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# Important genetic terms

Given position in the genome (i.e. locus) has several associated alleles (A and G) which produce genotypes r<sub>A</sub>/r<sub>G</sub>



> Haplotypes

- Combination of alleles at different loci

### **GWAS**





Tutorial in Biostatistics | 🖻 Open Access | 😋 🚺 🗐 😒

## A guide to genome-wide association analysis and post-analytic interrogation

Eric Reed, Sara Nunez, David Kulp, Jing Qian, Muredach P. Reilly, Andrea S. Foulkes 🔀

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SECTIONS

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#### Abstract

This tutorial is a learning resource that outlines the basic process and provides specific software tools for implementing a complete genome-wide association analysis. Approaches to post-analytic visualization and interrogation of potentially novel findings are also presented. Applications are illustrated using the free and open-source R statistical computing and graphics software environment, Bioconductor software for bioinformatics and the UCSC Genome Browser. Complete genome-wide association data on 1401 individuals across 861,473 typed single nucleotide polymorphisms from the PennCATH study of coronary artery disease are used for illustration. All data and code, as



# **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
ATGCAGTT	control
TTGCAGTT	control
CTGCAGTT	control
ATGCGGTT	case
TTGCGGTT	case
CTGCCGTT	case
SNP	





The era of hypothesis generating research



- Select your chip
- Complete your genotyping









1

Complement Factor H Variant Increases the Risk of Age-Related Macular Degeneration Jonathan L. Haines *et al. Science* **308**, 419 (2005): DOI: 10.1126/science.1110359

EXTENDED FOF FORMA!

Characterizatio

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Verify GBI00002

# **Relationship between Genotypes and Phenotypes**

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



# **Uses of GWAS**

≻Identify genes that are responsible for traits of interest:

- Humans
- Animals
- Plants





➤Understanding biological mechanisms related to the trait of interest



# **Human Genome Statistics**

Number of Chromosomes : 23 pairs
Genome Size : 3,079,843,747 Base pairs
No of Genes : 32,185

**Gene:** This is a sequence of nucleotides in the DNA that codes for a molecule (e.g., a protein)



### Gene Structure





### Let us identify signal (in from of SNPs) from GWAS DATA

### **PLINK : Introduction**

- PLINK is a free, open-source designed to perform a range of basic, large-scale analyses in a computationally efficient manner.
- PLINK is whole genome association analysis tool.
- PLINK has a well documented manual.
- Available for linux, MAC ansd MAC-DOS.
- Command line version is faster than graphical PLINK.

### **PLINK : Multi-feature tool**

- Merge two or more files
- Extracts subsets (SNPs or individuals)
- Compress data in a binary file format
- PLINK has numerous useful features for managing and analyzing genetic data
- Read data in a variety of formats
- Recode and reorder files

### **Input Files**

- Genotype data is a text file
- Pedigree file (.ped)
- Map file (.map)
- Genotype data is a compressed binary file
- Fam File (.fam)
- Bim file (.bim)
- Bed file (.bed)

## **PED Input File**

Pedigree File - the first six columns are mandatory:

- Family ID
- Individual ID
- Paternal ID
- Maternal ID
- Sex (1=male; 2=female; other=unknown)
- Phenotype

Column	Column2	Column	Column4	Column5	Column6		
1	1	ø	0	1	1	ΑΑ	GΤ
2	1	0	0	1	1	AC	ΤG
3	1	0	0	1	1	СС	GG
4	1	0	0	1	2	AC	тт
5	1	0	0	1	2	СС	GΤ

## **MAP Input File**

MAP File has 4 columns:

- chromosome (1-22, X, Y or 0 if unplaced)
- rs# or snp identifier
- Genetic distance (morgans)
- Base-pair position (bp units)

Column1 Column2 Column3 Column4

1 snp1 0 1 1 snp2 0 2

### **Others Input File**

\*.ped

		-	ŝ	-	-
		п	п	-	n
	٠			•	~

FID	IID	PID	MID	Sex	Ρ	rs1	rs2	rs3
1	1	0	0	2	1	CT	AG	AA
2	2	0	0	1	0	cc	AA	AC
3	3	0	0	1	1	CC	AA	AC

Chr	SNP	GD	BPP
1	rs1	0	870000
1	rs2	0	880000
1	rs3	0	890000

#### \*.fam

FID	IID	PID	MID	Sex	Ρ
1	1	0	0	2	1
2	2	0	0	1	0
3	3	0	0	1	1

*.bed	
Contains	binary version of the
SNP inf	o of the *.ped file.
(not in a	format readable for
	humans)

Chr	SNP	GD	BPP	Allele 1	Allele 2
1	rs1	0	870000	С	т
1	rs2	0	880000	А	G
1	rs3	0	890000	A	с

### Covariate file

FID	IID	C1	C2	C3	Ī
1	1	0.00812835	0.00606235	-0.000871105	
2	2	-0.0600943	0.0318994	-0.0827743	
3	3	-0.0431903	0.00133068	-0.000276131	

	Legend				
FID	Family ID	rs{x}	Alleles per subject per SNP		
IID	Individual ID	Chr	Chromosome		
PID	Paternal ID	SNP	SNP name		
MID	Maternal ID	GD	Genetic distance (morgans)		
Sex	Sex of subject	BPP	Base-pair position (bp units)		
Ρ	Phenotype	C{x}	Covariates (e.g., Multidimensional Scaling (MDS) components)		

### QC of genetic DATA

- A vital step that should be part of any GWAS is the use of appropriate QC.
- Without extensive QC, GWAS will not generate reliable results because raw genotype data are inherently imperfect.
- Errors in the data can arise for numerous reasons, for example, due to poor quality of DNA samples, poor DNA hybridization to the array, poorly performing genotype probes, and sample mix-ups or contamination.

### QC of genetic DATA

The QC steps consist of filtering out of SNPs and individuals based on the following:

(1) individual and SNP missingness,

(2) inconsistencies in assigned and genetic sex of subjects (see sex discrepancy),

(3) minor allele frequency (MAF),

(4) deviations from Hardy–Weinberg equilibrium (HWE),

### **Important Commands**

Step	Command	Function
1: Missingness of SNPs and individuals	geno	Excludes SNPs that are missing in a large proportion of the subjects. In this step, SNPs with low genotype calls are removed.
	mind	Excludes individuals who have high rates of genotype missingness. In this step, individual with low genotype calls are removed.
2: Sex discrepancy	check-sex	Checks for discrepancies between sex of the individuals recorded in the dataset and their sex based on X chromosome heterozygosity/homozygosity rates.
3: Minor allele frequency (MAF)	maf	Includes only SNPs above the set MAF threshold.
4: Hardy–Weinberg equilibrium (HWE)	hwe	Excludes markers which deviate from Hardy–Weinberg equilibrium.

### **PLINK SESSION**

- Data Preparation
- > Quality Control
- > Clustering



# **Example data**

•Download the example data from the course website (PLINK FOLDER)

- HapMap\_3\_r3\_1.bed
- HapMap\_3\_r3\_1.bim
- HapMap\_3\_r3\_1.fam

By looking into file extension, BED FORMAT





Detection of LD, population stratification (comes under Filteration step) Lets Perform Quality filteration

# **Quality control processes**

Missing genotype

Hardy-Weinberg Equilibrium

Minor Allele frequency

Linkage disequilibrium pruning

## Missing genotype (1)



# Missing genotype (2)

- Download Example files from website
- Copy all Files in PLINK Directory

plink --bfile HapMap\_3\_r3\_1 --missing

- output:
  - plink.imiss and
  - plink.lmiss,
- These files show respectively the proportion of missing SNPs per individual and the proportion of missing individuals per SNP.

Command Prompt

C:\Users\archana>cd C:\Users\archana\Desktop\GBIO2\_2020\CLASS 2\plink\_win64\_20200616

C:\Users\archana\Desktop\GBIO2 2020\CLASS 2\plink win64 20200616>plink --bfile HapMap 3 r3 1 --missing PLINK v1.90b6.18 64-bit (16 Jun 2020) www.cog-genomics.org/plink/1.9/ (C) 2005-2020 Shaun Purcell, Christopher Chang GNU General Public License v3 Logging to plink.log. Options in effect: --bfile HapMap 3 r3 1 --missing 16268 MB RAM detected; reserving 8134 MB for main workspace. 1457897 variants loaded from .bim file. 165 people (80 males, 85 females) loaded from .fam. 112 phenotype values loaded from .fam. Using 1 thread (no multithreaded calculations invoked). Before main variant filters, 112 founders and 53 nonfounders present. Calculating allele frequencies... done. Warning: 225 het. haploid genotypes present (see plink.hh ); many commands treat these as missing. Total genotyping rate is 0.997378. -missing: Sample missing data report written to plink.imiss, and variant-based missing data report written to plink.lmiss.

C:\Users\archana\Desktop\GBIO2\_2020\CLASS 2\plink\_win64\_20200616> C:\Users\archana\Desktop\GBIO2\_2020\CLASS 2\plink\_win64\_20200616>

# Missing genotype (3)

# Generate plots

indmiss<-read.table(file="plink.imiss", header=TRUE)
snpmiss<-read.table(file="plink.lmiss", header=TRUE)</pre>

*hist(indmiss[,6],main="Histogram individual missingness")* #selects column 6, names header of file

hist(snpmiss[,5],main="Histogram SNP missingness")
#selects column 5, names header of file



# Missing Rate Per Person (1)

- The initial step in all data analysis is to exclude individuals with too much missing Genotype data.
- A line in the terminal will appear, indicating how many individuals were removed due to low genotyping. If any individuals were removed, a file called plink.irem will be created, listing the Family and Individual IDs of these removed individuals.

# Missing Rate Per Person (2)

### *# Delete individuals with missingness >0.02.*

plink --bfile HapMap\_3\_r3\_1 --mind 0.02 --make-bed --out HapMap\_3\_r3\_2

C:\Users\archana\Desktop\GBIO2\_2020\CLASS 2\PLINK\_2>plink --bfile HapMap\_3\_r3\_1 --mind 0.02 --make-bed --out HapMap\_3\_r3\_2 PLINK v1.90b6.20 64-bit (21 Sep 2020) www.cog-genomics.org/plink/1.9/ (C) 2005-2020 Shaun Purcell, Christopher Chang GNU General Public License v3 Logging to HapMap 3 r3 2.log. Options in effect: --bfile HapMap 3 r3 1 --make-bed --mind 0.02 --out HapMap 3 r3 2 16268 MB RAM detected; reserving 8134 MB for main workspace. 1457897 variants loaded from .bim file. ÷ 165 people (80 males, 85 females) loaded from .fam. 112 phenotype values loaded from .fam. 1 person removed due to missing genotype data (--mind). ID written to HapMap 3 r3 2.irem . Using 1 thread (no multithreaded calculations invoked). Before main variant filters, 112 founders and 52 nonfounders present. Calculating allele frequencies... done. Warning: 225 het. haploid genotypes present (see HapMap 3 r3 2.hh ); many commands treat these as missing. Total genotyping rate in remaining samples is 0.997486. 1457897 variants and 164 people pass filters and QC. Among remaining phenotypes, 56 are cases and 56 are controls. (52 phenotypes are missing.) --make-bed to HapMap\_3\_r3\_2.bed + HapMap\_3\_r3\_2.bim + HapMap\_3\_r3\_2.fam ... done.

## **Missing Rate Per Person (3)**

### plink --bfile HapMap\_3\_r3\_2 --mind 0.2 --make-bed --out HapMap\_3\_r3\_3

Command Prompt	- 0
make-bed out HapMap_3_r3_4	
16268 MB RAM detected; reserving 8134 MB for main workspace. Error: Failed to open HapMap_3_r3_3.bed.	
C:\Users\archana\Desktop\GBIO2_2020\CLASS 2\PLINK_2>plinkbfile HapMap_3_r3_2mind 0.2make-bedout HapMap_3_ PLINK v1.90b6.20 64-bit (21 Sep 2020) www.cog-genomics.org/plink/1.9/ (C) 2005-2020 Shaun Purcell, Christopher Chang GNU General Public License v3 Logging to HapMap_3_r3_3.log. Options in effect: bfile HapMap_3_r3_2 make-bed mind 0.2 out HapMap_3_r3_3	r3_3
<pre>16268 MB RAM detected; reserving 8134 MB for main workspace. 1457897 variants loaded from .bim file. 164 people (79 males, 85 females) loaded from .fam. 112 phenotype values loaded from .fam. 0 people removed due to missing genotype data (mind). Using 1 thread (no multithreaded calculations invoked). Before main variant filters, 112 founders and 52 nonfounders present. Calculating allele frequencies done. Warning: 225 het. haploid genotypes present (see HapMap_3_r3_3.hh ); many commands treat these as missing. Total genotyping rate is 0.997486. 1457897 variants and 164 people pass filters and QC. Among remaining phenotypes, 56 are cases and 56 are controls. (52 phenotypes are missing.) make-bed to HapMap_3_r3_3.bed + HapMap_3_r3_3.bim + HapMap_3_r3_3.fam done.</pre>	
C:\Users\archana\Desktop\GBIO2_2020\CLASS 2\PLINK_2>	
# Missing Rate Per SNP (1)

Subsequent analyses can be set to automatically exclude SNPs on the basis of missing genotype rate, with the --geno option: the default is to include all SNPS (i.e. --geno 1).
To include only SNPs with a 90% genotyping rate (10% missing) use

--bfile file --geno 0.1

 As with the --maf option, these counts are calculated after removing individuals with high missing genotype rates.

# Missing Rate Per SNP(2)

#### plink --bfile HapMap\_3\_r3\_3 --geno 0.2 --make-bed --out HapMap\_3\_r3\_4

```
C:\Users\archana\Desktop\GBIO2_2020\CLASS 2\PLINK_2>plink --bfile HapMap_3_r3_3 --geno 0.2 --make-bed --out HapMap_3_r3_4
PLINK v1.90b6.20 64-bit (21 Sep 2020)
PLINK v1.90b6.20 64-bit (21 Sep 2020)www.cog-genomics.org/plink/1.9/(C) 2005-2020 Shaun Purcell, Christopher ChangGNU General Public License v3
Logging to HapMap 3 r3 4.log.
Options in effect:
  --bfile HapMap 3 r3 3
  --geno 0.2
  --make-bed
  --out HapMap_3_r3_4
16268 MB RAM detected; reserving 8134 MB for main workspace.
                                                                   ÷
1457897 variants loaded from .bim file.
164 people (79 males, 85 females) loaded from .fam.
112 phenotype values loaded from .fam.
Using 1 thread (no multithreaded calculations invoked).
Before main variant filters, 112 founders and 52 nonfounders present.
Calculating allele frequencies... done.
Warning: 225 het. haploid genotypes present (see HapMap 3 r3 4.hh ); many
commands treat these as missing.
Total genotyping rate is 0.997486.
0 variants removed due to missing genotype data (--geno).
1457897 variants and 164 people pass filters and QC.
Among remaining phenotypes, 56 are cases and 56 are controls. (52 phenotypes
are missing.)
 --make-bed to HapMap_3_r3_4.bed + HapMap_3_r3_4.bim + HapMap_3_r3_4.fam ...
done.
C:\Users\archana\Desktop\GBI02 2020\CLASS 2\PLINK 2>
```

#### **Missing Rate Per SNP : Delete SNPs**

#### *# Delete SNPs with missingness >0.02.*

plink --bfile HapMap\_3\_r3\_4 --geno 0.02 --make-bed --out HapMap\_3\_r3\_5

```
:\Users\archana\Desktop\GBI02_2020\CLASS 2\PLINK_2>plink --bfile HapMap_3_r3 4 --geno 0.02 --make-bed --out HapMap_3_r3_5
LINK v1.90b6.20 64-bit (21 Sep 2020)
                                              www.cog-genomics.org/plink/1.9/
C) 2005-2020 Shaun Purcell, Christopher Chang GNU General Public License v3
ogging to HapMap 3 r3 5.log.
ptions in effect:
 --bfile HapMap_3_r3_4
 --geno 0.02
 --make-bed
 --out HapMap_3_r3_5
.6268 MB RAM detected; reserving 8134 MB for main workspace.
                                                               ∗Å•
457897 variants loaded from .bim file.
64 people (79 males, 85 females) loaded from .fam.
12 phenotype values loaded from .fam.
sing 1 thread (no multithreaded calculations invoked).
efore main variant filters, 112 founders and 52 nonfounders present.
alculating allele frequencies... done.
larning: 225 het. haploid genotypes present (see HapMap 3 r3 5.hh ); many
ommands treat these as missing.
otal genotyping rate is 0.997486.
6686 variants removed due to missing genotype data (--geno).
431211 variants and 164 people pass filters and QC.
mong remaining phenotypes, 56 are cases and 56 are controls. (52 phenotypes
re missing.)
-make-bed to HapMap 3 r3 5.bed + HapMap 3 r3 5.bim + HapMap 3 r3 5.fam ...
one.
```

#### **Check for sex discrepancy**

- Subjects who were a priori determined as females must have a F value of <0.2, and subjects who were a priori determined as males must have a F value >0.8.
- This F value is based on the X chromosome inbreeding (homozygosity) estimate.
- Subjects who do not fulfil these requirements are flagged "PROBLEM" by PLINK.

plink --bfile HapMap\_3\_r3\_5 --check-sex

C:\Users\archana\Desktop\GBIO2\_2020\CLASS 2\PLINK\_2>plink --bfile HapMap\_3\_r3\_5 --check-sex PLINK v1.90b6.20 64-bit (21 Sep 2020) www.cog-genomics.org/plink/1.9/ (C) 2005-2020 Shaun Purcell, Christopher Chang GNU General Public License v3 Logging to plink.log. Options in effect: --bfile HapMap\_3\_r3\_5 --check-sex ÷ 16268 MB RAM detected; reserving 8134 MB for main workspace. 1431211 variants loaded from .bim file. 164 people (79 males, 85 females) loaded from .fam. 112 phenotype values loaded from .fam. Using 1 thread (no multithreaded calculations invoked). Before main variant filters, 112 founders and 52 nonfounders present. Calculating allele frequencies... done. Warning: 181 het. haploid genotypes present (see plink.hh ); many commands treat these as missing. Total genotyping rate is 0.997997. 1431211 variants and 164 people pass filters and QC. Among remaining phenotypes, 56 are cases and 56 are controls. (52 phenotypes are missing.) --check-sex: 23430 Xchr and 0 Ychr variant(s) scanned, 1 problem detected. Report written to plink.sexcheck .

