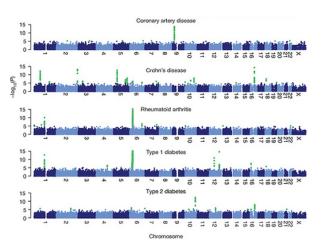
Genome-Wide Association Studies (GWAS) Workshop



Ida Moltke & Shyam Gopalakrishnan Genomes and Biodiversity, Nov 2019

Learning objectives for today

By the end of today you should:

- be able to explain the basic idea behind a GWAS
- be able to perform the most basic steps of a GWAS
- ▶ be able to interpret the plots typically used in GWAS
 - ► Manhattan plots
 - QQ-plots
- be aware of some important potential pitfalls (poor quality data, batch effects, multiple testing, population structure)

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The plan is to reach these goals via a lecture with exercises along the way

Outline

- 1. Introduction
 - Why GWAS?
 - What is GWAS?
- 2. The different steps of a GWAS
 - Step 1: Collect samples and phenotypic data
 - Step 2: Genotype samples
 - Step 4: Statistically test each SNP for association
 - Step 5: Assess the results
 - Step 3: Lots and lots of QC
 - Step 7: Replication
- 3. Additional potential pitfalls

What is the goal?

- ► To find (map) genetic variants that have an effect on a trait, e.g. height
- ► Often focused on disease traits (also our main focus today)
 - ▶ i.e. studies where the phenotype of interest is whether the participants have a disease (cases) or not (controls)





What is the goal?

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 - ▶ i.e. studies where the phenotype of interest is whether the participants have a disease (cases) or not (controls)



- ► The motivation is that reaching this goal can hopefully
 - reveal the role genetics play in the disease
 - ▶ hopefully lead to better understanding the disease etiology
 - ▶ ideally lead to better treatment and/or prevention

Why learn about GWAS?

- ► Several approaches to such mapping, e.g. linkage mapping
- ► GWAS the most used approach to mapping since 2007:

HTRA1 Promoter Polymorphism in V Age-Related Macular Degeneration

Andrew DeWas, ³ Nugen Lis, ³ Stephen Hartman, ³ Samuel Shao-Min Zhang, ³ Clavid T. Comic Zhao, ³ Parcy O. S. Tan, ³ Wai Man Chan, ³ Demis S. C. Lan, ³ Michael Snyder, ³ Calls Bernetable, ² Chi Pang, ³ Josephine Bah, ² J

www.sciencemag.org SCIENCE VOL 314 10 NOVEMBER 2006

A Genome-Wide Association Study Identifies *IL23R* as an Inflammatory Bowel Disease Gene

Hickard R. Daer, ^{1,4} Kent D. Taylor, ^{1,4} Saven R. Brast, ^{1,4} John D. Hisur, ^{1,4} Mark S. Silverberg, ¹
Ker's Y. Dely, ^{1,5} A. Hillery, Serichert, ¹Cleo & Norsham, ¹-Mijer i Reyerin, ²Ause Griffitts, ^{1,5}
Hermitotics Desoporcies, ²Ause Histon, ³ Major J. Paylor, ³ Saphan Taylor, ^{2,5}
Lisa Wa Data, ³ Seriy G. Costen, ³ L. Pally Schoms, ^{3,5}
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Lee, ^{3,6}
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Lee, ^{3,6}

www.eciencemeg.org SCIENCE VOL 314 1 DECEMBER 2006

A genome-wide association study identifies novel risk loci for type 2 diabetes

A genome-wide association scan of nonsynonymous SNPs identifies a susceptibility variant for Crohn disease in ATG16L1

