Session 10: Rare variant association studies

Side note... R packages and other notes

Some notes

- There are MANY, MANY R packages to conduct genetic analyses. There is very likely a package that does what you want to do.
- Input data is key make sure the format is correct!
- Spend time reading manuals, google examples, google errors.
- My most important advice is to take programming classes that focuses on programming only (doesn't matter which language). Programming + content learning (e.g., genetics) might distract each other.
- There is no shortcut to learn programming
 - Even though you get sample code for one specific analysis/problem, chances are you won't be able to use the same code next time.

General packages

- HardyWeinberg
 - Contains tools for exploring Hardy-Weinberg equilibrium for bi and multiallelic genetic marker data.
 - <u>https://cran.r-project.org/web/packages/HardyWeinberg/index.html</u>
- SNPlocs.Hsapiens.dbSNP144.GRCh37
 - SNP locations and alleles for Homo sapiens extracted from NCBI dbSNP
 - <u>http://bioconductor.org/packages/release/data/annotation/html/SNPlocs.Hs</u> <u>apiens.dbSNP144.GRCh37.html</u>
 - <u>https://bioconductor.org/packages/release/data/annotation/html/SNPlocs.Hs</u> <u>apiens.dbSNP151.GRCh38.html</u>

GWAS

- GWAStools
 - Classes for storing very large GWAS data sets and annotation, and functions for GWAS data cleaning and analysis.
 - <u>https://www.bioconductor.org/packages/release/bioc/html/GWASTools.html</u>
- GENESIS
 - Methodology for estimating, inferring, and accounting for population and pedigree structure in genetic analyses. Performs a Principal Components Analysis on genome-wide SNP data for the detection of population structure in a sample that may contain known or cryptic relatedness. Functions are provided to perform mixed model association testing for both quantitative and binary phenotypes.
 - <u>https://bioconductor.org/packages/release/bioc/html/GENESIS.html</u>

Gene-Environment Interactions

- GxEScanR
 - Genome-wide association study (GWAS) and genome-wide by environmental interaction study (GWEIS) scans using imputed genotypes stored in the BinaryDosage format. The phenotype to be analyzed can either be a continuous or binary trait. The GWEIS scan performs multiple tests that can be used in two-step methods.
 - <u>https://github.com/USCbiostats/GxEScanR</u>

Rare variant analyses

- Rvtests
 - Rare variant test software for next generation sequencing data
 - <u>http://zhanxw.github.io/rvtests/</u>
- SKAT
 - <u>https://cran.r-project.org/web/packages/SKAT/index.html</u>

Mendelian Randomization

- Encodes several methods for performing Mendelian randomization analyses with summarized data. Summarized data on genetic associations with the exposure and with the outcome can be obtained from large consortia. These data can be used for obtaining causal estimates using instrumental variable methods.
- <u>https://cran.r-project.org/web/packages/MendelianRandomization/index.html</u>

The Epidemiologist R Handbook

The Epidemiologist R

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- <u>https://epirhandbook.com/index.html</u>
- Serve as a quick R code reference manual
- Provide task-centered examples addressing common epidemiological problems
- Assist epidemiologists transitioning to R
- Be accessible in settings with low internetconnectivity via an <u>offline version</u>
- Basics, Data Management, Analysis, Data Visualization, Reports and dashboards, Miscellaneous: writing functions, directory interactions, version control and collaboration with Git and Github, common errors, getting help, R on network drives, data table



R for applied epidemiology and public health

This handbook strives to:

- Serve as a quick R code reference manual
- Provide task-centered examples addressing common epidemiological problems
- Assist epidemiologists transitioning to R
- Be accessible in settings with low internet-connectivity via an offline version



Written by epidemiologists, for epidemiologists

We are applied epis from around the world, writing in our spare time to offer this resource to the community. Your encouragement and feedback is most welcome:

- Structured feedback form
- Email epiRhandbook@gmail.com or tweet @epiRhandbook
- Submit issues to our Github repository

How to use this handbook

- Browse the pages in the Table of Contents, or use the search box
- Click the "copy" icons to copy code
- You can follow-along with the example data
- See the "Resources" section of each page for further material

