# **Session 07 - Exercises**

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The R template to do the exercises is here (https://github.com/joellembatchou/SISG2022\_Association\_Mapping/tree/master/code).

Set your working directory to your home directory using in R\*

The data files are in the folder /data/SISG2022M15/data/.

## Rare Variant Analysis

#### Introduction

We will look into a dataset collected on a quantitative phenotype which was first analyzed through GWAS and a signal was detected in chromosome 1. Let's determine whether the signal is present when we focus on rare variation at the locus. In our analyses, we will define rare variants as those with  $MAF \leq 5\%$ .

The file "rv pheno.txt"

(https://github.com/joellembatchou/SISG2022\_Association\_Mapping/tree/master/data)" contains the phenotype measurements for a set of individuals and the file "rv\_geno\_chr1.bed" is a binary file in PLINK BED format with accompanying BIM and FAM files which contains the genotype data.

### **Exercises**

Here are some things to try:

- 1. Using PLINK, extract rare variants in a new PLINK BED file. (Hint: use options

   --max-maf to select rare variants and --maj-ref force so that the minor allele is the effect allele)
- 2. Load the data in R:
- Load the phenotype data from rv\_pheno.txt

```
vars n mean sd median trimmed mad min max range skew kurtosis
Pheno 3 9949 0.01 1.01 0.02 0.01 1.02 -3.95 3.66 7.61 -0.01 -0.05
se
Pheno 0.01
```

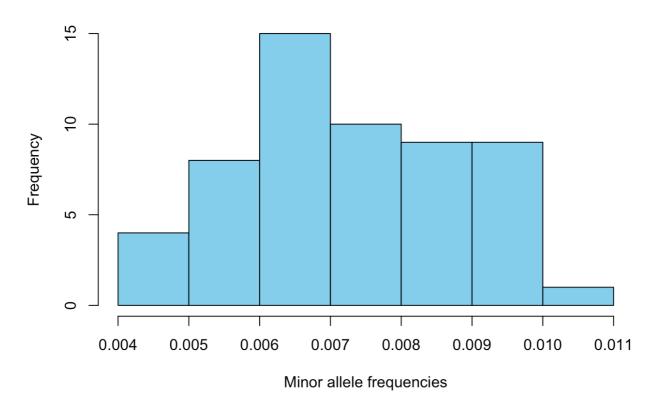
• Keep only samples who are present both in the genotype as well as phenotype data and who don't have missing values for the phenotype

```
[1] "Initial Number of samples: 9953"
```

```
[1] "Initial Number of samples: 9953"
```

- [1] "Number of samples filtered for missing data: 9949"
- 3. Examine the genotype data:
- Compute the minor allele frequency (MAF) for each SNP and plot histogram. (hint: use na.rm=TRUE when calling mean())

#### **Distribution of MAF**

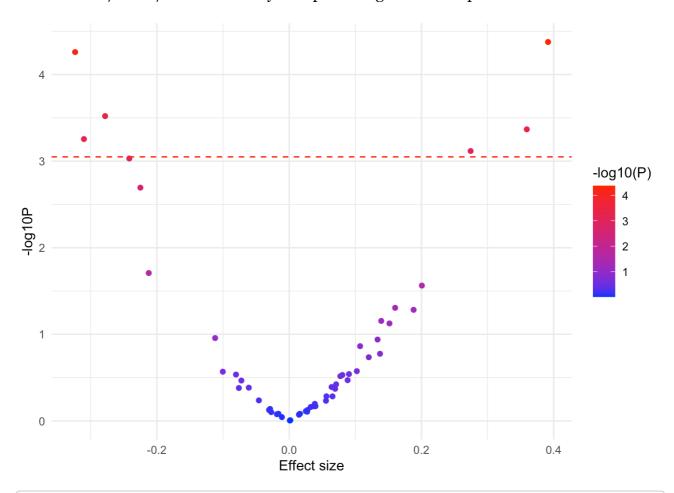


• Check for missing values (hint: use function is.na() which returns TRUE/FALSE value for missing status)

- 4. Run the single variant association tests in PLINK (only for the extracted variants).
- What would be your significance threshold after applying Bonferroni correction for the multiple tests (assume the significance level is 0.05)? Is anything significant after this correction?
- [1] "Number of SNPs: 56"
- [1] "alpha= 0.05"
- [1] "Boferonni corrected p: 0.000892857142857143"