C:\Users\archana\Desktop\GBIO2 2020\CLASS 2\PLINK 2> Capture Effects Tools Help

#### **Generate plots to visualize**

# These checks indicate that there is one woman with a sex discrepancy, F value of 0.99.

(When using other datasets often a few discrepancies will be found).

#### **#READ plink.sexcheck**

gender <- read.table(file.choose(), header=T)</pre>

hist(gender[,6],main="Gender", xlab="F")

male=subset(gender, gender\$PEDSEX==1)
hist(male[,6],main="Men",xlab="F")

female=subset(gender, gender\$PEDSEX==2)
hist(female[,6],main="Women",xlab="F")

#### Visualization



#### **Delete individuals with sex discrepancy (1)**

- Read plink.sexcheck file
- Select specific row (164)
- Select first two column value
- Store information in dd\_filter.txt

#### Delete individuals with sex discrepancy (2)

This command removes the list of individuals with the status "PROBLEM".

plink --bfile HapMap\_3\_r3\_5 --remove dd\_filter.txt --make-bed --out HapMap\_3\_r3\_6

Select Command Prompt --out HapMap 3 r3 6 --remove dd filter.txt 16268 MB RAM detected; reserving 8134 MB for main workspace. 1431211 variants loaded from .bim file. 164 people (79 males, 85 females) loaded from .fam. 112 phenotype values loaded from .fam. --remove: 163 people remaining. Using 1 thread (no multithreaded calculations invoked). Before main variant filters, 112 founders and 51 nonfounders present. Calculating allele frequencies... done. Warning: 181 het. haploid genotypes present (see HapMap\_3\_r3\_6.hh ); many commands treat these as missing. Total genotyping rate in remaining samples is 0.998078. 1431211 variants and 163 people pass filters and QC. Among remaining phenotypes, 56 are cases and 56 are controls. (51 phenotypes are missing.) --make-bed to HapMap 3 r3 6.bed + HapMap 3 r3 6.bim + HapMap 3 r3 6.fam ... done.

# Allele Frequency

how often an form of a gene shows up in a population over several generations

the number of copies of a particular allele divided by the number of copies of all alleles at the genetic place in a population.



GG

88





B



Gg







### Genotypes

- PLINK uses the following two-bit coding of genotypes
  - 00 = A1/A1 (Homozygous non-reference)
  - 01 = A1/A2 (Heterozygous)
  - 11 = A2/A2 (Homozygous reference)
  - 10 = 0/0 (Missing)

### **Genotypes specific SNP matrix**

Suppose we have n individuals genotypes for N SNPs

$$\mathbf{X} = \begin{bmatrix} AA & CG & TT & \dots & GG \\ AG & CG & AT & \dots & CG \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ GG & CG & 00 & \dots & CC \end{bmatrix} \leftarrow \text{Individual 1} \\ \leftarrow \text{Individual 2} \\ \vdots \\ \leftarrow \text{Individual n} \\ \text{SNP1 SNP2 SNP3} \qquad \text{SNPN}$$

The genotypes correspond to a matrix X of size n x p

# **Allele Frequency**

•To generate a list of minor allele frequencies (MAF) for each SNP, based on all founders in the sample:

- This will create a file: **plink.frq** with five columns:
  - CHR Chromosome
  - SNP SNP identifier
  - A1 Allele 1 code (minor allele)
  - A2 Allele 2 code (major allele)
  - MAF Minor allele frequency

NCHROBS Non-missing allele count

#### Minor Allele Frequency (MAF)

- Once individuals with too much missing genotype data have been excluded, subsequent analyses can be set to automatically exclude SNPs on the basis of MAF (minor allele frequency).
- Include SNPs with MAF >= 0.05.
- The default value is 0.01. This quantity is based only on founders

#### **Minor Allele Frequency (MAF)**

Minor allele frequency (MAF) is the frequency at which the second most common allele occurs in a given population

#### plink --bfile HapMap\_3\_r3\_6 --freq --out MAF\_check

Command Prompt	
PLINK v1.90b6.20 64-bit (21 Sep 2020) (C) 2005-2020 Shaun Purcell, Christopher Chang Logging to MAF_check.log. Options in effect: bfile HapMap_3_r3_6 freq out MAF_check	
<pre>16268 MB RAM detected; reserving 8134 MB for main workspace. 1431211 variants loaded from .bim file. 163 people (79 males, 84 females) loaded from .fam. 12 phenotype values loaded from .fam. Jsing 1 thread (no multithreaded calculations invoked). Before main variant filters, 112 founders and 51 nonfounders present. Calculating allele frequencies done. Varning: 181 het. haploid genotypes present (see MAF_check.hh ); many commands treat these as missing. Total genotyping rate is 0.998078. freq: Allele frequencies (founders only) written to MAF_check.frq .</pre>	

**Exercise : Visualize the MAF** 

- Read the MAF\_check.frq
- Draw the histogram plot in R

#### **Visualize the MAF**

maf\_freq <- read.table("/path/MAF\_check.frq", header =TRUE) #change "path" with working directory</pre>

hist(maf\_freq[,5],main = "MAF distribution", xlab = "MAF")



#### **Filtration based on MAF**

**#** Remove SNPs with a low MAF frequency.

plink --bfile HapMap\_3\_r3\_6 --maf 0.05 --make-bed --out HapMap\_3\_r3\_7

# A conventional MAF threshold for a regular GWAS is between 0.01 or 0.05, depending on sample size.

# Count SNPs under MAF < 0.01 ?

### Hardy-Weinberg Equilibrium (1)

•To generate a list of genotype counts and Hardy-Weinberg test statistics for each SNP, use the option:

--hardy

which creates a file: **plink.hwe.** The file has the following format

SNP SNP identifier

TEST Code indicating sample

- A1 Minor allele code
- A2 Major allele code

GENO Genotype counts:11/12/22

O(HET) observed hetrozygosity

E(HET) Expected hetrozygosity

P H-W p-value

#### Hardy–Weinberg equilibrium (2)

Selecting SNPs with HWE p-value below 0.00001

plink --bfile HapMap\_3\_r3\_7 --hwe 1e-6 --make-bed --out HapMap\_hwe\_filter\_step1



- Linkage disequilibrium (LD): This is a measure of non-random association between alleles at different loci at the same chromosome in a given population.
- SNPs are in LD when the frequency of association of their alleles is higher than expected under random assortment.
- LD concerns patterns of correlations between SNPs.

# Linkage disequilibrium pruning (1)

•Sometimes it is useful to generate a pruned subset of SNPs that are in approximate linkage equilibrium with each other. This can be achieved via two commands:

--indep which prunes based on the variance inflation factor (VIF), which recursively removes SNPs within a sliding window;

plink --bfile HapMap\_3\_r3\_7 --indep 100 5 2 --make-bed --out HapMap\_3\_r3\_8

### Linkage disequilibrium pruning (2)



## Linkage disequilibrium pruning (3)

•Each is a simlpe list of SNP IDs; both these files can subsequently be specified as the argument for a -- extract or --exclude command.

•The parameters for --indep are: window size in SNPs (e.g. 50), the number of SNPs to shift the window at each step (e.g. 5), the VIF threshold. The VIF is 1/(1-R^2) where R^2 is the multiple correlation coefficient for a SNP being regressed on all other SNPs simultaneously.

•That is, this considers the correlations between SNPs but also between linear combinations of SNPs.

# How many snp in LD with window size "150", "200" ?

# clustering

plink.exe --bfile HapMap\_3\_r3\_8 --cluster

which generates four output files:

plink.cluster0

plink.cluster1

plink.cluster2

plink.cluster3

that contain similar information but in different formats. The

The \*.cluster0 file contains some information on the clustering process. This file can be safely ignored by most users.

The \*.cluster1 file contains information on the final solution, listed by cluster.

The \*.cluster2 file contains the same information but listed one line per individual

The \*.cluster3 file is in the same format as cluster2 (one line per individual) but contains all solutions (i.e. every step of the clustering from moving from N clusters each of 1 individual (leftmost column after family and individual ID) to 1 cluster (labelled 0) containing all N individuals (the final, rightmost column)

#### Plink.cluster1



#### There is only one cluster.

What if we have more than one cluster?



# We will perform this analysis in other R package

# **Association Analysis**

Case/control

Multiple-testing correction

# Basic case/control association test

To perform a standard case/control association analysis, use the option: plink.exe --bfile HapMap\_3\_r3\_8 --assoc --noweb which generates a file

plink.assoc

which contains the fields:

- CHR Chromosome
- SNP SNP ID
- BP Physical position (base-pair)
- A1 Minor allele name (based on whole sample)
- F\_A Frequency of this allele in cases
- F\_U Frequency of this allele in controls
- A2 Major allele name
- CHISQ Basic allelic test chi-square (1df)
- P Asymptotic p-value for this test
- OR Estimated odds ratio (for A1, i.e. A2 is reference)

# Adjustment for multiple testing

To generate a file of adjusted significance values that correct for all tests performed and other metrics, use the option:

plink.exe --bfile HapMap\_3\_r3\_8 --assoc --adjust

which generates the file

plink.adjust

which contains the fields

CHR	Chromosome number	
SNP	SNP identifer	
UNADJ	Unadjusted p-value	
GC	Genomic-control corrected p-values	
BONF	Bonferroni single-step adjusted p-values	
HOLM	Holm (1979) step-down adjusted p-values	
SIDAK_SS	Sidak single-step adjusted p-values	
SIDAK_SD	Sidak step-down adjusted p-values	
FDR_BH	Benjamini & Hochberg (1995) step-up FDR control	
FDR_BY	Benjamini & Yekutieli (2001) step-up FDR control	
sightly is control by significance value with an them see and in location, the		

This file is sorted by significance value rather than genomic location, the most significant results being at the top.

# Let us visualize GWAS result

# **LETS INSTALL R Pakcage**

 Open R window
 Install.packages("qqman")
 Load in library library("qqman") > gwas <- data.frame(read.table(file="plink.assoc",header=TRUE))</pre>

manhattan(gwas, main = "Manhattan Plot", ylim = c(0, 10),col="blue")

#### Manhattan Plot


### **Unit of information in Bioinformatics**

# What "unit of information" do we deal within bioinformatics ?

- DNA
- RNA
- Protein



- Sequence
- Structure
- Evolution



- Pathways
- Interactions
- Mutations







# Central Dogma of Molecular Biology

### https://www.genome.gov/human-genome-project



### Human Genome- 1990-2003

The first printout of the human genome to be presented as a series of books, displayed at the <u>Wellcome Collection</u>, London



### **Genomic information**



### **More information :**

DNA sequence, RNA sequence, Protein sequence



### http://humanproteomemap.org/ (Human Proteome Map (HPM)

 $\leftarrow$   $\rightarrow$  C (i) Not secure | humanproteomemap.org



Home O

Query Download

FAQs Contact us

### About Human Proteome Map

The Human Proteome Map (HPM) portal is an interactive resource to the scientific community by integrating the massive peptide sequencing result from the draft map of the human proteome project. The project was based on LC-MS/MS by utilizing of high resolution and high accuracy Fourier transform mass spectrometry. All mass spectrometry data including precursors and HCD-derived fragments were acquired on the Orbitrap mass analyzers in the high-high mode. Currently, the HPM contains direct evidence of translation of a number of protein products derived from over 17,000 human genes covering >84% of the annotated protein-coding genes in humans based on >290,000 non-redundant peptide identifications of multiple organs/tissues and cell types from individuals with clinically defined healthy tissues. This includes 17 adult tissues, 6 primary hematopoietic cells and 7 fetal tissues. The HPM portal provides an interactive web resource by reorganizing the label-free quantitative proteomic data set in a simple graphical view. In addition, the portal provides selected reaction monitoring (SRM) information for all peptides identified.

Statistics	
otatistics	

Organs/cell types	30
Genes identified	17,294
Proteins identified	30,057
Peptide sequences	293,700
N-terminal peptides	4,297
Splice junctional peptides	66,947
Samples	85
Adult tissues	17
Fetal tissues	7
Cell types	6



Adult tissues







# **Bioinformatics Significance**

### **RESEARCH NEWS**

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### **Missing Alzheimer's Gene Found**

Researchers find the gene that causes Alzheimer's disease in "Volga German" families. It shows a remarkable similarity to another recently discovered Alzheimer's gene

pinpointed as the likely site of the Alzheimer's gene. "That was like a sledgehammer to the forehead," says Schellenberg. "It went from being a ho-hum project to ... saying 'oh my God this is the gene.' "

Within a few days, the team sequenced the gene from Volga German family members, with help from David Galas and his col-

> close on the heels of the chromosome 14 gene discovery," says Alzheimer's researcher Dennis Selkoe of Harvard Medical School. "It is very important that the new gene on chromosome 1 has high homology to \$182," he adds. The similarity between the two genes may mean that the proteins they encode have similar functions. According to Selkoe, the resemblance "suggests that something about this type of ... protein is very important for the biology of Alzheimer's disease."

discovery was provocative because it provided a direct link to a characteristic feature of e, has Altheimer's pathology: APP is the source of a peptide called B-amyloid that is found in the abnormal "senile plaques" that stud Alzcovery. heimer's patients' brains. But mutant APP genes turned out to account for only 2% to 3% of familial Alzheimer's cases. orm of

About a year later, several teams, including Schellenberg's, showed that many more cases of familial Alzheimer's are caused by an unknown defective gene on chromosome 14. That gene was identified earlier this year by a team led by Peter St. George-Hyslop of the

University of Toronto; the results were reported in the 29 June issue of Nature.

Intriguing as these discoveries were, they left untouched one handful of Alzheimer's-carrying families, which had been identified by Thomas Bird at the Veterans Affairs Medical Center in Seattle: the socalled Volga Germans, who were all descended from a colony of ethnic Germans liv-

sequence tagged (EST) sequences, short DNA sequences known to come from active genes. Wasco found an EST with a sequence similar to \$182, Tanzi recalls, and said, "maybe this is the Volga German gene."

After the S182 sequence was published, Tangi and Wasco told Schellenberg about Wasco's idea. "Having seen a zillion candidates [for the Volga German gene] come and go, I wasn't excited," Schellenberg recalls. But Ephrat Levy-Lahad, in his lab group, went ahead and checked. She found that the new gene was not only on chromosome 1, but was in the very stretch of DNA that she had



Family resemblance. Mutations in the similar proteins made by the genes S182 and STM2 cluster around the membrane-spanning regions.

# Changes in the number and order of genes (A-D) create genetic diversity within and between populations.



# Why do we need DATABASES ?



### Genome sequencing generates lots of data



### DATABASES



# What are Biological Databases??

### **Biological Database**

- It is a collection of data that is structured, searchable, updated periodically and cross-referenced.
- Stores biological data in electronic form.
- · Purpose-
- Systemization of database
- Availability of biological data
- Analysis of computed biological data

### Features of Biological

### Databases

- 1. Heterogeneity
- 2. High volume data
- 3. Uncertainity
- 4. Data curation
- 5. Data integration
- 6. Data sharing
- 7. Dynamics

# **Types of Biological Databases??**

There are many different types of database but for routine sequence analysis, the following are initially the most important.

Primary databases
 Secondary databases
 Composite databases



### **Interconnections between Databases**



# **Primary Databases**

Theses are the primary sources of data used to store nucleic acid, protein sequences and structural information of biological macromolecules.

Some primary databases-

- NCBI(The National Centre for Biotechnology Information)
  - GenBank
  - DDBJ (DNA data bank of Japan)
- SWISS-PROT(Swiss-Prot)
- PIR (Protein Information Resource)
- PDB(Protein Data Bank)

This sequence collection of this database is due to the efforts of basic research from academic industrial and sequencing lab)

# **Classification : Primary Databases**

- ✓ Sequence Information
  - ✓ DNA: EMBL, Genbank, DDBJ
  - ✓ Protein: SwissProt, TREMBL, PIR, OWL
- ✓ Genome Information
  - ✓ GDB, MGD, ACeDB
- ✓ Structure Information
   ✓ PDB, NDB, CCDB/CSD

# The National Center for Biotechnology Information





### Created in 1988 as a part of the National Library of Medicine at NIH

- Establish public databases
- Research in computational biology
- Develop software tools for sequence analysis
- Disseminate biomedical information

# **Primary Databases - GenBank**

# Database from NCBI, includes sequences from publicly available resources

S NCBI Resources	How To 🕑	
GenBank	Nucleotide 🗸	Search
GenBank 🔻 Submi	✓ Genomes ▼ WGS ▼ Metagenomes ▼ TPA ▼ TSA ▼ INSDC ▼ Other ▼	
GenBank Overvie	W	GenBank Resources
What is GenBank?		GenBank Home
GenBank <sup>®</sup> is the NIH ge Research, 2013 Jan;41(E	etic sequence database, an annotated collection of all publicly available DNA sequences ( <u>Nucleic Acids</u> 1):D36-42). GenBank is part of the International Nucleotide Sequence Database Collaboration, which comprises	Submission Tools
the DNA DataBank of Ja	an (DDBJ), the European Nucleotide Archive (ENA), and GenBank at NCBI. These three organizations exchange	Search GenBank
data on a daily basis.		Update GenBank Records
A GenBank release occu	s every two months and is available from the <u>ftp site</u> . The <u>release notes</u> for the current version of GenBank	

provide detailed information about the release and notifications of upcoming changes to GenBank. Release notes for <u>previous GenBank</u> releases are also available. GenBank growth statistics for both the traditional GenBank divisions and the WGS division are available from each release. GenBank growth <u>statistics</u> for both the traditional GenBank divisions and the WGS division are available from each release.

