

Lab: genomic BLUP and ridge regression BLUP

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Learning Objectives

1. Participants will be able to calculate a GRM
2. Participants will be able to run gBLUP
3. Participants will be able to run rrBLUP
4. Participants will be understand the equivalency of gBLUP and rrBLUP

Outline

A. Demonstration with Spindel data

B. On your own (1) gBLUP and rrBLUP Zhao data set, (2) cross validation

Spindel data set

- ▶ 299 elite rice lines from IRRI
- ▶ genotyped with 73,147 SNPs
 - ▶ we'll use 39,560
- ▶ phenotyped for 19 traits
 - ▶ **grain yield (GY)**
 - ▶ measured in dry and wet seasons

RESEARCH ARTICLE

Genomic Selection and Association Mapping in Rice (*Oryza sativa*): Effect of Trait Genetic Architecture, Training Population Composition, Marker Number and Statistical Model on Accuracy of Rice Genomic Selection in Elite, Tropical Rice Breeding Lines

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Loading data

```
##Clear all objects
```

```
rm(list = ls())
```

```
# Load the data
```

```
pheno <- read.csv("~/Downloads/Spindel/pheno_WS.csv")
```

```
dim(pheno)
```

```
## [1] 299 20
```

```
geno <- read.table("~/Downloads/Spindel/Spindel_geno.txt",  
                  sep = "\\t", header = T, row.names = 1)
```

```
dim(geno)
```

```
## [1] 39560 299
```

```
geno <- t(geno)
```

```
dim(geno)
```

```
## [1] 299 39560
```

```
sum(row.names(geno) == pheno$GHID)
```

```
## [1] 299
```

Calculate a GRM

```
head(geno[,1:5])
```

```
##           S1_189590 S1_196811 S1_204765 S1_211589 S1_212693
## A1257             2           2           2           2           2
## A1258             2           2           2           2           2
## A1302             2           2           2           2           2
## B1053             2           2           2           2           2
## A1260             2           2           2           2           2
## A1304             0           0           0           0           0
```

```
Zsc <- scale(x = geno, center = T, scale = T)
GRM <- tcrossprod(Zsc)/ncol(geno)
```

```
dim(GRM)
```

```
## [1] 299 299
```

gBLUP using rrBLUP package

```
library(rrBLUP)

#MM with rrBLUP regression on G
gBLUP <- mixed.solve(y = pheno$YLD, K = GRM)
names(gBLUP)

## [1] "Vu"    "Ve"    "beta" "u"     "LL"

length(gBLUP$u)

## [1] 299
```

rrBLUP using rrBLUP package

```
library(rrBLUP)
Zc <- scale(x = geno, center = T, scale = F)

#MM with rrBLUP regression on markers
rrBLUP <- mixed.solve(y = pheno$YLD, Z = Zc)
names(rrBLUP)
```

```
## [1] "Vu"    "Ve"    "beta"  "u"     "LL"
```

```
length(rrBLUP$u)
```

```
## [1] 39560
```


Are rrBLUP and gBLUP equivalent?

- ▶ Recall

$$\hat{g} = W\hat{a}$$

- ▶ Thus, here we'll leverage that to calculate the breeding values (GEBVs) from the predicted marker effects

#calculate GEBVs from predicted marker effects

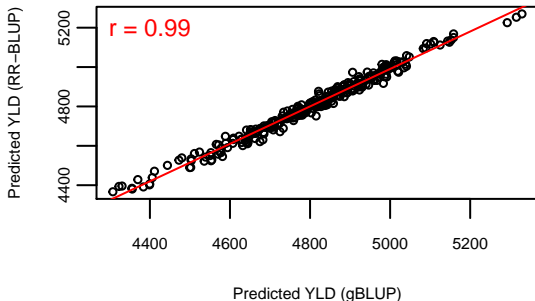
```
gBLUP_rr <- Zc %*% rrBLUP$u
```

```
gBLUP_YLD <- gBLUP$u + as.numeric(gBLUP$beta)
```

```
gBLUP_rr_YLD <- gBLUP_rr + as.numeric(rrBLUP$beta)
```

Are rrBLUP and gBLUP equivalent?

```
par(mar=c(3,4,0.5,0.5), mgp=c(1.8,0.5,0), xpd = F, cex.lab = 0.5,  
    cex.axis = 0.5)  
plot(gBLUP_YLD, gBLUP_rr_YLD, ylab = "Predicted YLD (RR-BLUP)",  
     xlab = "Predicted YLD (gBLUP)", pch = 21, cex = 0.5)  
  
abline(lm(gBLUP_rr_YLD ~ gBLUP_YLD), col = "red")  
  
text(x = 4400, y = 5200, paste0("r = ",  
    round(cor(gBLUP_YLD, gBLUP_rr_YLD),2)), col = "red", cex = 0.75)
```



On your own

- ▶ Download the Zhao data set and repeat the analysis above
 - ▶ https://github.com/malachycampbell/StatisticalMethodsforOmicsAssistedBreeding/gBLUP_rrBLUP/ZhaoData.zip
 - ▶ You will have to (1) recode the SNP data, (2) partition and mask the data for cross validation
 - ▶ See the examples in the file 'gBLUP_RRBLUP_ex.Rmd'