File S1: confidence intervals for broad-sense heritability

Confidence intervals for the broad-sense heritability estimates obtain from the ANOVA mean sums of squares are traditionally obtained from the ratio $F = MS(G)/MS(E)$ and the quantiles of the F-distribution with the corresponding degrees of freedom. Given n genotypes with r_1, \ldots, r_n replicates, the intervals are given by

$$
\frac{F/F_{\mathrm{df1,df2,0.95}}-1}{F/F_{\mathrm{df1,df2,0.95}}+\bar{r}-1} < H^2 < \frac{F/F_{\mathrm{df1,df2,0.05}}-1}{F/F_{\mathrm{df1,df2,0.05}}+\bar{r}-1},
$$

where df1 = $n-1$, df2 = $\sum (r_i-1)$ and $\bar{r} = (n-1)^{-1}(\sum r_i - (\sum r_i^2)/(\sum r_i))$. In case of a balanced design with $r_i = r$ replicates, this reduces to $\bar{r} = r$ and $df2 = n(r - 1)$. See [1] (p.563) or [2].

File S2: analysis of flowering traits of [3]

Our broad-sense heritability estimates differ from those reported in Supplementary table 7 of [3], for the following three reasons. First, the broad-sense heritability estimates in [3] were calculated using the formula

$$
\frac{MS(G)}{MS(G) + MS(E)}.\tag{1}
$$

Although this quantity may be an adequate criterion to compare heritabilities of traits within the same experiment (as long as they have the same number of replicates), this is a biased estimator of broad-sense-heritability. Since the expectation of $MS(G)$ is $r\sigma_G^2 + \sigma_E^2$, $MS(G)/(MS(G) + MS(E))$ will tend to overestimate heritability. The usual estimator defined in the materials and methods section is also biased, but this bias is usually small, and (in contrast to (1)) tends to zero when the number of genotypes increases ([4], [2]).

Second, broad-sense heritability estimates in [3] were based on more accessions: 189 for LDV and 186 for LD. To allow a direct comparison with mixed model analysis we restricted our analysis to genotyped accessions, excluding 21 accessions for LDV and for 19 LD. This had little impact on heritability estimates.

Third, the analysis of variance in [3] did not include a replicate effect. In our analysis, the mean sums of squares for replicates removes some environmental variance, therefore giving higher estimates than in an analysis without a replicate effect. This however did not compensate for the use of (1); hence our heritability estimates are lower than those reported in [3].

File S3: the likelihood is constant for a kinship matrix with compound symmetry structure

Mixed model based estimation of heritability using genotypic means may become problematic when the sample size is small and the kinship matrix is close to compound symmetry, i.e. the structure where all off-diagonal elements are equal. Here we show that in the case the kinship matrix is exactly compound symmetry, the likelihood is constant in $\eta = \sigma_E^2/\sigma_A^2$. We use the notation η to avoid confusion with $\delta = \sigma_A^2/\sigma_E^2$, used in our results on genomic prediction. We write 1_n for the $n \times 1$ column vector of ones, and I_n for the *n*-dimensional identity matrix. Finally, let J_n be the $n \times n$ matrix of ones.

Suppose that $K = I_n + aJ_n$, for some $a > 0$. The key observation is that the covariance matrix of the data can be written as

$$
\Sigma = \sigma_A^2 K + \sigma_E^2 I_n = \tilde{\sigma}_A^2 \tilde{K} + \tilde{\sigma}_E^2 I_n = \tilde{\sigma}_A^2 (\tilde{K} + \tilde{\eta} I_n),
$$

where $\tilde{\sigma}_A^2 = \sigma_A^2$, $\tilde{\sigma}_E^2 = \sigma_A^2 + \sigma_E^2$, $\tilde{K} = aJ_n = a1_n1_n^t$ and $\tilde{\eta} = (\sigma_A^2 + \sigma_E^2)/\sigma_A^2 > 0$. We can then directly apply the results in section 3 of [5], with (in their notation) $k = 1$, $d = 1$ and $X = 1$ _n (we only include an intercept, and no marker effect), and replacing σ_A^2 , σ_E^2 , η and K by respectively $\tilde{\sigma}_A^2$, $\tilde{\sigma}_E^2$, $\tilde{\eta}$ and \tilde{K} . In particular, we have the spectral decomposition