On this page R for applied epidemiology and

public health

How to use this handbook Acknowledgements

Terms of Use and Contribution

Some additional software beyond R: PLINK

- What is PLINK?
 - Statistical software for analyzing phenotype/genotype data
 - Purcell S, et al. <u>PLINK: a tool set for whole-genome</u> <u>association and population-based linkage analyses.</u> Am J Hum Genet. 2007.
 - Chang CC, et al. <u>Second-generation **PLINK**: rising to the</u> <u>challenge of larger and richer datasets.</u> Gigascience. 2015.
- Why PLINK?
 - It is arguably the most commonly used software for largescale genetic association studies
 - It is fast
 - It is designed to conduct data quality control steps as well as generate descriptive statistics and run association analysis (just to mention a few things)
 - Many GWAS datasets are created in PLINK files (.bed, .bim, .fam)

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|--|--|--|------------------------------|
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| MAGIC_FUSION_Results.txt.gz am | d.ped | meta2.txt | plink.frq |
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| amd.bim ha | rdy2.log | meta3.txt | plink.hwe |
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| blocks,distance,genome, | homozyg,make-rel | ,make-grm-gz, | |
| rel-cutoff,cluster,pca, | neighbour,ibs-te | st,regress-distance, | |
| model,bd,gxe,logistic, | dosage,lasso, | test-missing, | |
| make-perm-pheno,tdt,qfam, - meta-analysis,epistasis,fa | annotate,clump st-epistasis, and - | o,gene-report, score. | |
| 'plinkhelp more' describes al | l functions (warnin | ig: long). | |
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Risk Prediction

- LDPred
 - LDpred is a Python based software package that adjusts GWAS summary statistics for the effects of linkage disequilibrium (LD).
 - <u>https://github.com/bvilhjal/ldpred</u>
- PRSics-2
 - PRSice (pronounced 'precise') is a Polygenic Risk Score software for calculating, applying, evaluating and plotting the results of polygenic risk scores (PRS) analyses.
 - http://www.prsice.info

Some additional software: Large scale data

- GATK
 - Variant Discovery in High-Throughput Sequencing Data. Includes multiple tools with a primary focus on variant discovery and genotyping.
 - https://gatk.broadinstitute.org/hc/en-us
- Hail
 - Python library that simplifies genomic data analysis. It provides powerful, easy-to-use data science tools that can be used to interrogate even biobank-scale genomic data (e.g., UK Biobank, gnomAD, TopMed, FinnGen, and Biobank Japan).
 - https://hail.is
- BOLT-LMM
 - The BOLT-LMM software package currently consists of two main algorithms, the BOLT-LMM algorithm for mixed model association testing, and the BOLT-REML algorithm for variance components analysis (i.e., partitioning of SNP-heritability and estimation of genetic correlations).
 - https://alkesgroup.broadinstitute.org/BOLT-LMM/BOLT-LMM_manual.html

One note about big data analyses

- Many research groups do their analysis on unix-based clusters
 - Firewalls, computational capacity, data storage
- Often packages come with great tutorials for analyses. The challenge will be for you to figure out how to run it on your cluster environment
- These are often specific things you will learn when you join a particular research group

Programming courses

- SISG 2021
 - https://si.biostat.washington.edu/suminst/sisg2021/modules
 - Module 3: Introduction to R
 - Module 13: Association Mapping: GWAS and Sequencing Data
 - Module 16: Computational Pipeline for WGS Data
- edX
 - <u>https://www.edx.org/learn/computer-programming</u>