Jochen Hampel, Lin, Andre Frenke, D. Hillip Rosenstiel, P., Andrew TBl, Markun Teober, Klaus Husel, Mario Albrecht, Gabriel Marri, Francisco M De La Veggi, June Engiger, Simmer Gimbrel, Namie J Pravoret, Glive M Omale, Robert Hislard, Rose Jospo Styllick, R Older, Thomas Lenguard, Matthias Hitzer, Christopher G Matthew, Michael Komezud, S. Stefan Schreibert, J. Martine Schuler, Vol. Martin, S. Stefan Schreibert, A. Martine Gameller, S. Wolland, Komezud, S. Stefan Schreibert, A. Martine, Gameller, S. Wolland, S. Stefan Schreibert, A. Martine, Gameller, S. Wolland, S. Stefan, Schreibert, M. Martine, Gameller, S. Wolland, S. Stefan, S. Stefan, Schreibert, M. M. Stefan, S. S

► So probably the single most important approach within disease mapping

- ▶ Previous methods successful for **Mendelian diseases**, where
 - environmental factors are less important than genetic factors
 - ► causal genetic variants have **high penetrance*** (close to 1)
 - only one or a few causal variants are involved
 - causal variants are typically rare

^{*}proportion of cases among individuals carrying the variant

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- BUT previous methods not successful for complex diseases, where
 - environmental factors are very important
 - causal genetic variants have low penetrance
 - many causal genetic variants are involved
 - causal variants are potentially common (we do not know)

^{*}proportion of cases among individuals carrying the variant

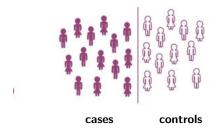
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 - causal variants are potentially common (we do not know)
- Most common diseases are complex! e.g. type 2 diabetes, CVD
- ► GWAS works for common, low penetrance variants (common disease)
 - *proportion of cases among individuals carrying the variant

The basic idea behind association studies

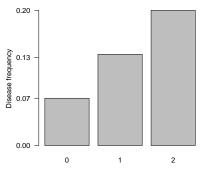
▶ We look at genetic data from unrelated, randomly sampled individuals



► Typically 500,000-5,000,000 SNP variants along the genome

The basic idea behind association studies

▶ We look for SNP variants that are associated (correlated) with disease



Genotype (number of copies of variant)

► Test each SNP for association & identify those with low p-value

Why?

Why?

► Expect to see association in locus with a causal variant!

Why?

- ► Expect to see association in locus with a causal variant!
- Expect to see it in loci highly correlated w. causal variant, e.g.

Causal	Other	locus
A	G	
A	G	
A	G	
A	G	
A	G	
C	T	
C	T	
C	T	

- ▶ We expect to see it in loci that are in high LD with the causal SNP
- ▶ NB LD measure usually used is r^2 (ranges 0-1, where 1=fully correlated)

p 2: Genotype samples

ep 4: Statistically test each SNP for association ep 5: Assess the results

Step 3: Lots and lots of (

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 - Step 7: Replication
- 3. Additional potential pitfalls

1: Collect samples and phenotypic data

ep 2: Genotype samples

tep 4: Statistically test each SNF for asso tep 5: Assess the results

Step 7: Replication

GWAS step-by-step

- 1. Collect samples and traits of interest
- 2. Genotype samples at a number (\geq 500,000) of SNP loci
- Lots and lots of quality control (QC)!
- 4. Statistically test each SNP that passed QC for association
- 5. Assess the results:
 - ► make sure things went OK
 - identify associated SNPs
- 6. Identify causal variant (if possible)
- 7. Replicate associations in a different dataset
- 8. Investigate what the underlying biological mechanism is
- 9. Ideal longterm goal/hope: better prevention or treatment

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GWAS step-by-step

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Step 1: Collect samples and phenotypic data

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ip 4. Statistically test each SIVP for association 5. Assess the results

Step 3: Lots and lots of Q

Step 1: Collect samples and phenotypic data

Two possible designs:

► Take a random sample from a population (population cohort):



Select samples based on traits:



Cases



Controls

► Both require informed consent! (and ethical approval)

Step 1: Collect samples and phenotypic data

p 2: Genotype sampies

Step 5: Assess the results
Step 3: Lots and lots of QC

Outcome

The outcome of collecting data:

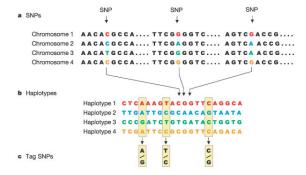
- ► Blood samples or similar (for later genotyping)
- ▶ Plus information about the traits of interest
 - ▶ disease status
 - e.g. have diabetes (case) vs do not have diabetes (control)
 - quantitative
 - e.g. cholesterol, blood pressure or blood sugar

Step 1: Collect samples and phenotypic data
Step 2: Genotype samples
Step 4: Statistically test each SNP for association
Step 5: Assess the results
Step 3: Lots and lots of QC

Step 2: Genotype samples

How does one choose genotyping platform?