$$
\tilde{K} = USU^{t} = [U_{1}, U_{2}] \begin{bmatrix} S_{1} & 0 \ 0 & S_{2} \end{bmatrix} [U_{1}, U_{2}]^{t}
$$
\n
$$
= \begin{pmatrix} n^{-\frac{1}{2}} & 0 & \cdots & 0 \\ \vdots & \vdots & & \vdots \\ n^{-\frac{1}{2}} & 0 & \cdots & 0 \end{pmatrix} \begin{pmatrix} na & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & \cdots & 0 \end{pmatrix} \begin{pmatrix} n^{-\frac{1}{2}} & \cdots & n^{-\frac{1}{2}} \\ 0 & \cdots & 0 \\ 0 & \cdots & 0 \end{pmatrix},
$$

i.e. the only non-zero eigenvalue of \tilde{K} is an, with eigenvector $(n^{-\frac{1}{2}}, \ldots, n^{-\frac{1}{2}})$.

For this choice of X and \tilde{K} , the expressions for the (RE)ML estimates of β and $\tilde{\sigma}_A^2$ given in sections 3.2 and 4 of [5] greatly simplify: $\hat{\beta} = \bar{y}$ and the REML-estimate of $\tilde{\sigma}_A^2$ is $\sum_{i=1}^n (y_i - \bar{y})^2 / (\tilde{\eta}(n-1))$. The extra terms

$$
\frac{1}{2}\left(d\log(2\pi\tilde{\sigma}_A^2)+\log|X^tX|-\log|X^t(\tilde{K}+\tilde{\eta}I_n)^{-1}X|\right)
$$

in the REML-log-likelihood (see the first equation in section 4 of [5]), now equal

$$
\frac{1}{2} \left(d \log(2\pi \tilde{\sigma}_A^2) + \log n - \log \left(\frac{n}{na + \tilde{\eta}} \right) \right).
$$

Combining this with their equation (3.7), it follows that the REML-log-likelihood is constant in $\tilde{\eta} = (\sigma_A^2 + \sigma_A^2)$ $\sigma_E^2/\sigma_A^2 > 0$, and hence also constant in $\eta = \tilde{\eta} - 1 = \sigma_E^2/\sigma_A^2$.

File S4: Simulation results for a different genetic architecture.

Table 1: Comparison of the marker-based estimators heritability estimators h_r^2 and h_m^2 for simulated data. We simulated 5000 traits, for random samples of 200 accessions drawn from the Structured regmap and Hapmap. A single QTL was simulated, which explained 90 percent of the genetic variance. The simulated heritability was 0.2, 0.5 and 0.8. Standard errors are given relative to those of the broad sense heritability estimator (H^2) .

Table 2: Marker-based estimation of heritability: width and coverage confidence intervals obtained from the individual plant data and the genotypic means. Results for broad sense heritability intervals are reported for comparison. We simulated 5000 traits, for random samples of 200 accessions drawn from the structured regmap (top) and Hapmap (bottom). A single QTL was simulated, which explained 90 percent of the genetic variance. The simulated heritability was 0.2, 0.5 and 0.8.

Figure 1: Heritability estimates for 5000 simulated traits for random samples of 200 accessions drawn from the Structured regmap (top panel) and the Hapmap (bottom panel). 1 QTL was simulated, which explained 90% of the genetic variance. The simulated heritability was 0.2 (left column), 0.5 (middle column) and 0.8 (right column). Within each panel, the first row shows the ANOVA-based estimates of broad-sense heritability, the second row the mixed model based estimates based on the individual data, and the third row the mixed model based estimates based on genotypic means.

File S5: prediction error variance in the training- and validation set.