۸1	#CHROM OMITTED	POS		ID	RE	F ALT	PROVISION	NAL_REF?
AI	-		•	<char></char>	<char< td=""><td>&gt; <char></char></td><td></td><td><char> <cha< td=""></cha<></char></td></char<>	> <char></char>		<char> <cha< td=""></cha<></char>
r>				CHarr	Terrar	, deliair		delia i delia
1:			1:126393	85:G:A		A G		Υ
G	Α							
2:	1	12057950	1:120579	50:C:T		T C		Υ
С	Т							
3:	1	12734720	1:127347	20:A:C		C A		Υ
Α	С							
		12405413	1:124054	13:T:C		C T		Υ
T	C							
5:		12360016	1:123600	16:G:A		A G		Υ
G G	Α	12102402	1.121024	02.6.4		۸ ۲		Υ
6: G	A	12183493	1:1218349	93:G:A		A G		Y
d		REO TEG	ST OBS CT		RFTΔ	SF	T_STAT	Р
A1_FREQ TEST OBS_CT BETA SE T_STAT P ERRCODE								
		um> <chai< td=""><td>r&gt; <int></int></td><td>&lt; </td><td>num&gt;</td><td><num></num></td><td><num></num></td><td><num></num></td></chai<>	r> <int></int>	<	num>	<num></num>	<num></num>	<num></num>
<char></char>								
1:	0.00567	896 AI	DD 9949	0.393	1421 0	.0955243	4.09761	4.20759e-05
2:	0.00789	024 AI	DD 9949	-0.323	3574 0	.0801934	-4.03492	5.50288e-05
•							0.04400	
3:	0.00849	332 AL	DD 9949	-0.278	8236 0	.0/69/09	-3.61482	3.02042e-04
4.	0 00107	486 AI	D 0040	0 250	0240 A	1010050	2 52250	4 202020 04
4:	<b>₩.₩48</b> /	400 AL	טע 9949	יככ וּש	9249 V	• T0TA020	3.32238	4.29282e-04
5:	0.00643	281 AF	)D 9949	-0.310	0260 A	.0898433	-3.45335	5.55975e-04
.	2.20013						21.0000	
6:	0.00773	947 A[	D 9949	0.274	4311 0	.0814842	3.36643	7.64368e-04

• Make a volcano plot (i.e. log10 p-values vs effect sizes). Which of the Burden/SKAT/ACAT tests do you expect will give us most power?



- [1] "P values lower than Boferonni corrected p: c(FALSE, TRUE)"
- [2] "P values lower than Boferonni corrected p: c(50, 6)"
  - 5. We will first compare three collapsing/burden approaches:
- CAST (Binary collapsing approach): for each individual, count where they have a rare allele at any of the sites

```
burden.cast
0 1
4352 5597
```

```
Call:
lm(formula = pheno$Pheno ~ burden.cast)
Residuals:
            1Q Median
   Min
                            30
                                   Max
-3.9531 -0.6880 0.0012 0.6822 3.6581
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.002423
                      0.015317
                                 0.158
                                          0.874
burden.cast 0.017757
                      0.020422
                                 0.870
                                          0.385
Residual standard error: 1.01 on 9947 degrees of freedom
Multiple R-squared: 7.6e-05, Adjusted R-squared: -2.452e-05
F-statistic: 0.7561 on 1 and 9947 DF, p-value: 0.3846
```

• MZ Test/GRANVIL (Count based collapsing): for each individual, count the total number of sites where a rare allele is present

```
burden.mz

0 1 2 3 4 5

4352 3690 1438 373 77 19
```

```
Call:
lm(formula = pheno$Pheno ~ burden.mz)
Residuals:
                            30
   Min
            10 Median
                                   Max
-3.9521 -0.6894 -0.0013 0.6805 3.6591
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.001444 0.013700
                                 0.105
                                          0.916
                                 1.189
burden.mz
           0.013492
                      0.011346
                                          0.234
Residual standard error: 1.01 on 9947 degrees of freedom
Multiple R-squared: 0.0001421, Adjusted R-squared:
F-statistic: 1.414 on 1 and 9947 DF, p-value: 0.2344
```

 Weighted burden test: for each individual, take a weighted count of the rare alleles across sites (for the weights, use weights <- dbeta(MAF, 1, 25))</li>

```
Call:
lm(formula = pheno$Pheno ~ burden.weighted)
Residuals:
             10 Median
    Min
                            30
                                   Max
-3.9519 - 0.6896 - 0.0014 0.6804 3.6593
Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)
               0.0012244 0.0136778
                                      0.090
                                               0.929
burden.weighted 0.0006577 0.0005402
                                      1.217
                                               0.223
Residual standard error: 1.01 on 9947 degrees of freedom
Multiple R-squared: 0.000149, Adjusted R-squared:
F-statistic: 1.482 on 1 and 9947 DF, p-value: 0.2235
```

For each approach, first generate the burden scores vector then test it for association with the phenotype using lm() R function.

6. Now use SKAT to test for an association. The basic command would look like

```
[1] "skat.null <- SKAT_Null_Model( <phenotype_vector> ~ 1 , out_type
= 'C')"
```

```
[1] "SKAT( <genotype_matrix>, skat.null )"
```

```
[1] 8.745405e-11
```

- 7. Run the omnibus SKAT, but consider setting  $\rho$  (i.e. r.corr) to o and then 1.
- Compare the results to using the CAST,MZ/GRANVIL and Weighted burden collapsing approaches in Question 5 as well as SKAT in Question 6. What tests do these  $\rho$  values correspond to?

```
rho0 rho.5 rho1
8.745405e-11 7.405918e-02 2.234603e-01
```

- [1] "Predictor p value CAST: 0.384579707780373"
- [1] "Predictor p value MZ Test/GRANVIL: 0.234411045400139"
- [1] "Predictor p value Weighted Burden Test: 0.223477961578584"

- [1] "Predictor p value SKAT 0 at rho 1: 0.223460298922282"
- 8. Now the omnibus version of SKAT, but use the "optimal.adj" approach which searches across a range of rho values.
- [1] 6.121784e-10
- 9. Run ACATV on the single variant p-values.
- [1] 0.00112117
- 10. Run ACATO combining the SKAT (only rho o and 1) and BURDEN p-values (from Question 7) with the ACATV p-value (from Question 9).
- [1] 2.623621e-10

Session information