# Estimating genomic breeding values using genomic BLUP and ridge regression BLUP

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#### Intro

$$\mathbf{y} = \mathbf{g} + \boldsymbol{\epsilon}$$

- What is **g**?

Plant ID	у	g	e
1	10	5	5
2	7	6	1
3	12	2	10

#### Intro

▶ Recall that **g** is the cumulative additive genetic effect

$$\mathbf{y} = 1\mu + \sum_{k} \mathsf{x}_{k} \beta + e$$

 ${f W}$  is a centered  $n \times m$  marker matrix,  ${f a}$  is vector of SNP effects

## Ridge regression BLUP

$$\mathbf{y} = 1\mu + \sum_{k} x_{k} \beta + \epsilon$$

- ▶ Proposed before the 'big data' trend by Meuwissen et al (2001)
- $\hat{\beta} = \mathbf{X}'(\mathbf{X}'\mathbf{X} + \lambda \mathbf{I})^{-1}\mathbf{y}$ 
  - $\lambda = \frac{\sigma_e^2}{\sigma_\beta^2}$

#### Genomic BLUP

$$\mathbf{y} = 1\mu + \mathbf{Z}\mathbf{u} + e$$

- $\hat{m{u}} = \left[ \mathbf{I} + \mathbf{G}^{-1} rac{\sigma_e^2}{\sigma_u^2} 
  ight] \mathbf{y}$
- ▶ How do these methods differ? How will the GEBVs differ?

#### Equivalence

- ► For gBLUP the  $Var(y) = \mathbf{ZGZ}'\sigma_u^2 + \mathbf{I}\sigma_e^2$
- lacksquare For rrBLUP the  $\mathit{Var}(y) = \mathbf{XX}'\sigma_{eta}^2 + \mathbf{I}\sigma_{\mathrm{e}}^2$ 
  - ▶ What does **XX**′ represent?

#### Demonstration with Spindel data

- 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

#### PLOS GENETICS

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







## Loading data

```
##Clear all objects
rm(list = ls())
# Load the data
pheno <- read.csv("~/Downloads/Spindel/pheno_WS.csv")</pre>
dim(pheno)
## [1] 299 20
geno <- read.table("~/Downloads/Spindel/Spindel_geno.txt",</pre>
                   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

## [1] 299 299

```
head(geno[,1:5])
         S1_189590 S1_196811 S1_204765 S1_211589 S1_212693
##
## A1257
## A1258
## A1302
## B1053
## A1260
## A1304
Zsc <- scale(x = geno, center = T, scale = T)</pre>
GRM <- tcrossprod(Zsc)/ncol(geno)</pre>
dim(GRM)
```

## gBLUP using rrBLUP package

```
library(rrBLUP)

gBLUP <- mixed.solve(y = pheno$YLD, K = GRM)
names(gBLUP)

## [1] "Vu" "Ve" "beta" "u" "LL"
length(gBLUP$u)

## [1] 299</pre>
```

## rrBLUP using rrBLUP package

## [1] 39560

```
library(rrBLUP)

rrBLUP <- mixed.solve(y = pheno$YLD, Z = Zsc)
names(rrBLUP)

## [1] "Vu" "Ve" "beta" "u" "LL"
length(rrBLUP$u)</pre>
```

- ▶ Why are the sizes rrBLUP\$u and gBLUP\$u different?
- ▶ How can we make the two comparable?

## Are rrBLUP and gBLUP equivalent?

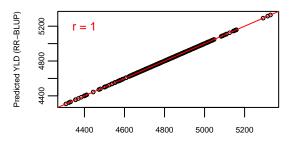
Recall

```
\hat{g} = W\hat{a}
#calculate GEBVs from predicted marker effects
gBLUP_rr <- Zsc %*% 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)
```



Predicted YLD (qBLUP)

## How accurate are our predictions?

► How can we estimate how accurate our predicted genomic breeding values are?

#### How accurate are our predictions?

- ► How can we estimate how accurate our predicted genomic breeding values are?
  - Compare predicted and observed breeding values for a new population
  - ▶ Partition dataset and use one for training and one for prediction

#### Two fold cross validation

- For some dataset
  - (1) randomly split the the individuals into two equal sized (or close to) sets
  - (2) mask the observations in one set (testing set), keep observations for other set (training set)
  - (3) fit the model using training set and predict the values for the missing individuals
  - (4) take the correlation between predicted GEBVs for test set and observed phenotypes for test set
  - (5) repeat 1 4

#### Two fold cross validation

```
pheno train <- pheno
#define the testing and training sets
set.seed(123)
train_set <- sample (1:length(pheno$GHID), size = length(pl
test_set <- setdiff(1:length(pheno$GHID), train_set)</pre>
length(train_set)
## [1] 149
length(test set)
## [1] 150
#Mask the phenotypes for the testing set
pheno_train[test_set ,]$YLD <- NA</pre>
```

## Run RRBLUP with training set

```
library(rrBLUP)
##rrBLUP
rrBLUP_train <- mixed.solve(y = pheno_train$YLD, Z = Zsc)
rrBLUP_train <- Zsc %*% rrBLUP_train$u
length(rrBLUP_train)</pre>
```

## [1] 299

## Assess predictive ability from rrBLUP approaches

## [1] 0.1618154

```
rrBLUP_test <- rrBLUP_train[test_set]
pheno_test <- pheno[test_set ,]
cor(pheno_test$YLD, rrBLUP_test)</pre>
```

#### References

- Endelman, J. B. Ridge regression and other kernels for genomic selection with R package rrBLUP. Plant Genome 4, 250–255 (2011).
- Habier, D., Fernando, R. L. & Dekkers, J. C. M. The impact of genetic relationship information on genome-assisted breeding values. Genetics 177, 2389–2397 (2007).
- Meuwissen, T. H. E., Hayes, B. J. & Goddard, M. E. Prediction of total genetic value using genome-wide dense marker maps. Genetics 157, 1819–1829 (2001).
- Spindel, J. et al. 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. PLoS Genet. 11, e1004982 (2015).