We assume a balanced and completely random design, with n genotypes and r replicates. Given the model $y_{i,j} = \mu + G_i + E_{i,j}$, the best linear unbiased predictor (BLUP) of $G = (G_1, \ldots, G_n)^t$ and the best linear unbiased estimator (BLUE) of μ are given by

$$
\hat{G} = \delta K Z^{t} (\delta Z K Z^{t} + I_{N})^{-1} (y - \hat{\mu} 1_{N}), \quad \hat{\mu} = \frac{1_{N}^{t} (\delta Z K Z^{t} + I_{N})^{-1} y}{1_{N}^{t} (\delta Z K Z^{t} + I_{N})^{-1} 1_{N}},
$$
\n(2)

where $\delta = \sigma_A^2/\sigma_E^2$ is the shrinkage parameter, N is the total number of individuals and Z is the $N \times n$ incidence matrix assigning individuals to genotypes. See e.g. [6] or [7], or equation (23) in the present work (Appendix C). The parameter $\delta = h^2/(1-h^2)$ is a function of the heritability, and determines the extent to which the phenotypic data y are 'shrunk' towards zero. When the heritability is high, δ is large, and there is little shrinkage, i.e. G will be close to the observed phenotypic observations y. For low heritability, δ is small, and y will be shrunk towards the vector of zeros. When BLUPs are based on the genotypic means the same expressions hold, with $N = n$ and $Z = I_n$, and $\hat{G} = \delta_r K (\delta_r K + I_n)^{-1} ((\bar{y}_1, \ldots, \bar{y}_n)^t - \hat{\mu} 1_n)$. Since the noise level is reduced from σ_E^2 to $r^{-1}\sigma_E^2$, the shrinkage parameter δ becomes $\sigma_A^2/(r^{-1}\sigma_E^2)$.

The preceding expressions assume the shrinkage parameter to be known, while it is usually estimated from the data. As a consequence, the standard error of $\hat{\mu}$ and prediction error variance of G obtained by setting $\delta = \hat{\delta} = \hat{h}^2/(1-\hat{h}^2)$ in (2) are larger than what would be obtained when δ is known ([8], [9]). Before we give examples of too much or too little shrinkage (section), we first give expressions for the prediction error variance for the training and validation set, for the case when heritability is known $(\hat{\delta} = \delta)$. These can be derived as a special case of the more general expressions in e.g. [6] or [7].

Prediction error variance when $\delta = \hat{\delta}$

First we consider the genetic effects $G = (G_1, \ldots, G_n)^t$ of the genotypes in the training sample. If we assume that $G \sim N(0, \sigma_A^2 K)$ (i.e. in equation (21) in the main text (Appendix B), γ and the QTL-effects α_m are zero), the prediction error variance is given by the diagonal elements of

$$
E(\hat{G} - G)(\hat{G} - G)^t = (Z^t Z + \delta^{-1} K^{-1} - J_n)^{-1},
$$
\n(3)

where Z is the $N \times n$ incidence matrix assigning plants to genotypes, and J_n is the $n \times n$ matrix with identical elements $1/n$. In case the phenotypic data consists of genotypic means, $N = n$. For efficient computation, see [10] [11].

The genetic effects $G_{\text{pred}} = (G_{n+1}, \ldots, G_{n+m})^t$ of m unobserved (but genotyped) genotypes can be predicted with the conditional mean

$$
\hat{G}_{\text{pred}} := E[G_{\text{pred}}|y] = \hat{\delta} K_{\text{pred.obs}} Z^t (\hat{\delta} Z K Z^t + I_N)^{-1} (y - \hat{\mu} 1_N),\tag{4}
$$