R exercises

http://faculty.washington.edu/tathornt/SISG2020.html

| Time | Торіс | Lecture | Exercises/Discussion |
|---------------------|---|--|---|
| 8:00am-9:20am | 1. Introduction, Case Control Association Testing | Slides: (Intro) [<u>.pdf</u>], (Lecture) [<u>.pdf</u>], video | Exercises [.pdf], video, R Script:[.R], Key: [.html], [.Rmd] |
| 9:40am-11:00ar | n 2. Association Testing with Quantitative Traits | Slides: [.pdf], video | Exercises: [.pdf], video_R Script:[.R], Key: [.html], [.Rmd] |
| 11:30am- 12:50pm | 3. Introduction to the PLINK Software for GWAS | Slides [<u>.pdf</u>], <u>video</u> | Exercises [.pdf], video, Plink Script: [.txt], R Script:[.R], Key (Rscript) : [.R] |
| 1:10am-2:30pm | 4. Gene and Pathway Level Analysis of Genetic Association Studies. | Slides [<u>.pdf</u>], <u>video</u> | Exercises [.pdf], video, Plink and R Script: [.txt] |
| Tuesday, July 2 | 18th | | |
| Time | Торіс | Lecture | Exercises/Discussion |
| 8:00am-9:20am | 5. Population Structure Inference | Slides [<u>.pdf</u>], <u>video</u> | Exercises [.pdf], video ,R Script: [.R], Key: [.html], [.Rmd] |
| 9:40am-11:00ar | n 6. GWAS in Samples with Structure | Slides [<u>.pdf</u>], <u>video</u> | Exercises [.pdf],video ,R Script:[.R] |
| 11:30am- 12:50pm | 7. Interaction Analysis | Slides [<u>.pdf</u>], <u>video</u> | Exercises [.pdf], video_, R Script:[.txt] |
| 1:10am-2:30pm | 8. Introduction to Rare Variant Analysis and Collapsing Tests | Slides [<u>.pdf</u>], <u>video</u> | Exercises [.pdf], video_, Key: R Script:[.txt] |
| Wednesday, Ju | ly 29th | | |
| Time | Торіс | Lecture | Exercises/Discussion |
| 8:00am-9:20am | 9. Rare Variant Analysis: Kernel (Variance Component) Tests and Omnibus Tests | Slides [.pdf], video | Exercises [.pdf], video, R Script:[.txt] |
| 9:40am-11:00ar | n 10. Power and Sample Size, Design Considerations, and Emerging Issues | Slides [<u>.pdf</u>], <u>video</u> | Exercises [<u>.pdf</u>], <u>video</u> , R Script:[<u>.txt</u>] |

Datasets

A zipped folder with the genetic relatdness matrix (GRM) and other files for exercise 6, where a linear mixed model analysis is performed, can be \$

Note: New link to zipped file with LMM files on dropbox posted below. The previously posted LMM zipped file was corrupted.

LMM_FILES_NEW.zip

All individual data files below can be downloaded as a single zipped folder from dropbox. This file can be downloaded here:

Note: New link to zipped file with the Data files on dropbox are posted below. The previously posted zipped file was corrupted.

SISG2020Data_NEW.zip

Alternatively, you can download each of the data files below. Before trying to read data into an R or PLINK session, we recommend looking at it first, in a text editor. Is the data comma- or tab delimited? Does it have a 'header' row containing variable names?

bpdata.csv
 Ht.pheno
 LHON.txt
 Population_Sample_Info.txt
 SNPlistHeight.txt
 SNPlistTransferrin.txt
 Tr.pheno
 YRI_CEU_ASW_MEX_NAM.bed
 YRI_CEU_ASW_MEX_NAM.fam

Identifying genetic variation associated with disease



Manolio et al, Nature 2009

Introduction – Rare variants

• Usually less than 1% (depending on who you ask)

- Traditional single variant association analysis have low statistical power and/or are not valid
 - MAF=1% in 1,000 cases and 1,000 controls implies 40 minor alleles
 - Low cell counts lead to invalid statistical tests/low power
- Because the genome has many more rare variants than common variants, more stringent significance levels might be required, further reducing power

A recent study sequenced 10,545 human genomes and found more than 150 million variants



Telenti, PNAS 2016

Allele Frequency

Poll: Why study rare variants?

Why do we care about rare variants when they only affect a small proportion of the population?