An <u>annotated sample GenBank record</u> for a Saccharomyces cerevisiae gene demonstrates many of the features of the GenBank flat file format.

### ✓ Open « Gene » and Search KRAS

S NCBI Resources	🖸 How T	'o 🕑					
Gene	Gene	∽ K	RAS reate RSS Create alert A	Advanced			× 😒 Search
<b>Gene sources</b> Genomic Mitochondria		Tabular - 20 pe	er page - Sort by Relevance			Send to: 🗸	Filters: Manage Filters
Organelles Categories Alternatively spliced		See <u>KRAS K</u> kras in <u>Homo</u>	RAS proto-oncogene, GTF sapiens Mus musculus Ra	Pase in the Gene database attus norvegicus All 238 Gene	records		Results by taxon Top Organisms [Tree]
Annotated genes Non-coding Protein-coding Pseudogene		Search resul Items: 1 to 20 o See also 16 o	ts of 1257 discontinued or replaced iter	<< First	< Prev Page 1 of 63 Next	> Last >>	Homo sapiens (755) Mus musculus (134) Rattus norvegicus (14) Cricetulus griseus (8) Xenopus laevis (7)
Sequence content		Name/Gene ID	Description	Location	Aliases	MIM	All other taxa <i>(339)</i> More
Ensembl RefSeq RefSeqGene Status	clear	☐ <u>KRAS</u> ID: 3845	KRAS proto-oncogene, GTPase [ <i>Homo sapiens</i> (human)]	Chromosome 12, NC_000012.12 (2520478925251003, complement)	C-K-RAS, CFC2, K-RAS2A, K-RAS2B, K-RAS4A, K-RAS4B, K-Ras, KI-RAS1, KRAS2, NS, NS3, RALD, RASK2, c-Ki-ras2, KRAS	190070	Find related data Database: Select Find items
<u>Clear all</u> Show additional filters		☐ <u>Kras</u> ID: 16653	Kirsten rat sarcoma viral oncogene homolog [ <i>Mus musculus</i> (house mouse)]	Chromosome 6, NC_000072.6 (145216699145250291, complement)	Al929937, K-Ras, K-Ras 2, K-ras, Ki-ras-2, Kras2, c-K-ras, c-Ki-ras, p21B, ras, Kras		Search details

ocation: 12p12.1 con count: 6					See	KRAS in <u>Genome Dat</u>	<u>i View</u>
Annotation release	Status	Assembly	Chr	Location			
09	current	GRCh38.p12 (GCF_000001405.38)	12	NC_000012.12 (2520478925251	003, complement)		
05	previous assembly	GRCh37.p13 (GCF_000001405.25)	12	NC_000012.11 (2535818025403	870, complement)		
Genomic regions, tran	scripts, and products 00012.12 Chromosome 12 Reference	e GRCh38.p12 Primary Assembly 🖂			Go	to <u>reference</u> quenc	
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Format Homo sapiens chromosome 12, GRCI	h38.p12 Primary Assembly
NCBI Reference Sequence: NC_000012.12	
FASTA Graphics	
LOCUS NC_000012 46215 bp DNA	linear CON 26-MAR-2018
DEFINITION Homo sapiens chromosome 12, GRCh38.p12 Prim	ary Assembly.
ACCESSION <u>NC_000012</u> REGION: complement(252047892525	1003)
Accession – DBLINK BioProject: PRINA168	
Assembly: GCF_000001405.38	
Key Identifier KEYWORDS RefSeq.	
SOURCE Homo sapiens (human)	
Spocios	tebrata: Euteleostomi:
Mammalia; Eutheria; Euarchontoglires; Prima	tes; Haplorrhini;
Catarrhini; Hominidae; Homo.	
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Dugan-Rocha.S., Gill.R., Gunaratne.P., Harr	is.R.A., Hawes.A.C.,
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	/note="Derived by automated computational analysis using	
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### FASTA -

### Homo sapiens chromosome 12, GRCh38.p12 Primary Assembly

NCBI Reference Sequence: NC\_000012.12

GenBank Graphics

>NC\_000012.12:c25251003-25204789 Homo sapiens chromosome 12, GRCh38.p12 Primary Assembly Header stars with ">" sign

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The FASTA format is now universal for all databases and software that handles
DNA and protein sequences
Specifications:
One header line

•starts with > with a ends with [return]



Search '6Q6I' : Lysine decarboxylase A from Pseudomonas aeruginosa Classification: OXIDOREDUCTASE (type) Organism(s): Pseudomonas aeruginosa Expression System: Escherichia coli

https://www.rcsb.org/

# **OMIM** database

- Online Mendelian Inheritance in Man (OMIM)
- "information on all known mendelian disorders linked to over 12,000 genes"
- "Started at 1960s by Dr. Victor A. McKusick as a catalog of mendelian traits and disorders"
- Linked disease data
- Links disease phenotypes and causative genes
- Used by physicians and geneticists



### **OMIM-search results**

• Look for the entires that link to the genes. Apply filters if needed



# **OMIM-entries**



### Description

Shondwloarthronathy (ShA) one of the commonest chronic rheumatic diseases includes a spectrum of related

### **OMIM Gene ID -entries**



TEXT

For background information on the major histocompatibility complex (MHC) and human leukocyte antigens

### **OMIM-Finding disease linked genes**

### Mapping

Gu et al. (2009) conducted a genomewide scan followed by fine mapping analysis in a 4-generation Han Chinese family with ankylosing spondylitis and obtained a maximum lod score of 4.02 at D6S273 (theta = 0.0) on chromosome 6, verifying the HLA-B locus.

### Linkage Heterogeneity

To identify major loci controlling clinical manifestations of AS, Brown et al. (2003) performed genomewide linkage analysis on 188 affected sib-pair families containing 454 affected individuals. Heritabilities of the traits studied were as follows: age at symptom onset, 0.33 (p = 0.005); disease activity assessed by the Bath Ankylosing Spondylitis Disease Activity Index (BASDAI), 0.49 (p = 0.0001); and functional impairment assessed by the Bath Ankylosing Spondylitis Functional Index (BASFI), 0.76 (p = 0.000001). No linkage was observed between the MHC and any of the traits studied. Significant linkage (lod = 4.0) was observed between a region on chromosome 18p and the BASDAI. Age at symptom onset showed suggestive linkage to chromosome 11p (lod = 3.3). Maximum linkage with the BASFI was seen at chromosome 2q (lod = 2.9; see SPDA3, new). Brown et al. (2003) concluded that these clinical manifestations are largely determined by a small number of genes not encoded within the MHC.

In a multistage study involving 12,701 SNPs and patients with autoimmune diseases, including ankylosing spondylitis, the Wellcome Trust Case Control Consortium and the Australo-Anglo-American Spondylitis Consortium (2007) identified significant association with SNPs in the ARTS1 gene (ERAP1; 606832) (combined results,  $p = 1.2 \times 10(-8)$  to  $3.4 \times 10(-10)$ ) on chromosome 5q15. Association was also found with SNPs in the IL23R gene (607562) on chromosome 1p31.3: in combined analysis, the strongest association was at rs11209032 (odds ratio, 1.3;  $p = 7.5 \times 10(-9)$ ). The association remained strong when only individuals who self-reported as not having inflammatory bowel disease (see IBD17, 612261) were considered, and was still strongest at rs11209032 ( $p = 6.9 \times 10(-7)$ ).

# **Secondary Databases**



# **Secondary Database : PROSITE**

### ✓ Open link <u>https://prosite.expasy.org/</u>



Database of protein domains, families and functional sites

PROSITE consists of documentation entries describing protein domains, families and functional sites as well as associated patterns and profiles to identify them [More... / References / Commercial users].

PROSITE is complemented by ProRule, a collection of rules based on profiles and patterns, which increases the discriminatory power of profiles and patterns by providing additional information about functionally and/or structurally critical amino acids [More...].

Release 2018\_08 of 12-Sep-2018 contains 1814 documentation entries, 1309 patterns, 1222 profiles and 1245 ProRule.

Search	Browse
e.g. PDOC00022, PS50089, SH3, zinc finger Search	<ul> <li>by documentation entry</li> <li><u>by ProRule description</u></li> <li>by taxonomic scope</li> <li>by number of positive hits</li> </ul>



# **Primary vs Secondary Databases**



# **Composite Databases**

- Collection of various primary
   Renders sequence searching databases sequences
  - highly efficient as it searches multiple resources


# **Other Databases**



# PubMed database

- <u>PubMed</u> is one of the best known database in the whole scientific community
- Most of biology related literature from all the related fields are being indexed by this database
- It has very powerful mechanism of constructing search queries
  - Many search fields Logical operators (AND, OR)
- Provides electronic links to most journals
- Example of searching by author articles published within 2012-2013

```
Search results
Items: 11
PLANET-SNP pipeline: PLants based ANnotation and Establishment of True SNP pipeline
1. Bhardwaj A, Bag SK.
    Genomics. 2019 Sep;111(5):1066-1077. doi: 10.1016/j.ygeno.2018.07.001. Epub 2018 Jul 3.
    PMID: 31533899
    Similar articles
Transcriptome analysis provides insight into prickle development and its link to defense and
2. secondary metabolism in Solanum viarum Dunal.
    Pandey S, Goel R, Bhardwaj A, Asif MH, Sawant SV, Misra P.
    Sci Rep. 2018 Nov 20;8(1):17092. doi: 10.1038/s41598-018-35304-8.
    PMID: 30459319 Free PMC Article
    Similar articles
    In Silico identification of SNP diversity in cultivated and wild tomato species: insight from molecular
3. simulations.
    Bhardwai A, Dhar YV, Asif MH, Bag SK.
    Sci Rep. 2016 Dec 8;6:38715. doi: 10.1038/srep38715.
```

# **Applications of Bioinformatics : Medical Implications**

### ✓ Pharmacogenomics

- ✓Not all drugs work on all patients, some good drugs cause death in some patients
- ✓ So by doing a gene analysis before the treatment the offensive drugs can be avoided
- ✓ Also drugs which cause death to most can be used on a minority to whose genes that drug is well suited volunteers wanted!
- ✓Customized treatment
- ✓ Gene Therapy
  - ✓ Replace or supply the defective or missing gene
  - ✓ E.g: Insulin and Factor VIII or Haemophilia

# **Applications of Bioinformatics : Diagnosis of Disease**

### ✓ Diagnosis of disease

□Identification of genes which cause the disease will help detect disease at early stage e.g. Huntington disease -

Symptoms – uncontrollable dance like movements, mental disturbance, personality changes and intellectual impairment

## ✓ Death in 10-15 years

✓ The gene responsible for the disease has been identified

- ✓ Contains excessively repeated sections of CAG
- $\checkmark$  So once analyzed the couple can be counseled

# **Applications of Bioinformatics : Drug Design**

- ✓ Can go up to 15yrs and \$700million
- ✓One of the goals of bioinformatics is to reduce the time and cost involved with it.
- $\checkmark$  The process
  - ✓ Discovery
    - ✓ Computational methods can improves this
  - ✓ Testing



### All about Post GWAS

## **Post GWAS : Interpreting SNPs**

Look at the functionality of your SNP (SNPdoc) Literature search – can you give biological plausibility?

Other tests: pathway analysis / Gene based tests

Manual Search = No

**Multiple softwares are available** 



## **Genomic Positions of SNPs**

### **IMPORTANT FINDING**



### Gene Structure





## **Genomic Positions of SNPs**



## **Classification of SNPs (Based on Genomic Position)**



## Why: From SNPs to Genes





### **Examples: From SNPs to Genes**

- rs6311 and rs6313 are SNPs in the Serotonin 5-HT2A receptor gene on human chromosome 13.
- rs3091244 is an example of a triallelic SNP in the CRP gene on human chromosome 1.
- rs148649884 and rs138055828 in the FCN1 gene encoding M-ficolin crippled the ligandbinding capability of the recombinant M-ficolin.

### List of Data sources for Post GWAS

Example data types	Select data sources*	UCSC genome browser navigation
DNA level data (non-somatic; genEric to all cells): I. Coordinates, e.g.		
(1) SNPs	NCBI dbSNP[a], ENSEMBL[b]	Variation: Common SNPs(141)
(2) Insertions and delations (INDELs)		
(3) Copy number variants (CNVs)		
II. Gene elements, e.g.		
(1) Protein-coding genes	NCBI RefSeq[c], NCBI GenBank[d], ENSEMBL[b]	Gene and Gene Predictions: UCSC Genes
(2) Non-protein-coding genes	NCBI RefSeq[c], NCBI GenBank[d], ENSEMBL[b]	Gene and Gene Predictions: UCSC Genes
Cell and tissue-specific regulation:		
III. Chromatin state, e.g.		
<ol> <li>DNA hypersensitivity (DNase-Seq)</li> </ol>	ENCODE[e], ENSEMBL[b]	Regulation: ENCODE Regulation
(2) FAIRE sequencing	ENCODE[e], ENSEMBL[b]	Regulation: ENC DNase/FAIRE
IV. Epigenetic marks, e.g.		
<ol> <li>Methylation promoter marks</li> </ol>	ENCODE[e], NIH Roadmap Epigenomics[f]	Regulation: ENCODE Regulation
(2) Methylation enhancer marks	ENCODE[e], NIH Roadmap Epigenomics[f]	Regulation: ENCODE Regulation
(3) Acetylation marks (e.g. #H3K27Ac histone mark)	ENCODE[e], NIH Roadmap Epigenomics[f]	Regulation: ENCODE Regulation
V. Transcription factor binding, e.g.		
(1) ChipSeq data	ENCODE[e], ENSEMBL[b], custom	Regulation: ENCODE Regulation
Cell and tissue-specific expression:		
VI. RNA expression, e.g.		
(1) historic mRNA	NCBI GenBank[d]	mRNA and EST: Human mRNAs
(2) genome-wide cell-specific RNA data (e.g. RNAseq)	ENCODE[e], GTex Portal[g], NCBI SRA[h]	Expression: ENC RNA-seq
VII. SNP-mRNA association, e.g.		
(1) Expression quantitative trait locis (eQTL)	GTex Portal[g], custom	N/A
(2) Allelic imbalance (AI); allele specific expression (ASE)	GTex Portal[g], custom	N/A
Biomarkers endophenotype:		
VIII. Other -omics data, e.g.		
(1) Proteomic (e.g. pOTLs)	UniProtKB[i]	N/A
(2) Metabolomic	HMDB[j]	N/A

### **Post GWAS : Terminology**

- Indels
- Epigenetic markers
- eQTL

SNPs could be linked to epigenetic markers and regulate the expression of other genes

## What are indels ?

- Indels can be contrasted with a point mutation.
- An indel inserts and deletes nucleotides from a sequence, while a point mutation is a form of substitution that replaces one of the nucleotides without changing the overall number in the DNA.

```
wild-type sequence
ATCTTCAGCCATAAAAGATGAAGTT
3 bp deletion
ATCTTCAGCCAAAGATGAAGTT
4 bp insertion (orange)
ATCTTCAGCCATATGTGAAAGATGAAGTT
```

## eQTL

- SNPs can be located in gene regions or intergenic ones.
- eQTL= expression Quantitative Trait Locus.
- This is a genomic locus that influences the expression level of mRNA (how much a gene is transcribed).
- This locus can be physically located close to the gene that gets regulated, or far away (even on another chromosome).