where $K_{\text{pred.obs}}$ is the $m \times n$ matrix of kinship coefficients for the unobserved versus observed genotypes. To give expressions for the prediction error variance $E(\hat{G}_{pred} - G_{pred})_{i'}^2$ $(i' = 1, ..., m)$ we assume again that $\gamma = 0$, all genetic signal being polygenic. Writing $K_{\text{pred.pred}}$ for the $m \times m$ kinship matrix of the unobserved genotypes, it is assumed that the kinship matrix is the $(n+m)\times(n+m)$ block matrix with K and $K_{\text{pred,pred}}$ on the diagonal and off-diagonal blocks $K_{\text{pred.obs}}$ and $K_{\text{pred.obs}}^t$. Then the conditional distribution of $G_{\text{pred}}|G$ is

$$
G_{\text{pred}}|G \sim N\left(K_{\text{pred.obs}}K^{-1}G, \sigma_A^2\left(K_{\text{pred.pred}} - K_{\text{pred.obs}}K^{-1}K_{\text{pred.obs}}^t\right)\right).
$$

Since $\hat{G}_{\text{pred}} = K_{\text{pred.obs}} K^{-1} \hat{G}$ (by comparing (2) and (4)), it follows that

$$
(\hat{G}_{\text{pred}} - G_{\text{pred}})|(\hat{G} - G) = K_{\text{pred.obs}} K^{-1} (\hat{G} - G) - Y,
$$

where $Y \sim N(0, \sigma_A^2 (K_{\text{pred.pred}} - K_{\text{pred.obs}} K^{-1} K_{\text{pred.obs}}^t)).$

Consequently, the prediction error variances $E(\hat{G}_{pred} - G_{pred})_i^2$ are the diagonal elements of

$$
E(\hat{G}_{\text{pred}} - G_{\text{pred}})(\hat{G}_{\text{pred}} - G_{\text{pred}})^t = E\left[E(\hat{G}_{\text{pred}} - G_{\text{pred}})(\hat{G}_{\text{pred}} - G_{\text{pred}})^t \mid (\hat{G} - G)\right]
$$

= $(K_{\text{pred.obs}}K^{-1})\left[E(\hat{G} - G)(\hat{G} - G)^t\right]K^{-1}K_{\text{pred.obs}}^t$
+ $\sigma_A^2(K_{\text{pred.pred}} - K_{\text{pred.obs}}K^{-1}K_{\text{pred.obs}}^t).$ (5)

Hence, the prediction error variance for the validation set contains a term depending on $\delta^{-1} = \sigma_E^2/\sigma_A^2$ (see (3)), as well as a term which depends only on the genetic variance σ_A .

Prediction error variance with incorrect shrinkage $(\delta \neq \hat{\delta})$

For the case that the amount of shrinkage is not chosen correctly $(\hat{\delta} \neq \delta = \sigma_A^2/(r^{-1}\sigma_E^2))$, we now give an expression for the prediction error variance for the training set based on genotypic means, under the additional assumption that μ is known to be zero. The BLUP for G then simplifies to

$$
\hat{G} = \hat{\delta}K(\hat{\delta}K + I_n)^{-1}\bar{y},\tag{6}
$$

where we recall that we still assume a balanced and completely random design. Hence $\bar{y}_i = G_i + \bar{E}_i$, with $\bar{E}_i \sim N(0, r^{-1}\sigma_E^2)$ and $G = (G_1, ..., G_n)^t \sim N(0, \sigma_A^2 K)$. Since $\bar{y} = (\bar{y}_1, ..., \bar{y}_n)^t \sim N(0, \sigma_A^2 K + r^{-1} \sigma_E^2 I_n)$ $N(0, \sigma_E^2(\delta K + r^{-1} I_n))$, the variance-covariance matrix of $\hat{G} - G$ equals

$$
Var(\hat{G} - G) = \sigma_A^2 K - 2\hat{\delta}K(\hat{\delta}K + I_n)^{-1}\sigma_A^2 K + \hat{\delta}K(\hat{\delta}K + I_n)^{-1}(\delta K + r^{-1}I_n)(\hat{\delta}K + I_n)^{-1}\hat{\delta}K\sigma_E^2,
$$

where we used that (by the independence of G and E)

$$
Cov(G, \hat{G}) = Cov(G, \hat{\delta}K(\hat{\delta}K + I_n)^{-1}G) = \hat{\delta}K(\hat{\delta}K + I_n)^{-1}\sigma_A^2K
$$