PCSK9 and LDL cholesterol



PCSK9 mutations and coronary heart disease



A PCSK9 antibody decreases LDL (8-week trial)



Study design for rare variant analysis

| | Advantage | Disadvantage |
|---------------------------|---|--|
| High-depth WGS | can identify nearly all variants in the genome with high confidence | very expensive |
| Low-depth WGS | cost-effective and useful approach for association mapping | has limited accuracy for rare- variant identification and genotype calling; compared to deep sequencing, is subject to power loss if the same number of subjects is sequenced |
| Whole-exome sequencing | can identify all exonic variants; is less expensive than WGS | is limited to the exome |
| GWAS chip and imputation | inexpensive | has lower accuracy for imputed rare variants Will miss any variants unique to your sample |
| Exome chip (custom array) | much cheaper than exome sequencing | provides limited coverage for very rare variants and for non- Europeans is limited to target regions |

Breakout room discussion

- You just got a large grant to identify rare variants associated with type 2 diabetes. You
 have colleagues around the world that can give you access to DNA from their casecontrol studies. If you were to design a study to identify rare (allele frequency <1%)
 variants associated with type 2 diabetes, what approach would you take and why?
 - High-depth whole genome sequencing
 - Low-depth whole genome sequencing
 - Whole exome sequencing
 - GWAS chip and imputation
 - Exome chip (custom array)

| | Advantage | Disadvantage |
|---------------------------|---|--|
| High-depth WGS | can identify nearly all variants in the genome with high confidence | very expensive |
| Low-depth WGS | cost-effective and useful approach for association mapping | has limited accuracy for rare- variant identification and genotype calling; compared to deep sequencing, is subject to power loss if the same number of subjects is sequenced |
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Rare variant analysis - What to do?

- Many different rare variant tests are available.
 - Some are based on aggregating variants ("burden" tests)
 - CMC (Li and Leal, 2008)
 - WSS (Madsen and Browning, 2009)
 - Variable Threshold approach (Price, 2010)
 - Some are based on studying the distribution of variants
 - C-alpha (Neale, 2011)
 - SKAT (Wu, 2011)

Burden tests

- Collapse many variants into a single risk score
 - Combine minor allele counts into one variable
- Collapsing approach
 - Gene, pathways, functional annotations, etc
 - Much more straight-forward for coding regions
- Weighing
 - Variant type (predicted function)
 - Variant frequency

The Cohort Allelic Sums Test - CAST

<u>Main Idea:</u> Combine rare variants according to some (arbitrary) feature (gene, genetic region, functional category) and assess the new variable

Step 1: Create an indicator variable X for individual *j*:

$$X_j = \begin{cases} 1 \text{ if rare variants are present} \\ 0 \text{ otherwise} \end{cases}$$

Step 2:
$$\ln\left(\frac{p}{1-p}\right) = \alpha + \beta X$$
 (logistic regression)

Morgenthaler, Mutat Res 2007

Variant Collapsing – 2 approaches

i)

| Subject | V1 | V2 | V3 | V4 | X | Subject | V1 | V2 | V3 | V4 | Х |
|---------|----|----|----|----|---|---------|----|----|----|----|---|
| 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| 2 | 0 | 1 | 0 | 0 | 1 | 2 | 0 | 1 | 0 | 0 | 1 |
| 3 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 |
| 6 | 0 | 0 | 0 | 0 | 0 | 6 | 0 | 0 | 0 | 0 | 0 |
| 7 | 0 | 0 | 1 | 1 | 1 | 7 | 0 | 0 | 1 | 1 | 2 |
| 8 | 0 | 0 | 0 | 1 | 1 | 8 | 0 | 0 | 0 | 1 | 1 |

ii)

The Weighted Sum Statistic (WSS) – often called "Madsen-Browning"

- Main idea: Variants are grouped according to function (e.g., gene), and each individual is scored by a weighted sum of the variant counts.
- Use permutation to test for an excess of variants in affected individuals.
- Variants of all frequencies can be included, but variants are weighted according to their frequency in unaffected individuals.

$$\widehat{w}_i = 1/\sqrt{q_i(1-q_i)}$$
 q_i is the estimated MAF in controls

Madsen and Browning, PLoS Genetics, 2009

Drawback with burden tests

- Assume all variants in a set are causal and associated with a trait in the same direction. The common assumption is often that the rare allele increases disease risk
- If this is not true, power is lost.
- Solution: Tests that look at the distribution of rare variants

The C-alpha test

- Main idea: Test whether observed variants either increase or decrease risk (or have no effect). Risk variants are expected to be more common in cases; protective variants more common in controls.
- If there is no association, variants are distributed randomly between cases and controls following a binomial (*n*,*p*) distribution.
- For example, if the case:control ratio is 1:1, a variant seen twice (doubleton) would be observed in cases y times where y is either 0, 1 and 2 with probability $\frac{1}{4}$, $\frac{1}{2}$ and $\frac{1}{4}$, respectively.