- ► Want to (indirectly) test as many (common) SNPs as possible CHEAPLY
- Which and how many SNPs are needed depend on LD.
- ▶ Often data from standard SNP arrays (500K-5M, the smaller the cheaper!)



Step 2: Genotype samples

Step 3: Lots and lots of QC

Skip for now:)

1: Collect samples and phenotypic data

Step 4: Statistically test each SNP for association Step 5: Assess the results

Step 3: Lots and lots of C

Overview of possible tests



- ► One can use many different tests
- ▶ Which to use depends on inheritance mode (additive, recessive, dominant)
- ► Mainly depends on type of data (case-control or quantitative)

Step 4: Statistically test each SNP for association

Overview of possible tests



- ► One can use many different tests
- Which to use depends on inheritance mode (additive, recessive, dominant)
- Mainly depends on type of data (case-control or quantitative)
- Additive model for inheritance mode is almost always assumed
- For quantitative traits, e.g. height, linear regression often used
- ► For case-control traits, e.g. T2D, **logistic regression** often used

Introduction The different steps of a GWAS Additional potential pitfalls Step 1: Collect samples and phenotypic data
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Test for association in case-control traits

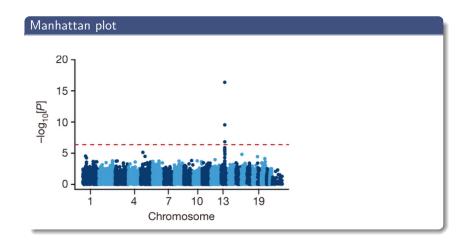
Can you think of a simple statistic to find SNPs associated with disease status?

Introduction The different steps of a GWAS Additional potential pitfalls p 1: Collect samples and phenotypic data

op 4: Statistically test of

Step 5: Assess the results

Identify associated SNPs



Collect samples and phenotypic data
 Genotype samples

tep 4: Statistically test each SNP for ass

Step 5: Assess the results

Step 7: Replication

What p-value threshold to use

- ▶ Usually for a single test we use a p-value threshold of $\alpha = 0.05$
- If you perform many tests w. this α you will get a lot of false positives!
- ► So we have to **correct for multiple testing**

Collect samples and phenotypic data
 Constype samples

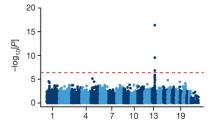
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Step 4: Statistically test each SNP for association

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What p-value threshold to use

- ▶ Usually for a single test we use a p-value threshold of $\alpha = 0.05$
- ▶ If you perform many tests w. this α you will get a lot of false positives!
- ► So we have to **correct for multiple testing**
- ▶ Often **Bonferroni correction** is used; α is divided by the number of tests:
 - ▶ 100000 SNPs and $\alpha = 0.05$
 - ▶ Bonferroni corrected $\alpha = 0.05/100000 = 0.0000005 = 5 \times 10^{-7}$
 - ▶ which on the Manhattan plot is $-log_{10}(5 \times 10^{-7}) = 6.3$



Introduction
The different steps of a GWAS
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Step 1: Collect samples and phenotypic data
Step 2: Genotype samples
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Step 3: Lots and lots of QC

Exercise

Solve exercise A, i.e. run your first GWAS! :)

p 1: Collect samples and phenotypic data

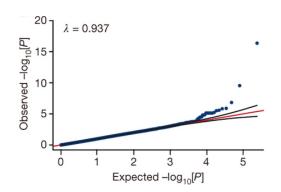
ep 2: Genotype samples

Step 5: Assess the results

Step 3: Lots and lots

Make sure things went OK!