and that (using $\bar{y} \sim N(0, \sigma_E^2(\delta K + r^{-1}I_n))$ and the symmetry of K and I_n)

$$
\hat{G} = \hat{\delta}K(\hat{\delta}K + I_n)^{-1}\bar{y} \sim N(0, \hat{\delta}K(\hat{\delta}K + I_n)^{-1}(\delta K + r^{-1}I_n)(\hat{\delta}K + I_n)^{-1}\hat{\delta}K\sigma_E^2).
$$

In particular, when $\hat{\delta} = \infty$ (i.e. $\hat{h}^2 = 1$), there is no shrinkage, and $\hat{G} = \bar{y}$. The prediction error variance is then completely determined by the residual variance, since $\hat{G} - \hat{G} = \bar{y} - \hat{G} = \bar{E}$, and

$$
E(\hat{G} - G)(\hat{G} - G)^t = r^{-1} \sigma_E^2 I_n.
$$

On the other hand, when $\hat{\delta} = 0$ (i.e. $\hat{h}^2 = 0$), there is 'total' shrinkage towards zero, i.e. $\hat{G} = 0$, and

$$
E(\hat{G} - G)(\hat{G} - G)^t = E(GG^t) = \sigma_A^2 K.
$$

This explains the asymmetry in the observed accuracy in our simulations, in particular when $h^2 = 0.5$: when the number of replicates r is sufficiently large, overestimating the heritability will have less impact on the prediction error variance (and hence accuracy) than underestimating it.

Figure S1: histograms of the off-diagonal kinship coefficients, for 4 sub-populations of the regmap.

Figure S1 : Off-diagonal coefficients of the genetic relatedness matrix (equation (1) in the main text), for 4 sub-populations of the regmap.

Figure S2: histograms of the off-diagonal identity-by-state coefficients, for 4 sub-populations of the regmap.

Figure S2 : Off-diagonal identity-by-state kinship coefficients, for 4 sub-populations of the regmap.

Figure S3 : Heritability estimates for 5000 simulated traits for random samples of 200 accessions drawn from the Swedish regmap (top panel) and the French regmap (bottom panel). 20 QTLs were simulated, which explained half of the genetic variance. The simulated heritability was 0.2 (left column), 0.5 (middle column) and 0.8 (right column). Within each panel, the first row shows the ANOVA-based estimates of broad-sense heritability, the second row the mixed model based estimates based on the individual data, and the third row the mixed model based estimates based on genotypic means.

Figure S4: Monotone likelihood

Figure S4 : Log-likelihood as function of the heritability, for one of the 5000 simulated traits from Figure 1 (in the main text), for accessions drawn from the HapMap and a simulated heritability of 0.5 Here we choose one of the 882 traits (17.6%) for which the heritability estimate based on means (\hat{h}_m^2) was larger than 0.99. For these traits, the heritability estimate based on replicates (\hat{h}_r^2) was on average 0.502. For the trait shown here, $\hat{h}_m^2 = 0.5087$ (left) and $\hat{h}_m^2 = 0.9999$ (right).

Figure S5 : Heritability estimates and confidence intervals for two flowering traits from [3] (LDV and LD), and 4 traits from new experiments. Three estimators were used: the ANOVA-based estimator of broad-sense heritability (\hat{H}^2 , green), the marker-based estimator using individual plant data (\hat{h}_r^2 , blue) and the marker-based estimator using genotypic means $(\hat{h}_m^2, \text{brown})$. Traits from different experiments are separated by the black horizontal lines. Trait abbreviations are given in Table 1 of the main text. The LD-adjusted kinship matrix was computed using version 2.0 of the LDAK-software [12].We used sections of 1000 SNPs, with a buffer of 200. The maximum distance considered for LD was 250kb; the 'halflife' parameter (modeling LD-decay) was set to 20kb.