### **Databases and Softwares**

Data source/tool	Used for	Links	Last update	Reference
1000 Genome Project Phase 3	Reference panel used to compute $r^2$ and MAF.	Info: http://www.internationalgenome.org/ Data: ftp://ftp.1000genomes.ebi.ac.uk/vol1/ftp/release/20130502/	27 May 2019	1000 Genomes Project Consortium, et al. 2015. A global reference for human genetic variation. <i>Nature</i> . 526, 68-74. PMID:28432245
PLINK v1.9	Used to compute r2 and MAF.	Info and download: https://www.cog-genomics.org/plink2	27 May 2019	Purcell, S., et al. 2007. PLINK: A tool set for whole-genome association and population-based linkage analyses. <i>Am.</i> <i>J. Hum. Genet.</i> 81, 559-575. PMID:17701901
MAGMA v1.07	Used for gene analysis and gene- set analysis.	Info and download: https://ctg.oncr.nl/software/magma	13 Feb 2019	de Leeuw, C., et al. 2015. MAGMA: Generalized gene-set analysis of GWAS data. PLoS Comput. Biol. 11, DOI:10.1371/journal.pcbi.1004219. PMCID:PMC4401857
ANNOVAR	A variant annotation tool used to obtain functional consequences of SNPs on gene functions.	Info and download: http://annovar.openbioinformatics.org/en/latest/	5 Dec 2018	Wang, K., Li, M. and Hakonarson, H. 2010. ANNOVAR: functional annotation of genetic variants from high-throughput sequencing data. Nucleic Acids Res. 38:e164 PMID:20801685
CADD v1.4	A deleterious score of variants computed by integrating 63 functional annotations. The higher the score, the more deleterious.	Info: http://cadd.gs.washington.edu/ Data: <u>http://cadd.gs.washington.edu/download</u>	27 May 2019	Kicher, M., et al. 2014. A general framework for estimating the relative pathogeneticity of human genetic variants. <i>Nat. Genet.</i> <b>46</b> , 310-315. PMID:24487276
RegulomeDB v1.1	A categorical score to guide interpretation of regulatory variants.	Info: http://regulomedb.org/index Data: http://regulomedb.org/downloads/RegulomeDB.dbSNP141.txt.gz	5 Dec 2018	Boyle, AP., et al. 2012. Annotation of functional variation in personal genomes using RegulomeDB. Genome Res. 22, 1790-7. PMID:22955989
15-core chromatin state	Chromatin state for 127 epigenomes was learned by ChromHMM derived from 5 chromatin markers (H3K4me3, H3K4me1, H3K30me3, H3K427me3, H3K9me3).	Info: http://egg2.wustl.edu/roadmapl/web_portal/chr_state_learning.ht ml Data: http://egg2.wustl.edu/roadmapi/data/byFileTypei/chromhmmSeg mentationsi/ChmmModels/coreMarksi/jointModel/final/all.mnemonics. bedFiles.tgz	5 Dec 2018	Roadmap Epigenomics Consortium, et al. 2015. Integrative analysis of 111 reference human epigenomes. Nature. 518, 317-330. PMID:2563363 Ernst, J. and Kellis, M. 2012. Chrom-HMM: automating chromatin-state disovery and characterization. Nat. Methods. 28, 215-6. PMID:22373907
GTEx v8/v7/v8	eQTLs and gene expression used in the pipeline were obtained from GTEx.	Info and data: http://www.gtexportal.org/home/	14 Oct 2019	GTEx Consortium. 2015. Human genomics, The genotype-tissue expression (GTEx) pilot analysis: multitissue gene regulation in humans. Science 348, 648-60. PMID:25964001 GTEx Consortium. 2017. Genetic effects on gene expression across human tissues. Nature. 550, 204-213. PMID:20202307 Aguet. et al. 2019. The GTEx consortium atlas of genetic regulatory effects across human tissues. bioRxiv. doi: https://doi.org/10.1101/1787003.

Blood eQTL Browser	eQTLs of blood cells. Only ciseQTLs with FDR $\leq 0.05$ are available in FUMA.	Info and data: http://genenetwork.nl/bloodeqt/browser/	17 January 2017	Westra et al. 2013. Systematic identification of trans eQTLs as putative divers of known disease associations. Nat Genet. 45, 1238-1243. PMID:24013639
BIOS QTL browser	eQTLs of blood cells in Dutch population. Only cis-eQTLs (gene-level) with FDR $\leq 0.05$ are available in FUMA.	Info and data: http://genenetwork.nl/biosqt/browser/	17 January 2017	Zhernakova et al. 2017. Identification of context-dependent expression quantitative trait loci in whole blood. Nat. Genet. 49, 139-146. PMID-27918533
BRAINEAC	eQTLs of 10 brain regions. Cis- eQTLs with nominal P-value < 0.05 are available in FUMA.	Info and data: http://www.braineac.org/	26 January 2017	Ramasamy et al. 2014. Genetic variability in the regulation of gene expression in ten regions of the human brain. <i>Nat. Neurosoi.</i> <b>17</b> , 1418-1428. PMID:27918633
MuTHER	eQTLs in Adipose, LCL and Skin samples (only cis eQTLs).	Info: http://www.muther.ac.uk/ Data: http://www.muther.ac.uk/Data.html	21 January 2018	Grundberg et al. 2012. Mapping cis and trans regulatory effects across multiple tissues in twins. <i>Nat. Genet.</i> 44, 1084- 1089. PMID:22941192
xQTLServer	eQTLs in dorsolateral prefrontal cortex samples.	Info and data: http://mostafavilab.stat.ubc.ca/xqt/	21 January 2018	Ng et al. 2017. An xQTL map integrates the genetic architecture of the human brain's transcriptome and epigenome. <i>Nat. Neurosci.</i> 20, 1418-1428. PMID:28889584
CommonMind Consortium	eQTLs in brain samples. Both cis and trans eQTLs are available	Info and data: https://www.synapse.org//#ISynapse.syn6585484	21 January 2018	Fromer et al. 2018. Gene expression elucidates functional impact of polygenic risk for schizophrenia. <i>Nat. Neurosci.</i> 16, 1442-1453. PMID:27668389
eQTLGen	Meta-analysis of cis and trans eQTLs based on 37 data sets (in total of 31,684 individuals).	Info: http://www.eqtigen.org/index.html Data: https://molganis28.goo.urg.nildownloads/eqtigen/cis-eqti/cis- eQTL_s_full_20180905.txt.gz, https://molganis28.goo.urg.nildownloads/eqtigen/trans-eqtit/rans- eQTL_significant_20181017.txt.gz	20 Oct 2018	Vosa et al. 2018. Unraveling the polygenic architecture of complex traits using blood eQTL meta-analysis. <i>bioRxiv</i> https://doi.org/10.1101/447387
DICE	eQTLs of 15 types of immune cells.	Info: https://dice-database.org/landing Data: https://dice-database.org/downloads	27 May 2019	Schmiedel et al. 2018. Impact of genetic polymorphisms on human immune cell gene expression. Cell 175, 1701- 1715.e18. PMID:30449622
van der Wijst et al. scRNA eQTLs	eQTLs based on scRNA-seq of 9 cell types.	Info and data: <u>https://molgenis28.target.rug.nl/downloads/soma-seo/</u>	27 May 2019	van der Wijst et al. 2018. Single-cell RNA sequencing identifies celltype- specific eQTLs and co-expression QTLs. Nat. Genet. 50, 403-407. PMID:20810479
PsychENCODE	SNP annotations (enhancer, H3K27ac markers), eQTLs and HIC based enhancer-promoter interactions.	Info and data: http://resource.psychencode.org/	27 May 2019	Wang et al. 2018. Comprehensive functional genomic resource and integrative model for the human brain. Science 14, eaat8464. PMID:30648867
FANTOM5	SNP annotations (enhancer and promoter) and enhancer-promoter correlations.	Info.http://fantom.gsc.riken.jp/5/ Data: http://fantom.gsc.riken.jp/5/data/, http://sidebase.binf.ku.dk/human_enhancers/presets	27 May 2019	Andersson et al. 2014. An atlas of active enhancers across human cell types and tissues. Nature <b>307</b> , 455-461. PMID:24407083 FANTOM Consortium. A promoter-level mammälian expression atlas. Neture <b>507</b> , 462-470. PMID:24670784

### **Databases and Softwares**

brainopan	developmental brain samples.	nno ana data, mponwww.oranispan.org/sato/download	January 2018	Transcriptome of the human brain. Nature 478, 483-489. PMID:22031440
GSE87112 (Hi- C)	Hi-C data (significant loops) of 21 tissue/cell types. Pre-processed data (output of Fit-Hi-C) is used in FUMA.	Info and data: https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi? acc=GSE87112	9 May 2017	Schmitt, A.D. et al. 2016. A compendium of chromatin contact maps reveals spatially active regions in the human genome. <i>Cell Rep.</i> <b>17</b> , 2042-2059. PMID:27851967
Giusti- Rodriguez et al. 2019 (Hi-C)	Hi-C data (significant loops) of adult and fetal cortex. Only significant loops after Bonferroni correction (Pbon < 0.001) are available.	The data was kindly shared by Patric F. Sullivan.	13 Feb 2019	Giusti-Rodriguez, P. et al. 2019. Using three-dimentional regulatory chromatin interactions from adult and fetal cortex to interpret genetic results for psychiatric disorders and cognitive traits. <i>bioRxiv</i> . https://doi.org/10.1101/408330
Enhancer and promoter regions	Predicted enhancer and promoter regions (including dyadio) from Roadmap Epigenomics Projects. 111 epigenomes are available.	Info: http://egg2.wustl.edu/roadmap/web_portal/DNase_reg.html Data: http://egg2.wustl.edu/roadmap/data/byDataType/dnase/	9 May 2017	Roadmap Epigenomics Consortium, et al. 2015. Integrative analysis of 111 reference human epigenomes. <i>Nature</i> . 518, 317-330. PMID:265093633 Ernst, J. and Kellis, M. 2012. ChromHMM: automating chromatin-state discovery and characterization. <i>Nat.</i> <i>Methods.</i> 28, 215-0. PMID:22373907
MsigDB v7.0	Collection of publicly available gene sets. Data sets include e.g. KEGG, Reactome, BioCarta, GO terms and so on.	Info and data: http://software.broadinstitute.org/gsea/msigdb	14 Oct 2019	Liberzon, A. et al. 2011. Molecular signatures database (MSigDB) 3.0. Bioinformatics. 27, 1739-40. PMID:21546393
WikiPathways v20191010	The curated biological pathways.	Info: http://wikipathways.org/index.php/WikiPathways Data: http://data.wikipathways.org/20161110/gmt/wikipathways-2016 1110-gmt-Homo_sapiens.gmt	14 Oct 2019	Kutmon, M., et al. 2018. WikiPathways: capturing the full diversity of pahtway knowledge. <i>Nucleic Acids Res.</i> 44, 488- 494. PMID:26481357
GWAS-catalog e96 2019-09- 24	A database of reported SNP-trait associations.	Info: https://www.ebi.ac.uk/gwas/ Data: https://www.ebi.ac.uk/gwas/downloads	14 Oct 2019	MacArthur, J., et al. 2016. The new NHGRI-EBI Catalog of published genome-wide association studies (GWAS Catalog). <i>Nuoleic Acids Res.</i> piirgkw1133. PMID:27899670
DrugBank v5.1.4	Targeted genes (protein) of drugs in DrugBank was obtained to assign drug ID for input genes.	Info: https://www.ncbi.nlm.nih.gov/pubmed/27899870 Data: https://www.drugbank.ca/releases/latest#protein-identifiers	14 Oct 2019	Wishart, DS., et al. 2008. DrugBank: a knowledgebase for drugs, drug actions and drug targets. <i>Nucleic Acis Res.</i> 36, D901-8. PMID:18048412
pLI	A gene score annotated to prioritized genes. The score is the probability of being loss-of-function intolerance.	Info: http://exac.broadinstitute.org/ Data: ftp://ftp.broadinstitute.org/pub/ExAC_release/release0.3.1/funct ional_gene_constraint	27 April 2017	Lek, M. et al. 2016. Analyses of protein- coding genetic variation in 60,706 humans. <i>Nature</i> . <b>536</b> , 285-291. PMID:27535533
ncRVIS	A gene score annotated to prioritized genes. The score is the non-coding residual variation intolerance score.	Info: http://journals.plos.org/plosgenetics/article? id=10.1371/journal.pgen.1005492 Data: http://journals.plos.org/plosgenetics/article/file? type=supplementary&id=info:doi/10.1371/journal.pgen.1005492.s011	27 April 2017	Petrovski, S. et al. 2015. The intolerance of regulatory sequence to genetic variation predict gene dosage sensitivity. <i>PLOS Genet.</i> <b>11</b> , e1005402. PMID:26332131

### Data bases and web servers

Let us discuss :

- ENCODE
- HelgoDB
- RegulomeDB
- UniprotKB
- ENSEMBL
- FUMA

### **ENCODE: Encyclopedia of DNA Elements**

#### https://www.encodeproject.org/



### **Encode : Data structures**



### Let us use Encode

### Go to link http://screen.encodeproject.org/

Enter snp id : rs4846913



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#### EH37E0145522 chr1:230,294,315-230,295,128 \* D

Тор	Nearby	TF and His-mod	FANTOM	Associated	Associated	Orthologous ccREs	Signal	Linked
Tissues	Genomic Features	Intersection	Intersection	Gene Expression	RAMPAGE Signal	in mm10	Profile	Genes

Search: H3K4me3 and

H3K4me3

#### H3K4me3 Z-scores 🟮 4

TSV		
Tri methylation	(me3): Chromatin markers	

cell type			D	lase		0	nly	
OCI-LY1						2	.13	
HepG2			2	.71		2	.11	
mid-neurogenesis radial glial cells derived from H9 stably expressing fusion protein	n					1	.96	
Caco-2			2	.14		1	.94	
BE2C			2	.31		1	.87	
radial glial cell derived from H9 stably expressing fusion protein						1	.83	
neuroepithelial stem cell derived from H9 stably expressing fusion protein						1	.83	
skeletal muscle male adult (54 years)						1	.82	
stomach smooth muscle female adult (84 years)						1	.80	
germinal matrix male fetal (20 weeks)						1	.70	
Total: 210	«	¢	1	2	3	21	>	*

### Total: 210 Chromatin markers

CTCFZ-scores 🟮 륮

137	Search:		150
cell type	CTCF and DNase	CTCF only	
BE2C	1.97	1.20	
H54		1.17	
MCF-7 treated with estradiol	1.74	1.14	
HGPS cell		1.13	
skin fibroblast female	0.51	0.97	
epithelial cell of proximal tubule	1.94	0.94	
spleen adult		0.94	
GM19240		0.92	
GM12874		0.91	
GM10266		0.89	
Total: 101	« < <b>1</b> 2	3 11 > »	Tota

Acety	lation (	Chromatin	markers
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#### H3K27ac 7 scores 🔒 👉

TSV	Search:	
cell type	H3K27ac and DNase	H3K27ac only
KMS-11		4.09
HepG2	3.52	3.73
neuroepithelial stem cell derived from H9 stably expressing fusion protein		3.68
right lobe of liver female adult (53 years)	3.47	3.58
HUES64-derived CD184+		3.54
small intestine male fetal (108 days)	3.23	3.40
hepatocyte derived from H9	2.98	3.39
KOPT-K1		3.30
liver male adult (31 years)		3.29
OCI-LY1		3.25
Total: 136	« < 1 2 3	14 > »

#### **Chromatin markers**



TSV	Search:	
cell type		Z-score
large intestine female fetal (108 days)		3.48
large intestine female fetal (107 days)		3.42
small intestine male fetal (105 days)		3.37
small intestine female fetal (108 days)		3.35
right lobe of liver female adult (53 years)		3.35
large intestine female fetal (91 days)		3.35
HepG2		3.31
small intestine female fetal (105 days)		3.29
small intestine female fetal (98 days)		3.26
large intestine female fetal (110 days)		3.21
Total: 462	« < 1 2	3 47 > »

### Z score data from multiple chromatin markers in different cell types

### **GTEx : Genotype-Tissue Expression (GTEx)**

Go to link <a href="https://gtexportal.org/home/">https://gtexportal.org/home/</a>

#### Enter snp id : rs712 [Homo sapiens]



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	ENSG00000133703.11	KRAS	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	5.5e-15	-0.18	Cells - Cultured fibroblasts	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	ENSG00000205707.10	ETFRF1	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	6.2e-8	0.11	Testis	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	ENSG00000118307.18	CASC1	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	6.2e-8	-0.11	Testis	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	ENSG00000118307.18	CASC1	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	2.0e-7	0.20	Skin - Sun Exposed (Lower leg)	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	ENSG00000205707.10	ETFRF1	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	2.0e-7	0.14	Skin - Not Sun Exposed (Suprapubic)	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	ENSG00000118307.18	CASC1	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	2.4e-7	0.25	Nerve - Tibial	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	ENSG00000205707.10	ETFRF1	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	0.0000020	0.13	Thyroid	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	ENSG00000205707.10	ETFRF1	chr12_25209618_A_C_b38	rs712	dbSNP 🗹	0.000027	0.23	Brain - Cerebellum	eQTL violin plot, IGV eQ	TL Browser, Multi-tissue eQTL	_ Plot				
	Showing 1 to 10 of 16 entries									First Previous 1 2	Next Last				

#### eQTLs of chr12\_25209618\_A\_C\_b38



Indicates snps has high expression in human blood and skin tissues

#### Multi-tissue eQTL Comparison o

ENSG00000205707.10 ETFRF1 and chr12\_25209618\_A\_C\_b38 eQTL (Meta Analysis RE2 P-Value: 1.938509999999999999e-60)

