dm2==1,]) [2]
$`Cumulative distr. of number of SNPs out of HWE, at different alpha`
      X<=1e-04 X<=0.001 X<=0.01 X<=0.05 all X
No          0          1  17.000  79.000  3533
Prop        0          0   0.005   0.022    1
```

**cases**

```
> descriptives.marker(Cdata2[phdata(Cdata2)$dm2==0,]) [2]
$`Cumulative distr. of number of SNPs out of HWE, at different alpha`
      X<=1e-04 X<=0.001 X<=0.01 X<=0.05 all X
No          0          0   7.000  91.000  3533
Prop        0          0   0.002   0.026    1
```

**controls**

- **Finally most of markers are within the HWE at  $\alpha < 0.05$**
- **Still controls have marker distribution that better follows HWE**

# Perform GWA on new data

## ➤ Perform the mixture model regression analysis

```
> Cdata2.qt <- qtscore(Cdata2@phdata$dm2, Cdata2, trait="binomial")  
  
> descriptives.scan(Cdata2.qt, sort="Pc1df")
```

Summary for top 10 results, sorted by Pc1df

	Chromosome	Position	Strand	A1	A2	N	effB	se_effB	chi2.1df	P1df	effAB	effBB	chi2.2df	P2df	Pc1df
rs1719133	1	4495479	+	T	A	124	0.3167801	0.08614528	13.522368	0.0002357368	0.3740771	0.0000000	14.677906	0.0006497303	0.0003048399
rs4804634	1	2807417	+	C	G	121	0.4119844	0.12480696	10.896423	0.0009635013	0.6315789	0.1739130	12.375590	0.0020543516	0.0011885463
rs8835506	2	6010852	+	A	T	121	3.5378209	1.08954331	10.543448	0.0011660066	4.0185185	4.0185185	12.605556	0.0018312105	0.0014292471
rs4534929	1	4474374	+	C	G	123	0.4547151	0.14160410	10.311626	0.0013219476	0.4830918	0.1739130	10.510272	0.0052206352	0.0016136479
rs1013473	1	4487262	+	A	T	124	2.7839368	0.86860745	10.272393	0.0013503553	3.0495868	5.8441558	10.926296	0.0042401869	0.0016471605
rs3925525	2	6008501	+	C	G	124	3.2807631	1.03380675	10.070964	0.0015062424	3.6923077	4.0000000	11.765985	0.0027864347	0.0018306610
rs3224311	2	6009769	+	G	C	124	3.2807631	1.03380675	10.070964	0.0015062424	3.6923077	4.0000000	11.765985	0.0027864347	0.0018306610
rs2975760	3	10518480	+	A	T	123	3.1802120	1.00916993	9.930784	0.0016253728	3.0000000	8.0000000	10.172522	0.0061810866	0.0019704699
rs2521089	3	10487652	-	T	C	123	2.7298775	0.87761175	9.675679	0.0018672326	3.0147059	5.0000000	10.543296	0.0051351403	0.0022533033
rs1048031	1	4485591	+	G	T	122	0.4510793	0.14548378	9.613391	0.0019316360	0.4844720	0.1714286	9.965696	0.0068545128	0.0023284084

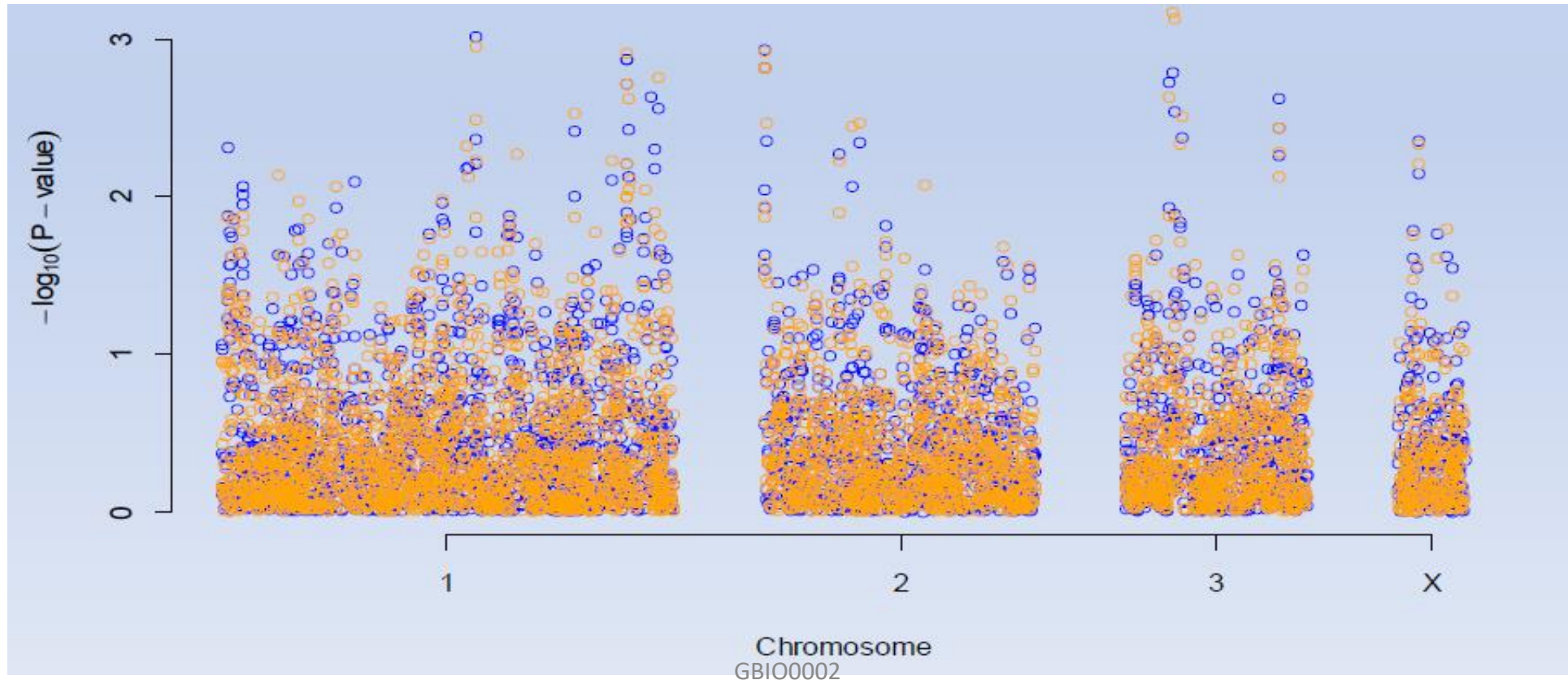
## ➤ Compare results to the previous QC round 1 results

# Manhattan plots

## ➤ Compare results QC round 1 vs QC round 2