Figure S6 : The first two principal component of the genetic markers for the panel of [3], restricted for the 168 accessions for which the trait LDV was measured. On the very right are the accessions with ecotype ID's 8233, 7526 and 7515.

Figure S7 : Rank correlation (Spearman ρ^2) between effect-size estimates obtained with a oneand two-stage approach, versus the heritability estimates obtained in the two-stage approach (\hat{h}_m^2) . 1000 traits were simulated for the Structured RegMap (first row) and the HapMap (second row), with a simulated heritability of 0.5. 10 QTLs were simulated, which explained 75% of the genetic variance. Left column: rank correlation between LOD-scores of all SNPs. Middle column: rank correlation between effect-size estimates for all SNPs. Right column: rank correlation between effect-size estimates for the 10 simulated QTLs.

Table S1: ecotype-IDs of the structured regmap.

Accession information was taken from the Bergelson lab

(http://bergelson.uchicago.edu/Members/mhorton/resources/snps/accession_coordinates.xls). The following table contains geographic information for 242 of the 250 accessions from our structured regmap. Geographic information was not available for eight accessions: 6909, 8428, 5712, 6143, 5708, 5730, 5829 and 8254. Accessions were selected based on the variance of the off-diagonal kinship coefficients of each row: the accessions corresponding to the rows with the 250 highest variances were chosen.

Table S2 : Comparison of the marker-based estimators heritability estimators h_r^2 and h_m^2 for simulated data. We simulated 5000 traits, for random samples of 200 accessions drawn from Swedish and French regmap. 20 unlinked QTLs were simulated, which explained 50 percent of the genetic variance. The simulated heritability was 0.2, 0.5 and 0.8. Standard errors are given relative to those of the broad sense heritability estimator (H^2) .

Table S3: : Marker-based estimation of heritability: width and coverage confidence intervals obtained from the individual plant data and the genotypic means. Results for broad sense heritability intervals are reported for comparison. We simulated 5000 traits, for random samples of 200 accessions drawn from the Swedish regmap (top) and French (bottom). 20 unlinked QTLs were simulated, which explained 50 percent of the genetic variance. The simulated heritability was 0.2, 0.5 and 0.8.

Table S4: : Heritability estimates and confidence intervals, for two flowering traits from [3] and four traits measured in new experiments (trait abbreviations given in Table 1 of the main text).

Three estimators were used: mixed model based on replicates (\hat{h}_r^2) , mixed model based on genotypic means (\hat{h}_m^2) , and the usual ANOVA-based broad-sense heritability estimator (\hat{H}^2) . An LD-adjusted kinship matrix was used in the mixed model for \hat{h}_r^2 and \hat{h}_m^2 .

The LD-adjusted kinship matrix was computed using version 2.0 of the LDAK-software [12], available at http://dougspeed.com/ldak/. We used sections of 1000 SNPs, with a buffer of 200. The maximum distance considered for LD was 250kb; the 'halflife' parameter (modeling LD-decay) was set to 20kb.

In the following tables, the second and third column contain the percentage of the 5000 traits for which the corresponding heritability estimates $(\hat{h}_r^2$ and \hat{h}_m^2) were contained in the intervals in the first column. The remaining columns show the correlation (r) between simulated and predicted genetic effects, averaged over these traits. 20 QTLs were simulated, which explained 50 percent of the genetic variance. Each trait was simulated for a randomly drawn training (200 accessions) and validation set (50 accessions). Genetic effects were predicted using G-BLUP, based on either a mixed model for the individual plants (replicates) or for the genotypic means.

interval	\hat{h}_r^2	\hat{h}_m^2	(replicates)	r (means)	r (replicates)	means) $\,r$
			Training set	Training set	Validation set	Validation set
[0, 0.1)	3.08%	$9.88\sqrt{2}$	0.637	0.654	0.216	0.218
[0.1, 0.3)	93.96 %	76.38 $%$	0.770	0.770	0.280	0.279
[0.3, 0.5)	$2.96~\%$	$13.52\,$ %	0.816	0.803	0.325	0.313
[0.5, 0.7)	0%	0.22%		0.782		0.287
[0.7, 0.9]	0%	0%				
[0.9, 1]	0%	0%				
[0,1]	100 %	100 %	0.767	0.763	0.279	0.278