							Single-tissue eQTL	Single-tissue eQTL p-value		p-value	
_		Tissue	Samples	NES	p-value	m-value	NES (with 95% CI)		versus Multi-tissue Poster	ior Probability	
		<ul> <li>Whole Blood</li> </ul>	670	0.234	8.7e-17	1.00					
$ \longrightarrow $		Brain - Cerebellum	209	0.231	2.7e-5	1.00					
L		<ul> <li>Skin - Sun Exposed (Lower leg)</li> </ul>	605	0.204	1.7e-16	1.00					
		<ul> <li>Ovary</li> </ul>	167	0.147	0.01	0.950					
		<ul> <li>Skin - Not Sun Exposed (Suprapubic)</li> </ul>	517	0.141	2.0e-7	1.00					
		Esophagus - Gastroesophageal Junction	330	0.131	4.9e-4	0.996		15-			
		<ul> <li>Thyroid</li> </ul>	574	0.126	2.0e-6	1.00					
		Vagina	141	0.113	0.2	0.543					
		<ul> <li>Testis</li> </ul>	322	0.109	6.2e-8	1.00					
		<ul> <li>Pituitary</li> </ul>	237	0.106	0.02	0.935					
		Lung	515	0.106	2.5e-4	1.00					
		<ul> <li>Cells - EBV-transformed lymphocytes</li> </ul>	147	0.0915	0.3	0.512					
		Esophagus - Mucosa	497	0.0895	3.5e-3	0.955					
		Pancreas	305	0.0850	0.05	0.740					
		<ul> <li>Heart - Atrial Appendage</li> </ul>	372	0.0794	0.008	0.906					
		Cells - Cultured fibroblasts	483	0.0761	4.3e-3	0.946					
		Spleen	227	0.0734	0.2	0.492					
		Uterus	129	0.0705	0.4	0.576		~			
		<ul> <li>Adipose - Visceral (Omentum)</li> </ul>	469	0.0703	0.03	0.714		n I			
		Esophagus - Muscularis	465	0.0701	0.03	0.791		<b>§</b> 10-			
		Heart - Left Ventricle	386	0.0645	2.3e-3	0.679		ė,			
		<ul> <li>Brain - Spinal cord (cervical c-1)</li> </ul>	126	0.0584	0.3	0.399		Ĕ			
		Liver	208	0.0571	0.1	0.408		8			
		Nerve - Tibial	532	0.0532	0.02	0.295		SUC			
		Colon - Transverse	368	0.0522	0.06	0.301		tis			
		Prostate	221	0.0486	0.4	0.326		e			
		Adrenal Gland	233	0.0396	0.4	0.188		<u>n</u>			
		Colon - Sigmoid	318	0.0306	0.4	0.102		s)			0
		Muscle - Skeletal	706	0.0282	0.1	0.00	T	5			
		Brain - Cerebellar Hemisphere	175	0.0281	0.6	0.190		ě			
		Small Intestine - Terminal Ileum	174	0.0200	0.7	0.162 -					
		Breast - Mammary Tissue	396	0.0177	0.5	0.00300					
		Brain - Hypothalamus	170	0.00978	0.9	0.123 -					
		Adipose - Subcutaneous	581	0.00428	0.9	0.00		5-			
		Artery - Aorta	387	-0.000668	31	0.00400					
		Stomach	324	-0.0158	0.6	0.00200					<b>V</b>
		Artery - Coronary	213	-0.0300	0.5	0.00700					
		Artery - Tiblai	584	-0.0368	0.1	0.00	_				0
		Minor Salivary Gland	144	-0.0404	0.6	0.0600					Ŏ
	J	Brain - Substantia nigra	114	-0.04/2	0.5	0.0810		0			
	]	Brain - Amygdala	129	-0.05/8	0.5	0.0790		T			
		Brain - Nucleus accumbens (basal ganglia)	202	-0.0644	0.2	0.00					
		<ul> <li>Kidney - Cortex</li> </ul>	73	-0.0715	0.2	0.00		0			<b>0</b>

## **Ensembl Database**

### https://www.ensembl.org/index.html

← → C			☆ G	🔶 💹 🛛 🔕
CERSEMBI BLAST/BLAT   VEP   Tools   BioMart   Downloads   Help & Docs   Blog	>		ies	Login/Regist
Search Human (Homo sapiens)         Search all categories          ✓ Search Human          e.g. BRCA2 or 17:63992802-64038237 or rs699 or osteoarthritis				
Genome assembly: GRCh38.p13 (GCA_000001405.28)         Image: More information and statistics         Image: Download DNA sequence (FASTA)         Image: Convert your data to GRCh38 coordinates         Image: Display your data in Ensemble         Other assemblies         GRCh37 Full Feb 2014 archive with BLAST, VEP and BioMart To Go	View karyotype	Gene annotation         What can I find? Protein-coding and non-coding genes, splice variants, cDNA and protein sequences, non-coding RNAs.            More about this genebuild             Lownload FASTA files for genes, cDNAs, ncRNA, proteins             Download GTF or GFF3 files for genes, cDNAs, ncRNA, proteins             W Download GTF or GFF3 files for genes, cDNAs, ncRNA, proteins             W Download GTF or GFF3 files for genes, cDNAs, ncRNA, proteins		Pax6 INS BRCA2 DMD ssh Example gene Example transcript
Comparative genomics What can I find? Homologues, gene trees, and whole genome alignments across multiple species. More about comparative analysis Download alignments (EMF)	Example gene tree	Variation         What can I find? Short sequence variants and longer structural variants; disease and other phenotypes         More about variation in Ensembl         Download all variants (GVF)         Variant Effect Predictor		ATCGAGCT ATCCAGCT ATCGAGAT Example variant
Regulation         What can I find? DNA methylation, transcription factor binding sites, histone modifications, and regulatory features such as enhancers and repressors, and microarray annotations.         Image: More about the Ensembl regulatory build and microarray annotation         Image: More about the Ensembl regulatory build and microarray annotation         Image: More about the Ensembl regulatory build and microarray annotation         Image: More about the Ensembl regulatory features (GFF)	ENCODE data in Ensembl	Variant annotation		Example phenotype

### **UNIPROT KB**

Available at https://www.uniprot.org/

• The UniProt Knowledgebase (UniProtKB) is the central hub for the collection of

functional information on proteins, with accurate, consistent and rich annotation.

In addition to capturing the core data mandatory for each UniProtKB entry (mainly, the amino acid sequence, protein name or description, taxonomic data and citation information), as much annotation information as possible is added.

← → C	0013			III 🛧 🖪 🔶 💹   🔕							
UniProt	Cross-referenced databases -										
BLAST Align Retrieve/ID mapping Per	btide search			Help Contact							
Database - dbSNI	C										
Map to	5 Format										
UniProtKB (12,533)											
	Name	Database of single nucleotide polymorphism									
	Servers	https://www.ncbi.nlm.nih.gov/SNP/									
	URL template	https://www.ncbi.nlm.nih.gov/SNP/snp_ref.cgi?type=rs&rs=%s									
	Citation	[PubMed:17170002][DOI:10.1093/nar/gkl1031]									
	Link type	Explicit									
	Category	Polymorphism and mutation databases									
Tools	Core data		Supporting data	Information							
BLAST	Protein knowledgeba	se (UniProtKB)	Literature citations	About UniProt							
Align	Sequence clusters (U	niRef)	Taxonomy	Help							
Retrieve/ID mapping	Sequence archive (U	niParc)	Keywords	FAQ							
Peptide search	Proteomes		Subcellular locations	UniProtKB manual							
			Cross-referenced databases	Technical corner							
			Diseases	Expert biocuration							
UniProt											
		© 2002 – 2019 UniProt Consortium	License & Disclaimer   Privacy Notice								
EMBL-EBI											

## Multiple web servers (for Post GWAS)

- Identifying causal variants remains a key challenge in post-GWAS (genome-wide association study) era, as many GWAS single-nucleotide polymorphisms (SNPs) (including imputed ones) fall into non-coding regions.
- Its making it difficult to associate statistical significance with predicted functionality.

 Therefore, researches developed web-based multiple tools which overlays functional annotation information, such as histone modification states, methylation patterns, transcription factor binding sites, eQTL and higher-order chromosomal structure, to GWAS results.



- methylation patterns,
- transcription factor binding sites
- eQTL and
- higher-order chromosomal structure



### HaploReg web server



https://pubs.broadinstitute.org/mammals/haploreg/haploreg.php

#### HaploReg v4.1



.

HaploReg is a tool for exploring annotations of the noncoding genome at variants on haplotype blocks, such as candidate regulatory SNPs at disease-associated loci. Using LD information from the 1000 Genomes Project, linked SNPs and small indels can be visualized along with chromatin state and protein binding annotation from the Roadmap Epigenomics and ENCODE projects, sequence conservation across mammals, the effect of SNPs on regulatory motifs, and the effect of SNPs on expression from eQTL studies. HaploReg is designed for researchers developing mechanistic hypotheses of the impact of non-coding variants on clinical phenotypes and normal variation.

Update 2015.11.05: Version 4.1 GWAS and eQTL have been updated; a simpler pruning strategy is applied when combining GWAS; and links out to other NHGRI/EBI GWAS hits and GRASP QTL hits are provided.

Update 2015.09.15: Version 4.0 now includes many recent eQTL results including the GTEx pilot, four different options for defining enhancers using Roadmap Epigenomics data, and a complete set of source files for download and local analysis. Older versions available: v3, v2, v1.

Build Query Set Options Documentation

Use one of the three methods below to enter a set of variants. If an r<sup>2</sup> threshold is specified (see the Set Options tab), results for each variant will be shown in a separate table along with other variants in LD. If r<sup>2</sup> is set to NA, only queried variants will be shown, together in one table.

Query (comma-delimited list of rsIDs OR a single region as chrN:start-end): or, upload a text file (one refSNP ID per line): Or, select a GWAS:

Submit

#### Query SNP: rs9271055 and variants with $r^2 >= 0.8$

chi	pos (hg38)	LD (r²)	LD (D')	variant	Ref	Alt	AFR freq	AMR freq	A SN freq	EUR freq	SiPhy cons	Promoter histone marks	Enhancer histone marks	DNAse	Proteins bound	Motifs changed	NHGRI/EBI GWAS hits	GRASP QTL hits	Selected eQTL hits	GENCODE genes	dbSNP func annot
6	32602082	0.88	0.94	rs9270815	Α	G	0.83	0.88	0.81	0.85			BLD			HNF4, PPAR			265 hits	12kb 5' of HLA-DRB1	intronic
6	32604152	0.81	0.96	rs4367411	С	Т	0.79	0.86	0.78	0.84		BLD, FAT	BLD	10 tissues	POL2	Maf,Spz1			263 hits	14kb 5' of HLA-DRB1	intronic
6	32604684	0.91	0.97	rs9270928	G	т	0.82	0.88	0.81	0.85		BLD, FAT	BLD, BRN, GI	16 tissues	5 bound proteins				265 hits	15kb 5' of HLA-DRB1	intronic
6	32606132	0.88	0.98	rs9270980	С	Α	0.82	0.88	0.81	0.84			BLD			Evi-1			264 hits	16kb 5' of HLA-DRB1	intronic
6	32606283	0.95	0.98	rs9270986	Α	С	0.83	0.89	0.81	0.85			BLD	BLD		Ascl2		34 hits	273 hits	16kb 5' of HLA-DRB1	intronic
6	32606473	0.95	0.98	rs9270994	Т	С	0.83	0.89	0.81	0.85			BLD	BLD,BLD					265 hits	17kb 5' of HLA-DRB1	
6	32606597	0.94	0.97	rs9270997	G	Α	0.83	0.89	0.81	0.85			BLD	BLD		FAC1,Pou1f1,STAT			265 hits	17kb 5' of HLA-DRB1	
6	32607592	1	1	rs9271055	G	т	0.83	0.88	0.81	0.85		BLD	BLD	5 tissues	BATF,EGR1,NFKB	4 altered motifs		4 hits	299 hits	18kb 5' of HLA-DRB1	
6	32607601	1	1	rs9271056	Т	С	0.83	0.88	0.81	0.85		BLD	BLD	5 tissues	BATF,EGR1,NFKB	BDP1,MIF-1,Myf			265 hits	18kb 5' of HLA-DRB1	
6	32607767	0.97	0.99	rs9271061	Α	Т	0.83	0.89	0.81	0.85		BLD	ESC, BLD, FAT	BLD,BLD,BLD	5 bound proteins	Hoxa13,Hoxb13			265 hits	18kb 5' of HLA-DRB1	
6	32607798	0.94	0.99	rs9271062	Т	Α	0.83	0.89	0.81	0.85		BLD	ESC, BLD, FAT	4 tissues	5 bound proteins	STAT			267 hits	18kb 5' of HLA-DRB1	
6	32607842	0.82	0.96	rs9271065	С	G	0.83	0.94	0.88	0.87		BLD	BLD, FAT	4 tissues	4 bound proteins				228 hits	18kb 5' of HLA-DRB1	
6	32608299	0.8	0.97	rs9271080	С	т	0.79	0.86	0.78	0.83		BLD	BLD	BLD,BLD	NFKB,TBP	HNF1,Ncx			264 hits	18kb 5' of HLA-DRB1	
6	32608309	0.81	0.98	rs9271082	Т	С	0.79	0.86	0.77	0.83		BLD	BLD	BLD,BLD	NFKB,TBP	Pax-6			229 hits	18kb 5' of HLA-DRB1	
6	32608375	0.86	0.98	rs9271085	Т	С	0.82	0.88	0.80	0.84		BLD	BLD	BLD,BLD,BLD	NFKB,TBP	4 altered motifs			264 hits	19kb 5' of HLA-DRB1	
6	32608564	0.9	0.95	rs9271093	G	Α	0.82	0.88	0.81	0.85		BLD	BLD	5 tissues	CTCF,NFKB,TBP	6 altered motifs			263 hits	19kb 5' of HLA-DRB1	
6	32609754	0.8	0.9	rs9271152	Т	G	0.83	0.88	0.81	0.86		5 tissues	11 tissues	16 tissues	6 bound proteins				265 hits	18kb 5' of HLA-DQA1	
## Advantage

- It was developed to systematically mine chromatin state data, along with conservation data and regulatory motif alterations.
- It uses Gtex , Encode databases in backend.
- Most importantly, it gives motif based regulatory impact of SNPs

ch	r pos (hg38)	LD (r²)	LD (D')	variant	Ref	Alt	AFR freq	AMR freq	A SN freq	EUR freq	SiPhy cons	Promoter histone marks	Enhancer histone marks	DNAse	Proteins bound	Motifs changed	NHGRI/EBI GWAS hits	GRA SP QTL hits	Selected eQTL hits	GENCODE genes	dbSNP func annot
6	32602082	0.88	0.94	rs9270815	А	G	0.83	0.88	0.81	0.85			BLD			HNF4,PPAR			265 hits	12kb 5' of HLA-DRB1	intronic
6	32604152	0.81	0.96	<u>rs4367411</u>	С	Т	0.79	0.86	0.78	0.84		BLD, FAT	BLD	10 tissues	POL2	Maf,Spz1			263 hits	14kb 5' of HLA-DRB1	intronic
6	32604684	0.91	0.97	rs9270928	G	Т	0.82	0.88	0.81	0.85		BLD, FAT	BLD, BRN, GI	16 tissues	5 bound proteins				265 hits	15kb 5' of HLA-DRB1	intronic
6	32606132	0.88	0.98	<u>rs9270980</u>	С	Α	0.82	0.88	0.81	0.84			BLD			Evi-1			264 hits	16kb 5' of HLA-DRB1	intronic
6	32606283	0.95	0.98	<u>rs9270986</u>	Α	С	0.83	0.89	0.81	0.85			BLD	BLD		Ascl2		34 hits	273 hits	16kb 5' of HLA-DRB1	intronic
6	32606473	0.95	0.98	<u>rs9270994</u>	Т	С	0.83	0.89	0.81	0.85			BLD	BLD,BLD					265 hits	17kb 5' of HLA-DRB1	
6	32606597	0.94	0.97	<u>rs9270997</u>	G	Α	0.83	0.89	0.81	0.85			BLD	BLD		FAC1,Pou1f1,STAT			265 hits	17kb 5' of HLA-DRB1	
6	32607592	1	1	<u>rs9271055</u>	G	Т	0.83	0.88	0.81	0.85		BLD	BLD	5 tissues	BATF,EGR1,NFKB	4 altered motifs		4 hits	299 hits	18kb 5' of HLA-DRB1	
6	32607601	1	1	<u>rs9271056</u>	Т	С	0.83	0.88	0.81	0.85		BLD	BLD	5 tissues	BATF,EGR1,NFKB	BDP1,MIF-1,Myf			265 hits	18kb 5' of HLA-DRB1	
6	32607767	0.97	0.99	rs9271061	Α	Т	0.83	0.89	0.81	0.85		BLD	ESC, BLD, FAT	BLD,BLD,BLD	5 bound proteins	Hoxa13,Hoxb13			265 hits	18kb 5' of HLA-DRB1	
6	32607798	0.94	0.99	rs9271062	Т	Α	0.83	0.89	0.81	0.85		BLD	ESC, BLD, FAT	4 tissues	5 bound proteins	STAT			267 hits	18kb 5' of HLA-DRB1	
6	32607842	0.82	0.96	rs9271065	С	G	0.83	0.94	0.88	0.87		BLD	BLD, FAT	4 tissues	4 bound proteins				228 hits	18kb 5' of HLA-DRB1	
6	32608299	0.8	0.97	<u>rs9271080</u>	С	Т	0.79	0.86	0.78	0.83		BLD	BLD	BLD,BLD	NFKB,TBP	HNF1,Ncx			264 hits	18kb 5' of HLA-DRB1	
6	32608309	0.81	0.98	<u>rs9271082</u>	Т	С	0.79	0.86	0.77	0.83		BLD	BLD	BLD,BLD	NFKB,TBP	Pax-6			229 hits	18kb 5' of HLA-DRB1	
6	32608375	0.86	0.98	<u>rs9271085</u>	Т	С	0.82	0.88	0.80	0.84		BLD	BLD	BLD,BLD,BLD	NFKB,TBP	4 altered motifs			264 hits	19kb 5' of HLA-DRB1	
6	32608564	0.9	0.95	<u>rs9271093</u>	G	Α	0.82	0.88	0.81	0.85		BLD	BLD	5 tissues	CTCF,NFKB,TBP	6 altered motifs			263 hits	19kb 5' of HLA-DRB1	
6	32609754	0.8	0.9	<u>rs9271152</u>	Т	G	0.83	0.88	0.81	0.86		5 tissues	11 tissues	16 tissues	6 bound proteins				265 hits	18kb 5' of HLA-DQA1	

SNP causes 4 altered motifs due to change in nucleotide from G to T

## RegulomeDB

### Access to the database at <u>http://RegulomeDB.org/</u>

	Download About Help
RegulomeDB	
v 1.1 TRY NEW BETA SITE Enter dbSNP IDs, 0-based coordinates, BED files, VCF files, GFF3 files (hg19).	
Submit	1
Use RegulomeDB to identify DNA features and regulatory elements in non-coding regions of the human genome by entering  dbSNP IDs Single nucleotides A chromosomal region	3
Enter dbSNP ID(s) (example) or upload a list of dbSNP IDs to identify DNA features and regulatory elements that contain the coordinate of the SNP(s).	
A project of the Center for Genomics and Personalized Medicine at Stanford University. RegulomeDB (TM) Copyright @2011 The Board of Trustees of Leland Stanford Junior University. Permission to use the information contained in this database was given by the researchers/ins Users of the database are solely responsible for compliance with any copyright restrictions, including those applying to the author abstracts. Documents from this server are provided 72-15° v RegulomeDB project 31 Stanford University is supported by a Genome Research Resource Grant from the US National Historica.	titutes who contributed or published the information. without any waranty, expressed or implied. The

## **Input Files Format**

 The integrated database is fully searchable using common variant formats (VCF, BED, GFF3, rsIDs) and through file upload of the same formats.