Neale, PLoS Genetics 2011

APOB variant counts in individuals with high/low triglyceride levels.

| Position | Annotation | High Lipid Level | Low Lipid Level |
|------------|------------|------------------|-----------------|
| 21078358 | Ala4481Thr | 2 | 5 |
| 21078359 | lle4314Val | 3 | 0 |
| 21078990 | Arg4270Thr | 6 | 3 |
| 21079417 | Val4128Met | 1 | 7 |
| 21083082 | Thr3388Lys | 2 | 1 |
| 21083637 | Ser3203Tyr | 6 | 0 |
| 21086035 | Leu2404lle | 2 | 3 |
| 21086072 | Glu2391Asp | 2 | 2 |
| 21086127 | Thr2373Asn | 2 | 2 |
| 21086308 | Val2313lle | 2 | 1 |
| 21087477 | His1923Arg | 6 | 12 |
| 21087504 | Asn1914Ser | 0 | 5 |
| 21087634 | Asp1871Asn | 2 | 0 |
| 21091828 | Pro1143Ser | 0 | 6 |
| 21091872 | Arg1128His | 0 | 3 |
| 21091918 | Asp1113His | 1 | 3 |
| 21106140 | Thr498Asn | 2 | 0 |
| Singletons | | 6 | 4 |

Nonsynonymous variants discovered via targeted pooled sequencing in 192 individuals with extreme triglyceride levels. High counts represent the number of copies of the variant discovered in 96 individuals who have high triglycerides (defined as exceeding the 5% upper tail of the population distribution). Low counts represent the number of copies of the variant discovered in 96 individuals who have low triglycerides (lower 5% tail). The singletons are grouped together and listed as the penultimate row because its total count is second largest (10, versus 18 for the His1923Arg). For details about pooled sequencing, see Text S1.

doi:10.1371/journal.pgen.1001322.t001

SKAT: sequence kernel association test

- In contrast to the C-alpha test, SKAT is regression-based and thereby allows for adjustment of covariates.
- Uses a variance-component score test in a mixed-model framework to assess regression coefficients for rare variants.

logit
$$P(y_i = 1) = \alpha_0 + \alpha' X_i + \beta' G_i$$

 y_i : case-control status; α_0 : intercept; $\mathbf{\alpha} = [\alpha_1, ..., \alpha_m]'$ is the vector of regression coefficients for the *m* covariates; X_i : fixed effects of covariates; $\mathbf{\beta} = [\beta_1, ..., \beta_p]'$ is the vector of regression coefficients for the *p* observed gene variants in the region; \mathbf{G}_i : $(G_{i1}, G_{i2}, ..., G_{ip})$ genotypes for the *p* variants within the region

$$H_0: \beta = 0 \text{ or } \beta_1 = \beta_2 = ... = \beta_p = 0$$

Wu, AJHG 2011

Combined tests

- SKAT-O
 - Picks the best combination of SKAT and a burden test, and then corrects for the flexibility afforded by this choice. Specifically, if the SKAT statistic is Q1, and the squared score for a burden test is Q2, SKAT-O considers tests of the form (1-rho)*Q1 + rho*Q2, where rho is between 0 and 1.