Table $S5(b)$: Prediction accuracy (r) of G-BLUP for 5000 simulated traits, for the structured regmap population and a simulated heritability of 0.5.

interval	\hat{h}_r^2	\hat{h}_m^2	(replicates)	means) r	(replicates) r	means)
			Training set	Training set	Validation set	Validation set
[0, 0.1)	0%	0.04%		0.709		0.328
[0.1, 0.3)	0%	5.24 %		0.836		0.269
[0.3, 0.5)	51.42 %	46.54%	0.886	0.887	0.302	0.300
[0.5, 0.7)	48.58 %	42.12 %	0.905	0.903	0.333	0.337
[0.7, 0.9)	0%	5.84 %		0.905		0.343
[0.9, 1]	0%	0.22%		0.888		0.386
[0,1]	100 %	100 %	0.895	0.892	0.317	0.317

Table $S_5(c)$: Prediction accuracy (r) of G-BLUP for 5000 simulated traits, for the structured regmap population and a simulated heritability of 0.8.

interval	\hat{h}_r^2	\hat{h}_m^2	(replicates) r	r (means)	r (replicates)	(means) r_{\rm}
			Training set	Training set	Validation set	Validation set
[0, 0.1)	1.74%	$28.64\ \overline{\%}$	0.616	0.632	0.259	0.273
[0.1, 0.3)	96.7%	40.7%	0.673	0.674	0.341	0.348
[0.3, 0.5)	1.56%	17.8 %	0.711	0.684	0.364	0.382
[0.5, 0.7)	0%	5.8%		0.681		0.366
[0.7, 0.9)	0%	2.84%		0.675		0.370
[0.9, 1]	0%	4.22%		0.669		0.357
[0,1]	100 %	100 %	0.672	0.664	0.340	0.335

Table S5(d) : Prediction accuracy (r) of G-BLUP for 5000 simulated traits, for the HapMap population and a simulated heritability of 0.2.

Table S5(e) : Prediction accuracy (r) of G-BLUP for 5000 simulated traits, for the HapMap population and a simulated heritability of 0.5.

interval	\hat{h}_r^2	\widehat{h}_m^2	(replicates)	(means) r_{\rm}	r (replicates)	(means) $\,r\,$
			Training set	Training set	Validation set	Validation set
[0, 0.1)	0%	6%		0.811		0.285
[0.1, 0.3)	0%	21.02%		0.851		0.366
[0.3, 0.5)	51.78 %	22.56 %	0.862	0.867	0.395	0.413
[0.5, 0.7)	48.22 %	17.5 $%$	0.877	0.871	0.416	0.428
[0.7, 0.9)	0%	10.86 %		0.873		0.426
[0.9, 1]	0%	22.06 %		0.871		0.422
[0,1]	100 %	100 %	0.869	0.863	0.405	0.401

Table S5(f) (given as Table 6 in the main text) : **Prediction accuracy** (r) of **G-BLUP** for 5000 simulated traits, for the HapMap population and a simulated heritability of 0.8.

interval	\hat{h}_r^2	\tilde{h}_m^2	(replicates)	(means) \boldsymbol{r}	(replicates)	(means) \boldsymbol{r}
			Training set	Training set	Validation set	Validation set
[0, 0.1)	0%	2.58%		0.890		0.289
[0.1, 0.3)	0%	8.34%		0.937		0.373
[0.3, 0.5)	0%	12.34 %		0.954		0.409
[0.5, 0.7)	0.04%	15.9%	0.942	0.959	0.208	0.423
[0.7, 0.9)	99.96 %	$15.62\,\,\%$	0.961	0.961	0.431	0.443
[0.9, 1]	0%	45.22%		0.961		0.448
[0,1]	100 %	100%	0.961	0.956	0.431	0.428

References

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