### rsID FORMAT

rs33914668 rs35004220 rs78077282 rs7881236

### **BED FORMAT**

#CHROM	POS	REF	ALT	INFO
chr1	100	G	A	AC=10;AF=0.05
chr1	200	C	T	AC=40;AF=0.20
chr1	300	G	Т	AC=20;AF=0.10

**VCF FORMAT** 

		0		5	<u> </u>	
1	#Chromosome	Start	End	SNP Id	Allele	
2	chr1	174	175	1	T/C	
3	chr1	5073	5074	2	T/G	
4	chr1	5635	5636	3	T/C	
5	chr1	6240	6241	4	T/C	
6	chr1	39160	39161	5	T/C	
7	chr1	50111	50112	6	C/T	
8	chr1	126968	126969	7	C/A	
9	chr1	223601	223602	8	C/T	
10	chr1	226507	226508	9	T/A	
11	chr1	251874	251875	10	C/T	
12	chr1	523060	523061	11	С/Т	

## **Output Files**

 The initial results table provides a list of the coordinates of the variants, a dbSNP rsID (if it exists), a score assigned by method, and links to external resources for each variant

 The list is sorted by our classification scheme, with the SNVs most likely to be functional listed first. This list of SNVs is also downloadable by the user for their own analysis.



### **Summary of SNP analysis**



 This display includes six major categories: Protein Binding, Motifs, Chromatin Structure, eQTLs, Histone Modifications, and Related Data (which includes gene information and other manual annotations).

Table	1.	Database	content

Data type	Types	Features	Genomic coverage (bp)
Transcription factor ChIP-seg (ENCODE)	495 conditions/cell lines	7,721,822	230,795,743
Transcription factor ChIP-seq (non-ENCODE)	32 conditions/cell lines	397,534	140,534,725
Transcription factor ChIP-exo	1 condition	35,161	2,604,066
Histone modifications	284 conditions/cell lines/marks	23, 055, 241	2,805,205,184
DNase I hypersensitive sites	114 conditions/cell lines	20,710,098	614,973,579
FAIRE sites	25 conditions/cell lines	4,816,196	476,386,909
DNase I footprints	50 cell lines	128,266,803	178,722,370
Predicted binding (PWMs)	1158 motifs	239,713,973	1,151,732,122
eQTLs	142,945 SNPs	142,945	142,945
dsQTLs	6069 SNPs	6069	6069
Manual annotations	6 genomic regions	282	11,607
VISTA enhancers	1448 enhancers	1325	1,658,146
Validated SNPs affecting binding	855 SNPs	855	855

Sources of data currently included in RegulomeDB. (Features) Specific entries in the database. (Genomic coverage) Total unique base pairs covered by each data type.



Each of these categories provides detailed information about the transcription factor, cell line, and a literature of the source information to provide the user with direct access for addressing their hypothesis.

Motifs		-		Filter:	
Method	Location ≎	Motif ≎	? Cell Type ≎	PWM ≎	Reference ≎
Footprinting	chr11:52469565246974	Tal1::Gata1	K562	Le ATTA	21106904
PWM	chr11:52469565246974	Tal1::Gata1		Le ACTA	18006571

Result indicate SNP is present in Gata Motif which could have regulatory impact on the gene expression

Histone mod	lifications			Filter:	
Method	Location ≎	Chromatin State ≎	Tissue Group ≎	Tissue	Reference ≎
ChromHMM	chr11:46482005617400	Quiescent/Low	Digestive	Colonic Mucosa	REMC
ChromHMM	chr11:46484005255400	Quiescent/Low	Thymus	Thymus	REMC
ChromHMM	chr11:46586005617400	Quiescent/Low	Digestive	Rectal Mucosa Donor 29	REMC
ChromHMM	chr11:46874005545600	Quiescent/Low	Digestive	Rectal Mucosa Donor 31	REMC
ChromHMM	chr11:47040005530600	Quiescent/Low	ES-deriv	H9 Derived Neuronal Progenitor Cultured Cells	REMC
ChromHMM	chr11:47424005617400	Quiescent/Low	Sm. Muscle	Colon Smooth Muscle	REMC
ChromHMM	chr11:47726005273800	Quiescent/Low	Blood & T-cell	Primary T helper memory cells from peripheral blood 2	REMC
ChromHMM	chr11:48152005351800	Quiescent/Low	Blood & T-cell	Primary T helper memory cells from peripheral blood 1	REMC
ChromHMM	chr11:48204005617400	Quiescent/Low	Digestive	Stomach Mucosa	REMC
ChromHMM	chr11:48598005371600	Quiescent/Low	Blood & T-cell	Primary T CD8+ naive cells from peripheral blood	REMC
ChromHMM	chr11:48850005272600	Quiescent/Low	Other	Placenta Amnion	REMC
ChromHMM	chr11:50860005617800	Quiescent/Low	Blood & T-cell	Primary T cells effector/memory enriched from peripheral blood	REMC
ChromHMM	chr11:50808005605600	Quiescent/Low	Blood & T-cell	Primary T CD8+ memory cells from peripheral blood	REMC
	Kesult Indic	ates SNP has	s chromat	in regulatory imp	act

Related data	data Filter:				
Method ^	Location ≎	? Cell Type ≎	Annotation	Reference ≎	
Transcript_expression_evidence	chr11:52469575246958	Cho	Canonical Three Prime Splice Site	2987809	

# Result indicates SNP has expression in cho cell type and affect Splice site

### Advantage of RegulomeDB

- An integrated database to quickly generate prioritized hypotheses for the function of variants affecting both coding and noncoding regions in a genome by combining a large array of data sources into a single, integrated database.
- In particular, it include extensive information on annotated and computed regulatory elements in the human genome.
- Access to this novel approach via a simple and straightforward interface allows for easy query submission, and the scoring system provides for instant classification of significant variants.
- In addition, the SNV summary page will allow a user to quickly form a hypothesis as to the true functional consequence of a variant.
- While our examples deal with single nucleotide variants only, the database can also be used to annotate insertions and deletions.

### **Comparision of HaploReg and RegulomeDB**

 Ward and Kellis (2012) published the HaploReg database which aims to provide a similar annotation by providing an intersect of SNVs with chromatin state (Ernst and Kellis 2010).

- RegulomeDB database provides additional information well beyond this by prioritizing SNVs within general regulatory regions based on specific TF, chromatin, eQTL, and PWM information.
- Furthermore, RegulomeDB allow for a query of personal SNPs which account for a large proportion of variation in the population.

### How many of these SNPs alter motifs sequence ?

rs4468290 rs11201609

## GWAS3D/GWAS4D

 GWAS3D: detecting human regulatory variants by integrative analysis of genomewide associations, chromosome interactions and histone modifications

http://mulinlab.tmu.edu.cn/gwas4d/gwas4d/gwas4d



### **From GWAS to Regulatory Function**

 Majority of GWAS risk loci localize to the noncoding genomic region with gene regulatory signal, suggesting that most trait/disease casual SNPs exert their phenotypic effects by altering gene expression. GWAS4D systematically analyzes GWAS summary data and identify context-specific regulatory variants by integrating latest multidimensional functional genomics resources and our recently published algorithms.

### **Context-dependent Prediction**

 By incorporating roadmap 127 tissue/cell type-specific epigenomes data, GWAS4D uses joint likelihood framework to measure the regulatory probability of genetic variants in a context-dependent manner. It also estimates possible altered TFBSs using large-scale motif collections and annotates non-coding variant with comprehensive functional predictions.

### **Link Variant to Target**

Connecting non-coding variant to their gene targets under particular chromatin organization is crucial to understand variant regulatory mechanism. GWAS4D uniformly processes Hi-C data and reports significant interactions at 5kb resolution across tissues/cell types of multiple human organs and different development stages. It also equips a highly interactive visualization function for variant-target interaction.

## **Comparision with RegulomeDB and HaploReg**

- Compared with recent software and databases such as HaploReg and RegulomeDB, GWAS3D integrates more features and can be used in many scenarios.
- User can identify the most probable functional variant associated with interesting trait in one risk locus or prioritize the leading variants when given a full list of GWAS result or evaluate the deleteriousness of genetic variants affecting the gene regulation without any prior effect.
- GWAS3D also provides flexible configurations, such as human population, cell type specificity and TF family classification, for users to deal with different aspects of complex disease/trait. For example, user may select a matched cell type/tissue satisfying with a specific phenotype or manually define motifs of interested TFs used in following scanning when considering the tissue specificity of TFs.
- Recently, researchers found that the disease/trait-associated variants are highly related to active chromatin marks in relevant cell types. Therefore, these distinct features will greatly facilitate the discovery of regulatory variants under particular condition.

## **Comparision with RegulomeDB and HaploReg**

- The computational process of our system is real-time, which is different from databases such as HaploReg and RegulomeDB, where the function annotations are pre-computed and stored in the database in advance.
- Therefore, it can dynamically deal with the genetic variants input by users with maximum flexibility.
- Despite large computational burden in the background when LD is considered, our system can finish the job of a meta GWAS data set (thousands of variants with moderate GWAS significance,  $P < 1.0 \times 10^{-5}$ ) within a few hours even with LD from the 1000 Genomes Project. It will be much quicker when using HapMap LD.
- To exploit the regulatory properties of personal genomics data, GWAS3D accepts VCF-like format and can evaluate the deleteriousness of rare/novel variation altering gene regulation associated with personalized trait.

## **List of Tools**

Tools	Format	GWAS summary statistics	LD	Functional consequences on genes	Regulatory elements	eQTLs	3D chromatin interactions	Prioritize SNPs	Map SNPs to genes	Gene expression	Pathways and gene sets	Prioria genes	
LD calculation	ı												
PLINK	St	x	x										
Variant annot	tations												
ANNOVAR	St			x	x			x	x				
VEP	St			x	x			x	x				
SCAN	Web		x			x		x		x			
ReglomeDB	Web				x	x		x					
HaploReg	Web		x		x	x		x					
Gene-based t	Sene-based test/Gene-set analyses												
VEGAS	St	x							x			x	
MAGMA	St	x							x		x	x	
Pascal	St	x							x		x	x	
MAGENTA	St	x							x		x	x	
INRICH	St	x							x		x		
DEPICT	St	x							x		x	x	
Visualization	tools												
LocusZoom	St/Web	x											
LocusTrack	St/Web	x			x								
3D genome browser	Web						x						
FUMA		-											
	Web	x	x	x	x	x	x	x	x	x	x	x	

### As discussed before

## Analyses and visualization



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PLoS Comput Biol. 2015 Apr; 11(4): e1004219. Published online 2015 Apr 17. doi: <u>10.1371/journal.pcbi.1004219</u> PMCID: PMC4401657 PMID: 25885710

#### MAGMA: Generalized Gene-Set Analysis of GWAS Data

Christiaan A. de Leeuw, <sup>1, 2,\*</sup> Joris M. Mooij, <sup>3</sup> Tom Heskes, <sup>2</sup> and Danielle Posthuma <sup>1, 4</sup>

#### Hua Tang, Editor

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#### Associated Data

- Supplementary Materials
- Data Availability Statement

#### Abstract

Go to: 🕑

By aggregating data for complex traits in a biologically meaningful way, gene and gene-set analysis constitute a valuable addition to single-marker analysis. However, although various methods for gene and gene-set analysis currently exist, they generally suffer from a number of issues. Statistical power for most methods is strongly affected by linkage disequilibrium between markers, multi-marker associations are often hard to detect, and the reliance on permutation to compute p-values tends to make the analysis computationally very expensive. To address these issues we have developed MAGMA, a novel tool for gene and gene-set analysis. The gene analysis is based on a multiple regression model, to provide better statistical performance. The gene-set analysis is built as a separate layer around the gene analysis for additional flexibility. This gene-set analysis also uses a regression structure to allow generalization to analysis of continuous properties of genes and simultaneous analysis of multiple gene sets and other gene

## **Gene analysis**

- The gene analysis in MAGMA is based on a multiple linear principal components regression model, using an F-test to compute the gene pvalue.
- This model first projects the SNP matrix for a gene onto its principal components (PC), pruning away PCs with very small eigenvalues, and then uses those PCs as predictors for the phenotype in the linear regression model.
- This improves power by removing redundant parameters, and guarantees that the model is identifiable in the presence of highly collinear SNPs.

### **Gene-set analysis**

• To perform the gene-set analysis, for each gene g the gene p-value  $p_g$  computed with the gene analysis is converted to a Z-value  $z_g = \Phi^{-1}(1 - p_g)$ , where  $\Phi^{-1}$  is the probit function. This yields a roughly normally distributed variable Z with elements  $z_g$  that reflects the strength of the association each gene has with the phenotype, with higher values corresponding to stronger associations.

 Gene based and Gene set based analysis are included as feature of FUMA webserver

## **FUMA : interrogation of GWAS**

#### nature communications

Article Open Access Published: 28 November 2017

## Functional mapping and annotation of genetic associations with FUMA

Kyoko Watanabe, Erdogan Taskesen, Arjen van Bochoven & Danielle Posthuma 🖂

Nature Communications8, Article number: 1826 (2017)Cite this article9563Accesses170Citations23AltmetricMetrics

#### Abstract

A main challenge in genome-wide association studies (GWAS) is to pinpoint possible causal variants. Results from GWAS typically do not directly translate into causal variants because the majority of hits are in non-coding or intergenic regions, and the presence of linkage disequilibrium leads to effects being statistically spread out across multiple variants. Post-GWAS annotation facilitates the selection of most likely causal variant(s). Multiple resources are available for post-GWAS annotation, yet these can be time consuming and do not provide integrated visual aids for data interpretation. We, therefore, develop FUMA: an integrative web-based platform using information from multiple biological resources to facilitate functional annotation of GWAS results, gene prioritization and interactive visualization. FUMA accommodates positional, expression quantitative trait loci (eQTL) and chromatin interaction mappings, and provides gene-based, pathway and tissue enrichment results. FUMA results directly aid in generating hypotheses that are testable in functional experiments aimed at proving causal relations.

#### http://fuma.ctglab.nl/

## **FUMA : Muti Steps**

- The main purpose of FUMA is to use functional, biological information to prioritize genes based on GWAS outcomes.
- FUMA consists of two separate process; SNP2GENE and GENE2FUNC.
- To annotate and prioritize SNPs and genes from your GWAS summary statistics, go to SNP2GENE which compute LD structure, annotates functions to SNPs, and prioritize candidate genes.
- You can then use the prioritized genes as input to GENE2FUNC to check expression patterns and shared molecular functions between genes. GENE2FUNC can also be used for any list of pre-selected genes (i.e. created outside of SNP2GENE).

### **FUMA : Discuss**

https://www.nature.com/articles/s41467-017-01261-5

Ready to use FUMA Webserver !!!



С



#### 2. Submit new job at SNP2GENE

A new job stats with a GWAS summary statistics file. A variety of file formats are supported. Please refer the section of Input files for details. If your input file is an output from PLINK, SNPTEST or METAL, you can directly submit the file without specifying column names.

The input GWAS summary statistics file could be a subset of SNPs (e.g. only SNPs which are interesting in your study), but in this case, MAGMA results are not relevant anymore.

Optionally, if you would like to pre-specify lead SNPs, you can upload a file with 3 columns; rsID, chromosome and position. FUMA will then use these SNPs to select LDrelated SNPs for annotation and mapping, instead of using lead SNPs identified by FUMA (it requires to disable an option for "identify additional lead SNPs").

In addition, if you are interested in specific genomic regions, you can also provide them by uploading a file with 3 columns; chromosome, start and end position. FUMA will then use these genomic regions to select LD-related SNPs for annotation and mapping, instead of determining the regions itself.

FUMAGWAS		Home	Tutorial	SNP2GENE	GENE2FUNC	Links	example -
< New Job 1	Upload your GWAS summar	y statistics and set parameters to obtain functional	annotati	ions of the ge	enomic loci as	sociated	I with your trait
My Jobs Q	1. Upload input files						^
Submit new j	ob <sub>GWAS</sub> summary statistics ⑦	Choose file No file chosen i The maximum file size is 600Mb. Please gzip if your file is bigger than 600Mb. Or  : Use example input (Crohn's disease, Franke et al. 2010).	Ø Mand	latory input			
	GWAS summary statistics file columns (?)	i case insensitive Chromosome: Position: rsID: P-value: Risk allele: Other allele: OR:	Option all colum	nal. Please fill as n names.	much as you can. I	t is not ner	cessary to fill

### 3. Set parameters

- On the same page as where you specify the input files, there are a variety of optional parameters that control the prioritization of genes.
- Please check your parameters carefully. The default settings are to perform identification of independent genome-wide significant SNPs at r<sup>2</sup> 0.6 and lead SNPs at r<sup>2</sup> 0.1, to maps SNPs to genes up to 10kb apart.
- To filter SNPs by specific functional annotations and to use eQTL mapping, please change parameters
- If all inputs are valid, 'Submit Job' button will be activated.
   Once you submit a job, this will be listed in My Jobs.

