

# **Module 3: Optimization of Training Sets Using R**

## **Fundamentals of Genomic Prediction and Data-Drive Crop Breeding**

**(August 4-8, 2025)**



### **Waseem Hussain**

Senior Scientist-I

International Rice Research Institute

Rice Breeding Innovations Platform

[waseem.hussain@irri.org](mailto:waseem.hussain@irri.org)

[whussain2.github.io](https://whussain2.github.io)

### **Mahender Anumalla**

Scientist-I

International Rice Research Institute

South-Asian Hub, Hyderabad

[m.anumalla@irri.org](mailto:m.anumalla@irri.org)

July 25, 2025

## Contents

<b>Load the Libraries</b>	<b>1</b>
<b>Load Marker Data</b>	<b>1</b>
<b>Build the Genomic Matrix</b>	<b>2</b>
<b>Extract the Training Set</b>	<b>3</b>
Extract the selected individuals . . . . .	3
How Good Training Set Represents Whole Set . . . . .	3
<b>Assignment</b>	<b>4</b>
<b>Additional Resources</b>	<b>4</b>

## Load the Libraries

```
> # Load the Required Libraries
> rm(list=ls()) # Remove previous work
> library(AGHmatrix)
> library(STPGA) # Package for Training Optimization
> library(FactoMineR)
> library(factoextra)
```

Here we will use R package **STPGA** to demonstrate how we can get optimized training set for performing genomic predictions **Additional Information**. We will use **CD Mean** to get the training set. There are various algorithms including **PEV Mean** and others to use for extracting the training. set.

## Load Marker Data

The marker data is **1K RiCA** with 887 high quality SNP markers. The data is filtered and low quality markers and minor allele frequency markers has been already removed. The data is on **1, 0** and **-1** format. For example for SNP1 if we have allele call as **A/T**, then we will have 3 types of genotypes **AA, TT** and **AT**. For this SNP, [**1==AA, 0==AT and TT=-1**].

More on filtering on How to filter low quality markers can be found here **How to Filter the SNP markers**

We will recode the marker data to [**2==AA, 1==AT and TT==0**] format for building the G matrix in **AGHMatrix** R package.

```
> # Genotype data
> geno<-readRDS("../Data/geno.oyt.filtered.rds") # Upload marker data
> dim(geno) # Check dimensions
```

```
[1] 616 887
```

```
> geno[is.na(geno)] <-0
> # Recode the matrix in 2,1 and 0 numeric format
> geno[geno==1]<-2
> geno[geno==-1]<-0
> geno[geno==0]<-0
> kable(head(geno)[1:6,1:2])
```

	IRRI_SNP0001_CHR01_194844	IRRI_SNP0002_CHR01_375814
IR129391.B.12.B.3.1	0	0
IR129391.B.19.B.2.1	0	0
IR129391.B.44.B.4.1	2	2
IR129391.B.46.B.1.1	2	2
IR129391.B.6.B.4.1	0	0
IR129391.B.9.B.4.1	0	0

## Build the Genomic Matrix

We will use AHGmatrix R package to build the various Relationship Matrices. More details on this package can be found here [AHGmatrix](#) and on [Github](#).

- Function **Gmatrix()** handles the molecular-marker matrix and builds the relationship matrices.
- Molecular markers data should be organized in a matrix format (individuals in rows and markers in columns) coded as 0 (BB), 1 (AB), 2 (AA) and missing data value (numeric or NA).
- Arguments in the function to control are: **Minor allele frequency** (*maf*), **Threshold** for missing data, and **Method** which one should be the method used to build the kernel.
- To run the example quickly we will use only small set of 200 genotypes.

```
> # Get subset of first 200 genotypes
> geno<-geno[1:200, ] # Subset
> geno<-as.matrix(geno) # Convert as matrix
> # Build the VanRaden 2008 G matrix
> G_additive <- Gmatrix(SNPmatrix=geno, missingValue=NA,
+                       maf=0.05, method="VanRaden")
```

Initial data:

```
Number of Individuals: 200
Number of Markers: 887
```

Missing data check:

```
Total SNPs: 887
0 SNPs dropped due to missing data threshold of 0.5
Total of: 887 SNPs
```

MAF check:

```
33 SNPs dropped with MAF below 0.05
Total: 854 SNPs
```

Heterozygosity data check:

```
No SNPs with heterozygosity, missing threshold of = 0
```

Summary check:

```
Initial: 887 SNPs
Final: 854 SNPs ( 33 SNPs removed)
```

Completed! Time = 0.056 seconds

## Extract the Training Set

In the *STPGA* R package the function **GenAlgForSubsetSelectionNoTest** is available to optimize the training set. The function has several arguments and here we will use few arguments to obtain the training set.

Here we will use G matrix derived above to extract the training set.

```
> # Define the number of individuals to select for the training set
> nSel <- 60 # Can be adjusted based on population size
>
> # Optimize the training set using CDmean in the argument errorstat
>
> result <- GenAlgForSubsetSelectionNoTest(
+   P = G_additive, # marker matrix or relationship matrix
+   ntoselect = nSel, # Number of individuals in the training set
+   npop = 100, # population size for the genetic algorithm
+   nelite = 5, # population size for the genetic algorithm
+   mutprob = 0.5, # probability of mutation for each generated solution
+   mutintensity = 1,
+   niterations = 50, # number of iterations.
+   minitbefstop = 50, # number of iterations before stopping
+   tabu = FALSE,
+   plotiters = FALSE, # plot the convergence
+   lambda = 1e-6, # scalar shrinkage parameter
+   errorstat = "CDMEAN"
+ )
```