```
> plot(Cdata2.qt)  
> add.plot(qTest_QC, col="orange")
```

Round 1 QC  
Round 2 QC  
(accounted for population stratification effects)



# Perform more rigorous GWA test computing GW (empirical) significance

- Will perform the GWA analysis 500 times obtaining GWA statistics

```
> Cdata2.qte <- qtscore(Cdata2@phdata$dm2, times=500, Cdata2, trait="binomial")
```

```
> descriptives.scan(Cdata2.qte, sort="Pc1df")
```

Summary for top 10 results, sorted by Pc1df

	Chromosome	Position	Strand	A1	A2	N	effB	se_effB	chi2.1df	P1df	Pc1df	effAB	effBB	chi2.2df	P2df
rs1719133	1	4495479	+	T	A	124	0.3167801	0.08614528	13.522368	0.346	0.402	0.3740771	0.0000000	14.677906	0.566
rs4804634	1	2807417	+	C	G	121	0.4119844	0.12480696	10.896423	0.844	0.894	0.6315789	0.1739130	12.375590	0.944
rs8835506	2	6010852	+	A	T	121	3.5378209	1.08954331	10.543448	0.886	0.938	4.0185185	4.0185185	12.605556	0.920
rs4534929	1	4474374	+	C	G	123	0.4547151	0.14160410	10.311626	0.922	0.946	0.4830918	0.1739130	10.510272	1.000
rs1013473	1	4487262	+	A	T	124	2.7839368	0.86860745	10.272393	0.924	0.952	3.0495868	5.8441558	10.926296	1.000
rs3925525	2	6008501	+	C	G	124	3.2807631	1.03380675	10.070964	0.942	0.960	3.6923077	4.0000000	11.765985	0.986
rs3224311	2	6009769	+	G	C	124	3.2807631	1.03380675	10.070964	0.942	0.960	3.6923077	4.0000000	11.765985	0.986
rs2975760	3	10518480	+	A	T	123	3.1802120	1.00916993	9.930784	0.948	0.966	3.0000000	8.0000000	10.172522	1.000
rs2521089	3	10487652	-	T	C	123	2.7298775	0.87761175	9.675679	0.964	0.978	3.0147059	5.0000000	10.543296	1.000
rs1048031	1	4485591	+	G	T	122	0.4510793	0.14548378	9.613391	0.966	0.982	0.4844720	0.1714286	9.965696	1.000

- Results had improved for the P2df statistic, but none of them fall under GW significance level of 0.05
  - rs1719133 does not pass the significance tests but is the one with the best level of association compared to other SNPs

# Biological interpretations

- For illustration purposes let's extract information on the rs1719133 from dbSNP
- Seems to target CCL3 - pro-inflammatory cytokine. The CCL2 was implicated in T1D [1]

Function class:  
rs1719133 is located in the intron region of [NM\\_002983.2](#).

NC\_000017.10: 34M..34M (200bp) | Find on Sequence: | Tools | Configure

SNP

Suspect

Somatic Allele

GMAF >= 0.01

Clinical Channel

Association Results

Cited Variants

Genes

GeneView via direct blast against RefSeq sequence

**Submitter records for this RefSNP Cluster**  
The submission [ss282753266](#) has the longest flanking sequence

**CCL3**  
Gene: CCL3  
Title: chemokine (C-C motif) ligand 3  
Location: complement(34,415,602..34,417,506)  
Length: 1,905

Links & Tools  
View GeneID: [6348 \(CCL3\)](#)  
View HGNC: [10627](#)  
View HPRD: [01656](#)  
View MIM: [182283](#)

NCBI Assay ID	Handle Submitter ID	Status	Alleles	5' Near Seq 30 bp	3' Near Seq 30 bp
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# Conclusions

- GWA studies are popular these days mainly due to high throughput technology development such as genotyping chips (i.e. SNP arrays) and sequences
- Analysis of GW data requires several steps of quality control in order to draw conclusions
- GenABEL provides tools to perform GWAs and automate some of the steps



# References

- [1] Ruili Guan et al. Chemokine (C-C Motif) Ligand 2 (CCL2) in Sera of Patients with Type 1 Diabetes and Diabetic Complications. PLoS ONE 6(4): e17822
- [2] Yurii Aulchenko, GenABEL tutorial <http://www.genabel.org/sites/default/files/pdfs/GenABEL-tutorial.pdf>
- [3] GenABEL project developers, GenABEL: genome-wide SNP association analysis 2012, R package version 1.7-2
- [4] Geraldine M Clarke et.al. Basic statistical analysis in genetic case-control studies. Nat Protoc. 2011 February ; 6(2): 121–133
- [5] Lobo, I. Same genetic mutation, different genetic disease phenotype. Nature Education 2008, 1(1)