| | Description | Methods | Advantage | Disadvantage | Software Packages ^a |
|-----------------------------|---|---|---|--|---|
| Burden tests | collapse rare variants into genetic scores | ARIEL test, ⁵⁰ CAST, ⁵¹ CMC method, ⁵² MZ test, ⁵³ WSS ⁵⁴ | are powerful when a large proportion of variants are causal and effects are in the same direction | lose power in the presence of both trait-increasing and trait-decreasing variants or a small fraction of causal variants | EPACTS, GRANVIL, PLINK/SEQ, Rvtests, SCORE-Seq, SKAT, VAT |
| Adaptive burden tests | DescriptionMethodsAdvantageDisadvantagecollapse rare variants into genetic scoresARIEL test, ⁵⁰ CAST, ⁵¹ CMC method, ⁵² MZ test, ⁵³ WSS ⁵⁴ are powerful when a large proportion of variants are causal and effects are in the same directionlose power in the presence of both trait-increasing and trait-decreasing variants or a small fraction of causal variantstsuse data-adaptive weights or thresholdsaSum, ⁵⁵ Step-up, ⁵⁶ KBAC method, ⁵⁹ RBT ⁶⁰ are more robust than burden tests using fixed weights or thresholds; some tests can improve result interpretationare often computationally intensive; VT requires the same assumptions as burden teststtest variance of genetic effectsSKAT, ⁶¹ SSU test, ⁶² C-alpha test ⁶³ are powerful in the presence of both trait- increasing and trait- decreasing variants or a small fraction of causal variantsare less powerful than burden tests when most variants are causal and effects are in the same directioncombine burden and variance-component testsSKAT-O, ⁶⁴ Fisher method, ⁶⁵ MiST ⁶⁶ are more robust with respect to the percentage of causal variants and the presence of both trait-increasing and trait- | | EPACTS, KBAC, PLINK/SEQ, Rvtests, SCORE-Seq, VAT | | |
| Variance-component tests | test variance of genetic effects | genetic SKAT, ⁶¹ SSU test, ⁶² C-alpha test ⁶³ are powerful in the presence of both trait- increasing and trait- decreasing variants or a small fraction of causal direction variants | | EPACTS, PLINK/SEQ, SCORE-Seq, SKAT, VAT | |
| Combined tests | combine burden and variance-component tests | SKAT-O, ⁶⁴ Fisher method, ⁶⁵ MiST ⁶⁶ | are more robust with respect to the percentage of causal variants and the presence of both trait-increasing and trait- decreasing variants | can be slightly less powerful than burden or variance-component tests if their assumptions are largely held; some methods (e.g., the Fisher method) are computationally intensive | EPACTS, PLINK/SEQ, MIST, SKAT |
| EC test | exponentially combines score statistics | EC test ⁶⁷ | is powerful when a very small proportion of variants are causal | is computationally intensive; is less powerful when a moderate or large proportion of variants are | no software is available yet |
| | | | | causal | Lee, AJHG 2014 |

| Table 2. | Summary | of | Statistical | Methods | for | Rare | Variant | Association | Testing |
|----------|---------|----|-------------|---------|-----|------|---------|-------------|---------|
|----------|---------|----|-------------|---------|-----|------|---------|-------------|---------|

Issues in rare variant analysis (i)

- Which variants to include?
 - All variants
 - Only those we think are deleterious
- How to group variants?
 - For exome analysis, rare variants are often grouped by gene making variant grouping straight-forward.
 - For whole-genome analysis, alternative approaches such as sliding window or additional functional annotations (conserved regions, regulatory regions etc.) can be used

Issues in rare variant analysis (ii)

- Which association test to use?
 - If there are multiple variants with risk-increasing effects, burden tests are most powerful
 - If there is a mixture of risk increasing and risk decreasing variants and/or most variants do not have an effect, variance-component methods are most powerful
 - If no prior information is available, conduct both burden and variance component tests. Have to consider multiple testing.
- Population stratification
 - It is not clear how effective PCs are for dealing with population stratification

Issues in rare variant analysis (iii)

- In general, rare variants are more difficult to impute
- Replication is more complex for rare variants:
 - Since the variants are by definition rare, they might be unique to the discovery population
 - Replication of single variants is straightforward: genotype the variant in the replication population
 - For gene-based association tests: Sequencing the gene (or region) can identify additional variants
 - KEY STRATEGY: Maximize number of samples in your replication!