## Supplemental material

## Equivalence between Standard Selection Index and BLUP

Consider a standard single-trait model of the form

 $oldsymbol{y} = oldsymbol{u} + oldsymbol{arepsilon}$ 

where  $\boldsymbol{y} = (y_1, ..., y_n)'$ ,  $\boldsymbol{u} = (u_1, ..., u_n)'$ , and  $\boldsymbol{\varepsilon} = (\varepsilon_1, ..., \varepsilon_n)'$  are vectors of phenotypes, genetic, and environmental effects, respectively. Here, for simplicity we assume that all these vectors have zero-mean.

In a standard G-BLUP model,  $\boldsymbol{u}$  and  $\boldsymbol{\varepsilon}$  are assumed to be independent (i.e.,  $cov(\boldsymbol{u}, \boldsymbol{\varepsilon}') = \boldsymbol{0}$ ), both have null means (i.e.,  $\mathbb{E}(\boldsymbol{u}) = \mathbb{E}(\boldsymbol{\varepsilon}) = \boldsymbol{0}$ ), and (co)variance matrices  $var(\boldsymbol{u}) = \sigma_u^2 \boldsymbol{G}$  and  $var(\boldsymbol{\varepsilon}) = \sigma_{\varepsilon}^2 \boldsymbol{I}$ , respectively; here  $\boldsymbol{G}$  is a relationship matrix that could be derived from a pedigree or from DNA sequences.

Consider now a partition of each of the data in into a training (trn) and a testing (tst) set. The objective is to predict the genetic values of the individuals in the testing set  $(\boldsymbol{u}_{tst})$  using the phenotype data available from the training set  $(\boldsymbol{y}_{trn})$ . The (co)variance matrix of the vector of breeding values can be partitioned as follows

$$var\left(\begin{bmatrix}\boldsymbol{u}_{trn}\\\boldsymbol{u}_{tst}\end{bmatrix}\right) = \sigma_u^2 \begin{bmatrix}\boldsymbol{G}_{trn} & \boldsymbol{G}_{trn,tst}\\\boldsymbol{G}'_{trn,tst} & \boldsymbol{G}_{tst}\end{bmatrix}$$

where  $G_{trn}$  and  $G_{tst}$  are the genetic relationship submatrices for the training and testing data points, respectively, and  $G_{trn,tst}$  is the genetic relationship submatrix between training and testing subjects. The Best Linear Predictor (BLP) of  $u_{tst}$  ( $\hat{u}_{tst}$ ) takes the form (e.g., Searle *et al.* 1992):

$$\begin{split} \mathbb{E}(\boldsymbol{u}_{tst}|\boldsymbol{y}_{trn}) &= \mathbb{E}(\boldsymbol{u}_{tst}) + cov(\boldsymbol{u}_{tst}, \boldsymbol{y}'_{trn}) \left[ var(\boldsymbol{y}_{trn}) \right]^{-1} (\boldsymbol{y}_{trn} - \mathbb{E}(\boldsymbol{y}_{trn})) \\ &= \boldsymbol{G}'_{trn,tst} \left( \boldsymbol{G}_{trn} + \lambda_0 \boldsymbol{I} \right)^{-1} \boldsymbol{y}_{trn}. \end{split}$$

Alternatively, one can write  $\hat{\boldsymbol{u}}_{tst} = \boldsymbol{H} \cdot \boldsymbol{y}_{trn}$ , where  $\boldsymbol{H} = \boldsymbol{G}'_{trn,tst}(\boldsymbol{G}_{trn} + \lambda_0 \boldsymbol{I})^{-1}$  is a "Hat" matrix. Thus, the BLUP of the genetic value of the  $i^{th}$  testing individual is  $\hat{\boldsymbol{u}}_{tst(i)} = \boldsymbol{H}'_i \boldsymbol{y}_{trn}$  where  $\boldsymbol{H}'_i$  is the  $i^{th}$  row of  $\boldsymbol{H}$ , that is  $\boldsymbol{H}'_i = \boldsymbol{G}'_i (\boldsymbol{G}_{trn} + \lambda_0 \boldsymbol{I})^{-1}$  which is equal to the weights of the standard selection index,  $\hat{\boldsymbol{\beta}}'_i = \boldsymbol{G}'_i (\boldsymbol{G}_{trn} + \lambda_0 \boldsymbol{I})^{-1}$  (see Equation 2 in the manuscript).

## References

Searle S. R., G. Casella, and C. E. McCulloch, 1992 Variance components. John Wiley & Sons, Inc.