	<										
New Job	2	Upload your G	NAS summary sta	atistics and set parameters to ob	tain functional annotations o	f the genomic loc					
My Jobs	Q	associated with	i your trait								
		1. Upload input	t files			~					
		2. Parameters	for lead SNPs an	d candidate SNPs identification		~					
		3-1. Gene Map	3-1. Gene Mapping (positional mapping)								
		3-2. Gene M	3-2. Gene Make sure all parameters here have non-								
		4. Gene types		red messag	e!!	~					
		5. MHC region				~					
		6. Title of job s	submission			~					
		Submit Job	(	Click to Submit J	ob						
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	<	My Jobs									
New Job	Ţ	List of Jobs	c								
My Jobs	۹					Delete selected jobs					
		Job ID	Job name	Submit date	Status (?)	Select					
		89	example	2017-01-19 14:31:01	NEW	0					
		22	example2	2016-12-23 13:31:37	Go to results						
		20	Subm	itted job will apr	pear here						

### 4. Check your results

After you submit files and parameter settings, a JOB has the status NEW which will be updated to QUEUES to RUNNING. Depending on the number of significant genomic regions, this may take between a couple of minutes and an hour. Once a JOB has finished running, you will receive an email. Unless an error occurred during the process, the email includes the link to the result page (this again requires login). You can also access to the results page from My Jobs page.

The result page displays 4 additional side bars.

Genome-wide plots: Manhattan plots and Q-Q plots for GWAS summary statistics and gene-based test by MAGMA, results of MAGMA gene-set analysis and tissue expression analysis.

Summary of results: Summary of results such as the number of lead and LD-related SNPs, and mapped genes for overall and per identified genomic risk locus. Results: Tables of lead SNPs, genomic risk loci, candidate SNPs with annotations, eQTLs (only when eQTL mapping is performed), mapped genes and GWAS-catalog reported SNPs matched with candidate SNPs. You can also create interactive regional plots with functional annotations from this tab.

Downloads: Download all results as text files.

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#### 1. Input files

Parameter	Mandatory	Description	Туре	Default
GWAS summary statistics	Mandatory	Input file of GWAS summary statistics. Plain text file or zipped or gzipped files are acceptable. The maximum file size which can be uploaded is 600Mb. As well as full results of GWAS summary statistics, subset of results can also be used. e.g. If you would like to look up specific SNPs, you can filter out other SNPs. Please refer to the Input files section for specific file format.	File upload	none
Pre-defined lead SNPs	Optional	Optional pre-defined lead SNPs. The file should have 3 columns, rsID, chromosome and position.	File upload	none
Identify additional lead SNPs	Optional only when predefined lead SNPs are provided	If this option is CHECKED, FUMA will identify additional independent lead SNPs after defining the LD block for pre-defined lead SNPs. Otherwise, only given lead SNPs and SNPs in LD of them will be used for further annotations.	Check	Checked
Pre-defined genetic region	Optional	Optional pre-defined genomic regions. FUMA only looks at provided regions to identify lead SNPs and SNPs in LD of them. If you are only interested in specific regions, this option will increase the speed of process.	File upload	none

### **FUMA : Parameter detail**

Parameter	Mandatory	Description	Туре	Default	Direction
Sample size (N)	Mandatory	The total number of individuals in the GWAS or the number of individuals per SNP. This is only used for MAGMA to compute the gene-based P-values. For total sample size, input should be an integer. When the input file of GWAS summary statistics contains a column of sample size per SNP, the column name can be provided in the second text box. <b>i</b> When column name is provided, please make sure that the column only contains integers (no float or scientific notation). If there are any float values, they will be rounded up by FUMA.	Integer or text	none	Does not affect any candidates
$\begin{array}{l} \text{Maximum lead SNP P-value} \\ (\leq) \end{array}$	Mandatory	FUMA identifies lead SNPs with P-value less than or equal to this threshold and independent from each other.	numeric	5e-8	lower: decrease #lead SNPs. higher: increase #lead SNPs.
Maximum GWAS P-value (≤)	Mandatory	This is the P-value threshold for candidate SNPs in LD of independent significant SNPs. This will be applied only for GWAS-tagged SNPs as SNPs which do not exist in the GWAS input but are extracted from 1000 genomes reference do not have P-value.	numeric	0.05	higher: decrease #candidate SNPs. lower: increase #candidate SNPs.
r <sup>2</sup> threshold for independent significant SNPs (≥)	Mandatory	The minimum $r^2$ for defining independent significant SNPs, which is used to determine the borders of the genomic risk loci. SNPs with $r^2 \ge$ user defined threshold with any of the detected independent significant SNPs will be included for further annotations and are used fro gene prioritisation.	numeric	0.6	higher: decrease #candidate SNPs and increase #independent significant SNPs. lower: increase #candidate SNPs and decrease #independent significant SNPs.
2nd r <sup>2</sup> threshold for lead SNPs (z)	Mandatory	The minimum $r^2$ for defining lead SNPs, which is used for the second clumping (clumping of the independent significant SNPs). Note that when this threshold is same as the first $r^2$ threshold, lead SNPs are identical to independent significant SNPs.	numeric	0.1	higher: increase #lead SNPs. lower: decrease #lead SNPs.
Reference panel	Mandatory	The reference panel to compute r <sup>2</sup> and MAF. Five populations from 1000 genomes Phase 3 and 3 versions of UK Biobank are available. See here for details.	Select	1000G Phase EUR	-
Include variants from reference panel	Mandatory	If Yes, all SNPs in strong LD with any of independent significant SNPs including non-GWAS-tagged SNPs will be included and used for gene mapping.	Yes/No	Yes	-
Minimum MAF (≥)	Mandatory	The minimum Minor Allele Frequency to be included in annotation and prioritisation. MAF is based the user selected reference panel. This filter also applies to lead SNPs. If there is any pre-defined lead SNPs with MAF less than this threshold, those SNPs will be skipped. When this value is 0 (by default), SNPs with MAF>0 are considered.	numeric	0	higher: decrease #candidate SNPs. lower: increase #candidate SNPs.
Maximum distance of LD blocks to merge (s)	Mandatory	This is the maximum distance between LD blocks of independent significant SNPs to merge into a single genomic locus. When this is set at 0, only physically overlapping LD blocks are merged. Defining genomic loci does not affect identifying which SNPs fulfil selection criteria to be used for annotation and prioritization. It will only result in a different number of reported risk loci, which can be desired when certain loci are partly overlapping or physically very close.	numeric	250kb	higher: decrease #genomic loci. lower: increase #genomic loci.

#### 3.1 Positional mapping

Parameter	Mandatory	Description	Туре	Default	Direction
Positional mapping	Optional	Check this option to perform positional mapping. Positional mapping is based on ANNOVAR annotations by specifying the maximum distance between SNPs and genes or based on functional consequences of SNPs on genes. These parameters can be specified in the option below.	Check	Checked	-
Distance to genes or functional consequences of SNPs on genes to map	Mandatory if positional mapping is activated.	Positional mapping criterion either map SNPs to genes based on physical distances or functional consequences of SNPs on genes. When maximum distance is provided SNPs are mapped to genes based on the distance given the user defined maximum distance. Alternatively, specific functional consequences of SNPs on genes can be selected which filtered SNPs to map to genes. Note that when functional consequences are selected, all SNPs are locating on the gene body (distance 0) except upstream and downstream SNPs which are up to 1kb apart from TSS or TSE. <b>i</b> When the maximum distance is set at > 0kb and < 1kb all upstream and downstream SNPs are included since the actual distance is not provided by ANNOVAR. Therefore, the maximum distance > 0kb and < 1kb is same as the maximum distance 1 kb. <b>i</b> For SNPs which are locating on a genomic region where multiple genes are overlapped, ANNOVAR has its own prioritization criteria to report the most deleterious function. For those SNPs, only prioritized annotations are used.	Integer / Multiple selection	Maximum distance 10 kb	

#### 3.2 eQTL mapping

Parameter	Mandatory	Description	Туре	Default	Direction
eQTL mapping	Optional	Check this option to perform eQTL mapping. eQTL mapping will map SNPs to genes which likely affect expression of those genes up to 1 Mb (cis-eQTL). eQTLs are highly tissue specific and tissue types can be selected in the following option. eQTL mapping can be used together with positional mapping.	Check	Unchecked	-
Tissue types	Mandatory if eQTL mapping is CHECKED	All available tissue types with data sources are shown in the select boxes. From FUMA v1.3.0, GTEx v7 became available but GTEx v6 are kept available. Therefore, when "all" is selected, both GTEx v6 and v7 are used for mapping. For detail of eQTL data resources, please refer to the eQTL section in this tutorial.	Multiple selection	none	-
eQTL maximum P- value (≤)	Optional	<ul> <li>The P-value threshold of eQTLs. Two options are available, Use only significant snp-gene pairs or nominal P-value threshold.</li> <li>When Use only significant snp-gene pairs is checked, only eQTLs with FDR ≤ 0.05 will be used. Otherwise, defined nominal P-value is used to filter eQTLs.</li> <li>i Some of eQTL data source only contained eQTLs with a certain FDR threshold. Please refer to the eQTLs section for details of each data sources.</li> </ul>	Check / Numeric	Checked / 1e-3	lower: increase #eQTLs and #mapped genes. higher: decrease #eQTLs and #mapped genes.
#### 3.3 Chromatin interaction mapping

Parameter	Mandatory	Description	Туре	Default	Direction
chromatin Optional interaction mapping		Check this option to perform chromatin interaction mapping.	Check	Unchecked	-
Builtin chromatin interaction data	Optional	Build in chromatin interaction data can be selected in this option. Details of available build in data are available in the Chromatin interactions section in this tutorial.	Multiple selection	none	
Custom chromatin interaction matrices	Optional	In addition to build in chromatin interaction data, user can upload custom data. The data should be pre-computed chromatin loops with significance (ideally FDR but another score can be used, see the Chromatin interactions section for details). The file should be gzipped and named as "(name-of-data).btt.gz". Multiple files can be uploaded. For each data, user can also provide data type, such as Hi-C, ChIA-PET or C5 which is not mandatory but will be used in the result table and regional plot. The file format is described in the Chromatin interactions section in this tutorial. <b>i</b> Please avoid uploading more than one file with identical file names. In that case, the files are over-written by the last uploaded one.	File upload (multiple)	none	-
FDR threshold (≤)	Mandatory if chromatin interaction mapping is CHECKED	FDR threshold for significant loops. The default value is set at 1e- 8 which is suggested by Schmitt et al. (2018) 1 This threshold will be applied both build in and user uploaded chromatin loops.	Numeric	1e-8	lower: increase #chromatin interactions and #mapped genes. higher: decrease #chromatin interactions and #mapped genes.
Promoter region window	Mandatory if chromatin interaction mapping is CHECKED	Promoter regions of genes to map in significantly interacting regions. The input format should be "(upstream bp)-(donwstream bp)" from transcription start site (TSS). For example, the default "250-500" means that promoter regions are defined as 250bp upstream and 500bp downstream of the TSS. By the chromatin interaction mapping, genes whose user defined promoter regions are overlapped with the significantly interacting regions will be mapped. Please refer the Chromatin interactions section in this tutorial for details.	text	250-500	lower: increase #mapped genes. smaller: decrease #mapped genes.
Annotate enhancer/promoter regions (Roadmap 111 epigenomes)	Optional	Predicted enhancer and promoter regions from Roadmap epigenomics project for 111 epigenomes can be annotated to significantly interaction regions. If any epigenome is not selected, enhancer and promoter regions are not annotated. Annotated enhancer/promoter regions can be used to filter SNPs and mapped genes in the next two options.	Multiple selection	none	-
Filter SNPs by enhancers	Optional	This option is only available when at least one epigenome is selected in the previous option to annotate enhancer/promoter regions. When this option is checked, SNPs are filtered on such that overlap with one of the annotated enhancer regions for chromatin interaction mapping. Please refer the Chromatin interactions section in this tutorial for details.	Check	Unchecked	-
Filter genes by promoters	Optional	This option is only available when at least one epigenome is selected in the previous option to annotate enhancer/promoter regions. When this option is checked, chromatin interaction mapping is only performed for genes whose promoter regions are overlap with one of the annotated promoter regions. Please refer the Chromatin interactions section in this tutorial for details.	Check	Unchecked	-

#### 3.4 Functional annotation filtering

Positional, eQTL and chromatin interaction mappings have the following options separately, for the filtering of SNPs based on functional annotation. All filters below apply to selected SNPs in LD with independent significant SNPs that are used to prioritize genes and influence the number of SNPs that are mapped to genes, and consequently influence the number of prioritized genes.

Parameter	Mandatory	Description	Туре	Default	Direction		
CADD score	Optional	Check this if you want to perform filtering of SNPs by CADD score. This applies to selected SNPs in LD with independent significant SNPs that are used to prioritize genes. CADD score is the score of deleteriousness of SNPs predicted by 63 functional annotations. 12.37 is the threshold to be deleterious suggested by Kicher et al (2014). Please refer to the original publication for details from links.	Check	Unchecked	•		
Minimum CADD score (2)	Mandatory if CADD score is checked	The higher the CADD score, the more deleterious.	numeric	12.37	higher: less SNPs will be mapped to genes. lower: more SNPs will be mapped to genes.		
RegulomeDB score	Optional	Check if you want to perform filtering of SNPs by RegulameDB score. This applies to selected SNPs in LD with independent significant SNPs that are used to prioritize genes. RegulameDB score is a categorical score representing regulatory functionality of SNPs based on eQTLs and chromatin marks. Please refer to the original publication for details from links.	Check	Unchecked	-		
Minimum RegulomeDB score (2)	Mandatory if Regulared6 score is checked	Regulareable score is a categorical score from 1a to 7) Score 1a means that those SNPs are most likely affecting regulatory elements and 7 means that those SNPs do not have any annotations. SNPs are recorded as NA if they are not present in the database. SNPs with NA will not be included for filtering on Regulareable score.	string	7	higher: more SNPs will be mapped to genes. lower: less SNPs will be mapped to genes.		
15-core chromatin state	Optional	Check if you want to perform filtering of SNPs by chromatin state. This applies to selected SNPs in LD with independent significant SNPs that are used to prioritize genes. The chromatin state represents accessibility of genomic regions (every 200p) with 15 categorical states predicted by ChromHMM based on 5 chromatin marks for 127 epigenomes.	Check	Unchecked	•		
15-core chromatin state tissue/cell types	Mandatory if 15- core chromatin state is Checked	Multiple tissue/cell types can be selected from the list.	Multiple selection	none	-		
Maximum state of chromatin(s)	Mandatory if 15- core chromatin state is checked	The maximum state to filter SNPs. Between 1 and 15. Generally, between 1 and 7 is open state.	numeric	7	higher: more SNPs will be mapped to genes. lower: less SNPs will be mapped to genes.		
Method for 15- core chromatin state filtering	Mandatory 8 15- core chromatin state is checked	When multiple tissue/cell types are selected, either any (filtered on SNPs which have state above than threshold in any of selected tissue/cell types), majority (filtered on SNPs which have state above than threshold in majority (55%) of selected tissue/cell type), or all (filtered on SNPs which have state above than threshold in all of selected tissue/cell type).	Selection	any	•		
Annotation datasets	Optional	Additional functional annotations can be annotated to candidate SNPs. All available data are regional based annotation (bed file format).	Multiple selection	none	-		
Annotation filtering method	Mandatory if any of Annotation datasets is selected.	By default, SNPs are not filtered by the annotations selected in Annotation datasets. To filter SNPs based on the selected annotation, select this options from any (filtered on SNPs which are overlapping with any selected annotations), majority (filtered on SNPs which are overlapping with majority (250%) of selected annotations), or all (filtered on SNPs which are overlapping with all of selected annotations).	Selection	No filtering	•		

#### 4. Gene types

Biotype of genes to map can be selected. Please refer to Ensembl for details of biotypes.

Parameter	Mandatory	Description	Туре	Default
Gene type	Mandatory	Gene type to map. This is based on gene_biotype obtained from BioMart of Ensembl build 85. Please see here for details	Multiple selection.	Protein coding genes.

#### 5. MHC region

The MHC region is often excluded due to its complicated LD structure. Therefore, this option is checked by default. Please uncheck to include MHC region. Note that it doesn't change any results if there is no significant hit in the MHC region.

Parameter	Mandatory	Description	Туре	Default
Exclude MHC region	Optional	Check if you want to exclude the MHC region. The default region is defined as between "MOG" and "COL11A2" genes.	Check	Checked
Options for excluding MHC region	Optional	MHC region can be excluded only from either annotations or MAGMA gene analysis, or from both by selecting this option.	Select	Only from annotations
Extended MHC region	Optional	User specified MHC region to exclude (for extended or shorter region). The input format should be like "25000000-34000000" on hg19.	Text	Null

#### 6. MAGMA analysis

MAGMA gene and gene-set analyses are performed for the input summary statistics by default, but user can also select to omit MAGMA process that reduce the run time of SNP2GENE process. Gene expression data sets for MAGMA gene expression analysis can be also selected from here.

Parameter	Mandatory	Description	Туре	Default
Perform MAGMA	Optional	UNCHECK to SKIP MAGMA analyses.	Check	Checked
MAGMA gene annotation window	Mandatory when MAGMA is active.	The window of the genes to assign SNPs (symmetric). e.g. when 5kb is selected, SNPs within 5kb window of a gene (both side) will be assigned to that gene. The option is available from 0, 5, 10, 15, 20kb window.	Select	0kb from both side of the genes
MAGMA gene expression analysis	Mandatory when MAGMA is active.	Gene expression data sets used for MAGMA gene-property analysis to test positive association between genetic associations and gene expression in a given label.	Select	GTEx v6

### Gene expression database used by Fuma

#### Gene expression data sets

#### 1. GTEx v6

#### Data source

RNAseq data set was downloaded from http://www.gtexportal.org/home/datasets. Gene level RPKM was used (GTEx\_Analysis\_v6\_RNA-seq\_RNA-seq\_Cv1.1.8\_gene\_rpkm.gct.gz).