QQ-plots and genomic control inflation factor λ



If so most of the dots will be on the x=y line and $\lambda \simeq 1$

Introduction
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Step 1: Collect samples and phenotypic data Step 2: Genotype samples Step 4: Statistically test each SNP for association Step 5: Assess the results Step 3: Lots and lots of QC

Exercise

Solve exercise B, i.e. check if your results look OK...

Collect samples and phenotypic data
 Genotype samples

Step 4: Statistically test each SNP for association

Step 3: Lots and lots of QC

Step 3 again: Lots and lots of QC

Now you have seen why one shouldn't skip QC...! :)

Let's therefore return to that step (we wont go through all QCs, but some important ones)

ep 2: Genotype samples

ep 4: Statistically test each SNP for ass

Step 3: Lots and lots of QC

Sample mislabeling?

- ▶ One thing that can go wrong is that the samples can be mislabeled
- ► If so, genotypes won't match phenotypes
- ► This is difficult to catch
- ▶ But a simple check is to see of gender is correct
- ▶ If not the disease status is likely not to be either...
- ▶ We can check this using PLINK
- **Exercise:** try checking it for your data (exercise C)

Collect samples and phenotypic data
 Genotype samples

step 4: Statistically test each SNP for association

Step 3: Lots and lots of QC

Closely related individuals or duplicates?

- ► Almost all association tests assume that the participants are **independent** samples from a population
- ► This would not be the case if some participants
 - ► are closely related
 - represented more than once
- One way to check if this is the case is to use PLINK (again)
- ► Exercise: try checking it for your data (exercise D)

Collect samples and phenotypic data
 Genotype samples

Step 4: Statistically test each SNP for association

Step 3: Lots and lots of QC

Batch biases/non-random genotyping error?

- Sometimes the data handling/generation process can lead to non-random genotyping errors
- ► E.g. if all cases were genotyped first and then all controls, then changes in genotyping procedure along the way may lead to non-random differences in genotypes between cases and controls
- ► This may lead the false positive association test results
- ► Exercise (if there is time): try checking it for your data (exercise E & F)

ep 1: Collect samples and phenotypic data ep 2: Genotype samples en 4: Statistically test each SNP for association

Step 3: Lots and lots of QC

Additional important checks?

- ► Other additional signs of something being wrong include:
 - ► high missingness in specific loci/individuals
 - ► loci out of Hardy-Weinberg Equilibrium (in controls)
- ► Furthermore, low frequency variants tend to be difficult to genotype
- Removing such loci/individuals can help a lot!
- ► Exercise: try rerunning your analyses with these QC filters (exercise G)

1: Collect samples and phenotypic in the properties of the properties o

Step 4: Statistically test each SNP for association

Step 3: Lots and lots of QC Step 7: Replication

Replication in a different dataset

- ► Some of the first GWAS results later turned out to be false positives
- Almost impossible to publish without replication now
- ▶ Basically consists of repeating the test of the SNP in a different dataset
- ► To make sure the result is not just a false positives
- ► This time correction for multiple testing not needed (unless you replicate more than one variant)

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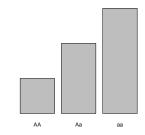
Confounding factors

- ► A few factors can sometimes confound your results
- ► One of these is gender
- We can correct for this by using a slightly more sophisticated test, namely logistic regression, which allows you to include "covariates" in your test and thereby take them into account
- ▶ If you want an example have a look at "Extra exercise if time allows"

Population structure

- ▶ All presented tests assume samples are from one homogeneous population
- If they are not this can lead to false positives
- ► E.g. if we look at height and mix Pygmies and Dutch in a GWAS.
- ▶ All loci where Pygmies mainly have A and Dutch a are associated:





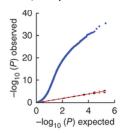
► Similar effect of admixture and relatedness

How can we deal with this?

Two ways

- ► Quality filtering: remove admixed individuals in QC
- Use other tests:
 - ▶ include first 5-10 PCs as covariates
 - ► a linear mixed model (extension of linear model)

QQ plot (linear model)



QQ plot (linear mixed model)