## Extract the selected individuals

```
> selected_ids <- data.frame(TrainingGenotypes=result$`Solution with rank 1`)
> kable(head(selected_ids$TrainingGenotypes))
```

x
IR129391.B.12.B.3.1
IR129391.B.44.B.4.1
IR129391.B.6.B.4.1
IR129398.B.14.B.4.1
IR129398.B.3.B.2.1
IR129398.B.37.B.1.1

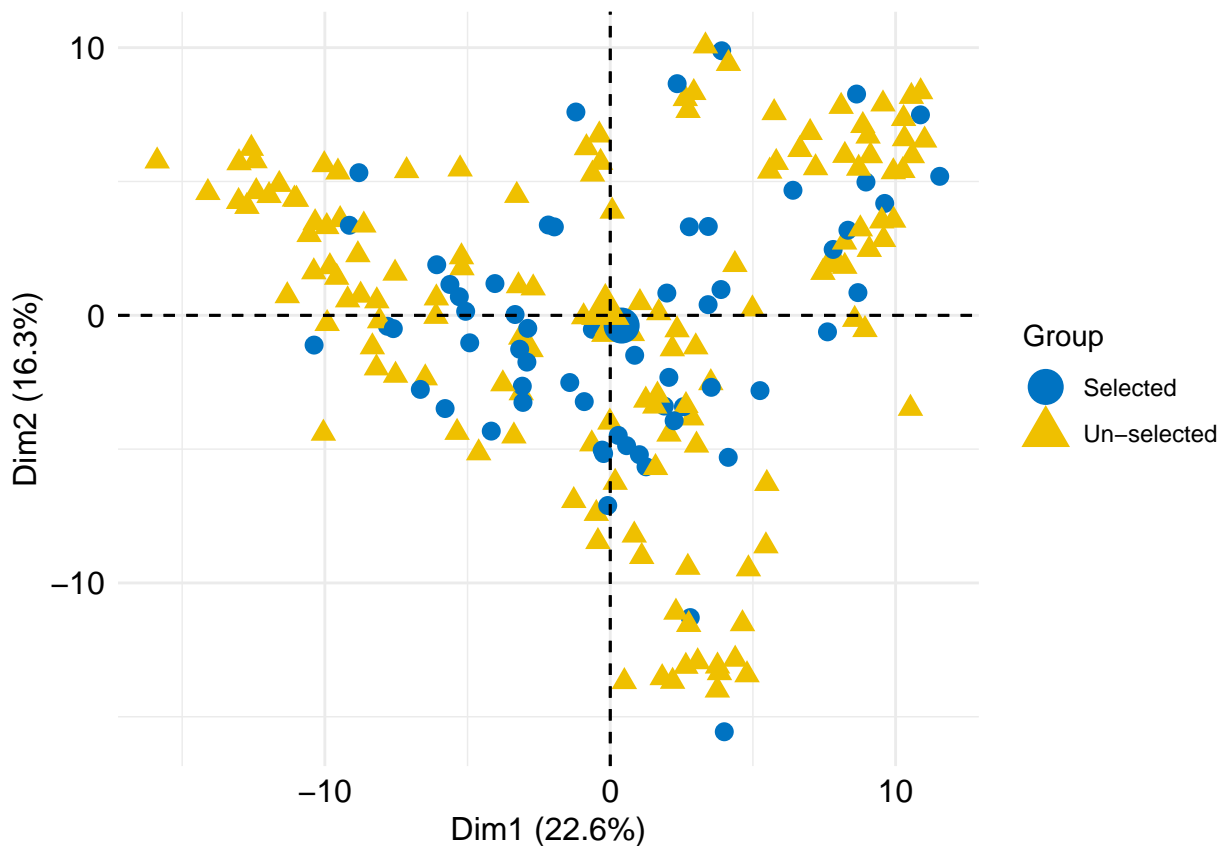
## How Good Training Set Represents Whole Set

```
> # Get lines from training set
> line.names<-data.frame(Genotype=ifelse(row.names(G_additive)%in%selected_ids$TrainingGenotypes, "Selected", "Not Selected"))
> row.names( line.names)<-row.names(G_additive)
>
> # Perform PCA on GM matrix
> pca<- PCA(G_additive, graph = FALSE)
> # Get the Biplot
> biplot.gm<-fviz_pca_biplot(pca, palette = "jco", axes = c(1, 2), geom="point",pointsize = 3,
+   addEllipses = FALSE,col.ind = line.names$Genotype,
+   geom.var= "none", label = "none", legend.title = "Group")+
```

```

+ theme_minimal()+
+ # add and modify the title to plot
+ theme (
+   plot.title = element_blank(),
+   # add and modify title to x axis
+   axis.title.x = element_text(color="black", size=12),
+   # add and modify title to y axis
+   axis.title.y = element_text(color="black", size=12)) +
+   # modify the axis text
+   theme(axis.text= element_text(color = "black", size = 12))
> biplot.gm

```



```

> #' #####End#####

```

## Assignment

- Learn the various arguments and Functions of STPGA R package.
- Also, run the example in TrainSel R package; Check Trainsel document as Example.

## Additional Resources

- Maximizing the Reliability of Genomic Selection by Optimizing the Calibration Set of Reference Individuals: Comparison of Methods in Two Diverse Groups of Maize Inbreds (Zea mays L.)
- Selection of training populations with an accelerated genetic algorithm STPGA R-package

- A comparison of methods for training population optimization in genomic selection
- TrainSel: An R Package for Selection of Training Populations
- Training Set Optimization for Sparse Phenotyping in Genomic Selection: A Conceptual Overview

---

For any suggestions or comments, please feel to reach at [waseem.hussain@irri.org](mailto:waseem.hussain@irri.org); and [m.anumalla@irri.org](mailto:m.anumalla@irri.org)

---