#### Pre-process

Primary gene ID was Ensemble ID. In total, 8,555 samples were available. From 56,318 annotated genes, genes were filtered on such that average RPKM per tissue is >1 in at least on of the 53 tissues. This resulted in 28,577 genes. RPKM was winsorized at 50 (replaced RPKM>50 with 50). Then average of log transformed RPKM with pseudocount 1 (log2(RPKM+1)) per tissue (for either 53 detail or 30 general tissues) was used as the covariates conditioning on the average across all the tissues.

#### 2. GTEx v7

#### Data source

RNAseq data set was downloaded from http://www.gtexportal.org/home/datasets. Gene level TPM was used (GTEx\_Analysis\_2016-01-15\_v7\_RNASeQCv1.1.8\_gene\_rpm.gct.gz).

#### Pre-process

Primary gene ID was Ensemble ID. In total, 11,688 samples were available. From 56,203 annotated genes, genes were filtered on such that average TPM per tissue is >1 in at least on of the 53 tissues. This resulted in 32,335 genes. TPM was winsorized at 50 (replaced TPM>50 with 50). Then average of log transformed TPM with pseudocount 1 (log2(TPM+1)) per tissue (for either 53 detail or 30 general tissues) was used as the covariates conditioning on the average across all the tissues.

#### 3. Brain Span

#### Data source

RNAseq data set was downloaded from http://www.brainspan.org/static/download. Gene level RPKM was used (genes\_matrix\_csv.zip).

#### Pre-process

Primary gene ID was Ensemble ID. In total, 524 samples were available. General developmental stages were annotated for each sample based on the age. We used 11 developmental stages and 29 ages as the label. For the label of age, we excluded age groups with <3 samples (25 pcw and 35 pcw). From 52,376 annotated genes, genes were filtered on such that average RPKM per label is >1 in at least one of the either developmental stage or age. This resulted in 19,601 and 21,001 genes for developmental stages and age groups, respectively. RPKM was winsorized at 50 (replaced RPKM>50 with 50). Then average of log transformed RPKM with pseudocount 1 (log2(RPKM+1)) per label (for either 11 developmental stages or 29 age groups) was used as the covariates conditioning on the average across all the labels.

## Fuma : Genomic risk loci Identification

#### Characterization of genomic risk loci based on GWAS

To define genomic loci of interest to the trait based on provided GWAS summary statistics, pre-calculated LD structure based on 1000G of the relevant reference population (EUR for BMI, CD and SCZ) is used. First of all, independent significant SNPs with a genome-wide significant P-value (< 5e-8) and independent from each other at  $r^2 < 0.6$  are identified. For each independent significant SNP, all known (i.e., regardless of being available in the GWAS input) SNPs that have  $r^2 \ge 0.6$  with one of the independent significant SNPs are included for further annotation (candidate SNPs). These SNPs may thus include SNPs that were not available in the GWAS input, but are available in the 1000G reference panel and are in LD with an independent significant SNP. Candidate SNPs can be filtered based on a user-defined minor allele frequency (MAF,  $\ge 0.01$  by default).

Based on the identified independent significant SNPs, independent lead SNPs are defined if they are independent from each other at  $r^2 < 0.1$ . Additionally, if LD blocks of independent significant SNPs are closely located to each other (< 250 kb based on the most right and left SNPs from each LD block), they are merged into one genomic locus. Each genomic locus can thus contain multiple independent significant SNPs and lead SNPs.

Besides using FUMA to determine lead SNPs based on GWAS summary statistics, users can provide a list of pre-defined lead SNPs. In addition, users can provide a list of pre-defined genomic regions to limit all annotations carried out by FUMA to those regions.

## Fuma : Gene and Gene set analysis

#### MAGMA for gene analysis and gene set analysis

FUMA uses input GWAS summary statistics to compute gene-based P-values (gene analysis) and gene set P-value (gene set analysis) using the MAGMA<sup>35</sup> tool. For gene analysis, the gene-based P-value is computed for protein-coding genes by mapping SNPs to genes if SNPs are located within the genes. For gene set analysis, the gene set P-value is computed using the gene-based P-value for 4728 curated gene sets (including canonical pathways) and 6166 GO terms obtained from MsigDB v5.2. For both analyses, the default MAGMA setting (SNP-wise model for gene analysis and competitive model for gene set analysis) are used, and the Bonferroni correction (gene) or FDR (gene-set) was used to correct for multiple testing. 1000G phase 3<sup>27</sup> is used as a reference panel to calculate LD across SNPs and genes.

## Lets run SNP2GENE

#### 1. Upload input files ~ Choose File No file chosen GWAS summary statistics ? ✓ OK. An example file will be used. Or 🗹 : Use example input (Crohn's disease, Franke et al. 2010). i case insensitive Chromosome: Position: rsID: P-value: Optional. Please fill as much as you can. It is not necessary to fill all GWAS summary statistics file columns Effect allele\*: column names. \* "A1" is effect allele by default Non effect allele: OR: Beta: SE: Pre-defined lead SNPs (?) Choose File No file chosen Optional. Optional. Identify additional independent lead 1 SNPs ?

	Total sample size (integer): 21389		
Sample size (N) 🕐	OR Column name for N per SNP (te	ext):	✓ OK. The total sample size will be applied to all SNPs.
Minimum P-value of lead SNPs (<)	5e-8		✓ OK.
Maximum P-value cutoff (<) (?)	0,05		<b>✓</b> OK.
$\mathbf{r}^2$ threshold to define independent significant SNPs (2)	0,6		<b>✓</b> OK.
2nd r <sup>2</sup> threshold to define lead SNPs ( $\geq$ ) (?)	0,1		<b>✓</b> OK.
Reference panel population	1000G Phase3 EUR	Y	✓ OK.
Include variants in reference panel (non-GWAS tagged SNPs in LD) (?	Yes	Y	✓ OK.
Minimum Minor Allele Frequency (≥) (?)	0		✓ OK.
Maximum distance between LD blocks to merge into a locus (< kb) (?)	250	kb	

eQTL mapping Perform eQTL mapping ? 🔲 🛛 Optional.		
-3. Gene Mapping (3D Chromatin Interaction	mapping)	~
-3. Gene Mapping (3D Chromatin Interaction chromatin interaction	mapping)	~
-3. Gene Mapping (3D Chromatin Interaction chromatin interaction mapping Perform chromatin interaction mapping ? Option	mapping) al	~

Ensembl version	v92	۳	✓ OK.
Gene type ⑦ i Multiple gene type can be selected.	All Protein coding	-	✔ OK.
	ncRNA	-	

### This is only valid when predefined lead SNPs are provided. Optional. Choose File No file chosen

Desitional man								
Positional mapp	bing							
Perform positional n	napping 🕜	×			VOK.			
Distance to genes or functional consequences of SNPs on genes to map 🍞		Maximum distance: OR Functional consequence clear exonic splicing intronic 3UTR	10 ences of SNPs o	kb on genes:	VOK. St	NPs are mapped to genes up to 10 kb		
Optional SNP filterin i This filtering only a All these annotations	g by functional annotations for pos pplies to SNPs mapped by positior s will be available for all SNPs with	itional mapping al mapping criterion. in LD of identified lead	When eQTL ma d SNPs in the re	pping is als sult tables,	so performe , but this filt	ed, this filtering can be specified separate tering affect gene prioritization.	ely.	
CADD	Perform SNPs filtering based on						Optional.	
CADD	Minimum CADD score (≥) 🍞	12,37					Optional.	
PagulamaDB	Perform SNPs filtering baed on F						Optional.	
Regulomedia	Maximum RegulomeDB score (c	7				Ŧ	Optional.	
	Perform SNPs filtering based on	chromatin state 🍞						Optional.
						Select all	Clear	
		Adrenal (1) E080 (Other) Fetal Adrenal Gland Blood (27) E029 (HSC & B-cell) Primary monocytes from peripheral blood						
15-core chromatin	Tissue/cell types for 15-core chro i Multiple tissue/cell types can be	matin state selected.	E030 (HSC & B-cell) Primary neutrophils from peripheral blood E031 (HSC & B-cell) Primary B cells from cord blood E031 (HSC & B-cell) Primary B cells from cord blood					Optional.
state			EU32 (InSU & D-ceil) Primary D ceils from peripheral blood E033 (Blood & T-cell) Primary T ceils from cord blood E034 (Blood & T-cell) Primary T ceils from peripheral blood E035 (HSC & B-cell) Primary hematopoletic stem cells				-	
	15-core chromatin state maximum	n state 🍞	7					Optional.
	15-core chromatin state filtering	method 🕐	any				•	Optional.

Predefined genomic region (?)

#### 2. Parameters for lead SNPs and candidate SNPs identification

5. MHC region		^
Exclude MHC region (?) from only annotations	<ul> <li>OK. Normal MHC region will be excluded from only annotations.</li> <li>Optional.</li> </ul>	

~

#### 6. MAGMA analysis

Perform MAGMA (?)	×.			<ul> <li>OK. MAGMA will be performed.</li> </ul>
Gene windows ?	0 i One value will set s downstream. e.g. 2,1 i Maximum window s	kb ame window size both sides, two values separated by comma will set different window sizes for up- and will set window sizes 2kb upstream and 1kb downstream of the genes. ize is limited to 50.		✓ OK.
MAGMA gene expression analysis ⑦	GTEx v8: 54 tissue GTEx v8: 30 gene GTEx v7: 53 tissue GTEx v7: 30 gene CTEx v6: 52 tissue	e types ral tissue types e types ral tissue types	* •	✔ OK.

Title of job submission: trail

i This is not mandatory, but job title might help you to track your jobs.

Submit Job After submitting, please wait until the file is uploaded, and do not move away from the submission page.

				Home Tutoria	I Browse Public Results	SNP2GENE GI	ENE2FUNC	Cell Type	Links	Updates	0
	My Jobs										
	List of Jobs	e									
							Delete selec	ted jobs			
	Job ID	Job name	Submit date	Status ?	Jump to GENE2FUNC	Publi	ish Se	elect			
	60609	trail	2019-11-04 10:51:43	Go to results	GENE2FUNC	Publi	sh				

# Result

### **GWAS PLOTS**



Manhattan Plot (GWAS summary statistics)

### **GWAS PLOTS (gene based test)**



i This is a manhattan plot of the gene-based test as computed by MAGMA based on your input GWAS summary statistics. The gene-based P-value is downloadable from 'Download' tab from the left side bar.

Input SNPs were mapped to 16510 protein coding genes. Genome wide significance (red dashed line in the plot) was defined at P = 0.05/16510 = 3.028e-6.

## Q-Q PLOTS (GWAS/gene based test)

QQ plot (GWAS summary statisics)

i This is a Q-Q plot of GWAS summary statistics. For plotting purposes, overlapping data points are not drawn (filtering was performed only for SNPs with P-value ≥ 1e-5, see tutorial for details).



Slight variation in Plots (From SNPs to Gene based QQ plot)

QQ plot (gene-based test)

i This is a Q-Q plot of the gene-based test computed by MAGMA.

## MAGMA gene set analysis

### Over represented Gene ontology :

Gene Set	🕨 N genes 🔶	Beta 🍦	Beta STD 🔶	SE 🕴	P 🔶	P <sub>bon</sub>
GO_bp:go_defense_response	1286	0.17241	0.046207	0.028022	3.9114e-10	6.05171808e-06
GO_bp:go_cytokine_production	627	0.22151	0.04234	0.039019	6.9857e-09	0.0001080757647
GO_pp:go_inflammatory_response	589	0.22743	0.042186	0.040501	9.9697e-09	0.000154231259
GO_bp:go_cytokine_mediated_signaling_pathway	614	0.21695	0.041054	0.038923	1.2674e-08	0.000196054106
Gp_bp:go_positive_regulation_of_signaling	1541	0.13826	0.04022	0.025461	2.8612e-08	0.000442570416
GO_bp:go_response_to_cytokine	958	0.17057	0.039878	0.031566	3.3194e-08	0.000513411598
GO_bp:go_positive_regulation_of_intracellular_signal_transduction	n 845	0.17471	0.038502	0.033458	8.9777e-08	0.001388491082
Curated_gene_sets:reactome_signaling_by_interleukins	538	0.21607	0.038364	0.041524	9.9138e-08	0.00153316917
GO_bp:go_positive_regulation_of_rna_biosynthetic_process	1351	0.13521	0.037064	0.026186	1.2264e-07	0.00189650496
Curated_gene_sets:qi_plasmacytoma_up	208	0.3429	0.038246	0.067423	1.8522e-07	0.00286405686

Defense response specific regulatory genes are highly significantly OR in this data.

Signifiant expression observed in Lung, Blood and spleen tissue.



### Summary of SNPs and mapped genes

#Genomic risk loci	52
#lead SNPs	75
#Ind. Sig. SNPs	164
#candidate SNPs	8717
#candidate GWAS tagged SNPs	1247
#mapped genes	256



## **Distribution of SNPs**



## **Fuma : Regional Plots**

Genomic ris	sk loci	lead SNPs	Ind. Sig. 9	SNPs	SNPs (ann	otations)	ANNOVAR	Mapped	Genes	GWAScatalog	Parameters	
Click row to	display a	regional plot	of GWAS sum	mary sta	atistics.							
Show 10	• entrie	9 <b>5</b>								1	Search:	
Genomic <sub>‡</sub> Locus	uniqID	÷	rsID 🕴	chr ≑	pos 🛛 🗍	P- value ▼	start 🕴	end 🔶	n SNPs ≑	nGWASSNPs	🕴 nIndSigSNPs	IndSigSI
21	6:1064	35025:A:G	rs6568421	6	106435025	4.4e- 08	106435025	106442096	4	2	1	rs656842
42	17:405	70772:A:C	rs11871801	17	40570772	2.5e- 08	40568094	40690118	72	7	1	rs118718
8	2:2549	2467:A:G	rs13428812	2	25492467	1.4e- 08	25488819	25506107	9	2	1	rs134288
20	6:2072	8731:C:T	rs6908425	6	20728731	1.4e- 08	20640419	20835260	27	7	2	rs690842
36	14:884	72595:C:T	rs8005161	14	88472595	1.3e- 08	88398949	88506864	29	4	1	rs800516
23	7:5030	4461:C:T	rs1456896	7	50304461	1.2e- 08	50257634	50323456	30	5	1	rs145689
7	1:2069	39904:A:G	rs3024505	1	206939904	8.3e- 09	206939904	206968955	8	1	1	rs302450
9	2:6122	4259:C:T	rs10181042	2	61224259	6.6e- 09	61186829	61231014	26	6	1	rs101810
51	22:305	92487:C:G	rs713875	22	30592487	5.7e- 09	30263026	30592487	32	8	1	rs713875
6	1:1977	27642:A:G	rs1998598	1	197727642	4.9e-	197342686	197784249	66	11	1	rs199859



#### Selected Locus top lead SNP rs6568421 Chrom 6 BP 106435025 P-value 4.4e-08 #Ind. Sig. SNPs 1 #lead SNPs 1 SNPs within LD 4 GWAS SNPs within LD 2

### **Moving from SNP2Gene to Gene2FUNC**

	<
New Job	<u>±</u>
Redo gene mapping	C
My Jobs	۹

### **Expression Heatmap plot**



Dark red color : high expression

**Tissue specific Expression** 



SNPs encoding genes have significant expression in spleen tissue

### **Functional Enrichment plots**







### Let us run Gene2FUNC

### Gene ID



AC008703.1

#### Summary of input genes

Number of input genes	32
Number of background genes	57241
Number of input genes with recognised Ensembl ID	26
Input genes without recognised Ensembl ID	CARMIL1, BABAM2, AL138720.1, LINC00824, AC007493.1, AF246928.1
Number of background genes with recognised Ensembl ID	57241
Background genes without recognised Ensembl ID	NA
Number of input genes with unique entrez ID	23
Number of background genes with unique entrez ID	35142





# **Enrichment : plots**

Hallmark gene sets (MsigDB h) (3)	
Positional gene sets (MsigDB c1) (1)	
Curated_gene_sets (0)	
Chemical and Genetic pertubation gene sets (MsigDB c2) (0)	
All Canonical Pathways (MsigDB c2) (0)	
BioCarta (MsigDB c2) (1)	
KEGG (MsigDB c2) (2)	there are two signifiant pathways
Reactome (MsigDB c2) (0)	
microRNA targets (MsigDB c3) (1)	
TF targets (MsigDB c3) (0)	
All computational gene sets (MsigDB c4) (0)	
Cancer gene neighborhoods (MsigDB c4) (0)	
Cancer gene modules (MsigDB c4) (0)	
GO biological processes (MsigDB c5) (2)	there are two signifiant gene ontology
GO cellular components (MsigDB c5) (0)	
GO molecular functions (MsigDB c5) (1)	
Oncogenetic signatures (MsigDB c6) (0)	
Immunologic signatures (MsigDB c7) (0)	
WikiPathways (0)	
GWAS catalog reported genes (8)	Informations found in GWAS catalog

# Exercise

- 1. Classify SNPs list based on genomic location (genic and non genic)
- 2. Identify chromatin markers affected by given SNPs list .
- 3. Identify over represented KEGG pathways and GO enrichment based on SNPs encoding genes
- 4. Identify which tissue is differentially expressed due to given SNP list (via genes)?

rs4468290 rs11201609 rs4933212 rs701546 rs1241901 rs8087497 rs2409457 rs1666559 rs12943387 rs2036660