

Additional file 2

Derivation of the full conditional likelihood function

The likelihood that marker j is from distribution k is

$$L(v_{j,k}|\sigma_k^2) = -0.5[\ln(2\pi) + \ln(|\mathbf{V}|) + \mathbf{y}_j^*'\mathbf{V}^{-1}\mathbf{y}_j^*]$$

where \mathbf{V} is the (residual) phenotypic variance-covariance matrix and $\mathbf{y}_j^*'\mathbf{V}^{-1}\mathbf{y}_j^*$ simplifies to $\mathbf{y}_j^*'\mathbf{R}^{-1}\mathbf{y}_j^* - \mathbf{y}_j^*'\mathbf{R}^{-1}\mathbf{W}_j\mathbf{v}_{j,k}$ (i.e. where $v_{j,k} = [\mathbf{W}_j'\mathbf{R}^{-1}\mathbf{W}_j + \sigma_k^{-2}]^{-1}\mathbf{W}_j'\mathbf{R}^{-1}\mathbf{y}_j^*$, following eq. [vi] in the main paper). Since $\mathbf{V} = \mathbf{W}_j\mathbf{W}_j'\sigma_k^2 + \mathbf{R}$, then using Sylvester's theorem $\ln(|\mathbf{V}|) = \ln(|\mathbf{R}|) + \ln(|\mathbf{I} + \mathbf{W}_j'\mathbf{R}^{-1}\mathbf{W}_j\sigma_k^2|)$ (see PART A below) and because $\ln(|\mathbf{R}|)$ is constant over any σ_k^2 , then the inverse phenotypic variance-covariance matrix is $\mathbf{V}^{-1} = \mathbf{R}^{-1} - \mathbf{R}^{-1}\mathbf{W}_j[\mathbf{W}_j'\mathbf{R}^{-1}\mathbf{W}_j + \sigma_k^{-2}]^{-1}\mathbf{W}_j'\mathbf{R}^{-1}$ (see PART B for proof of $\mathbf{V}\mathbf{V}^{-1} = \mathbf{I}$). Hence the full conditional likelihood is:

$$L(v_{j,k}|\sigma_k^2) = -0.5[\ln(1 + \mathbf{W}_j'\mathbf{R}^{-1}\mathbf{W}_j\sigma_k^2) + \mathbf{y}_j^*'\mathbf{R}^{-1}\mathbf{y}_j^* - \mathbf{y}_j^*'\mathbf{R}^{-1}\mathbf{W}_j\mathbf{v}_{j,k}] + \ln(pr_k),$$

where pr_k is the current estimate for the proportion of markers from distribution k .

PART A:

Sylvester's theorem states that:

$$|\mathbf{I}_n + \mathbf{AB}| = |\mathbf{I}_m + \mathbf{BA}|$$

where \mathbf{I}_n is an n by n identity matrix, \mathbf{A} is an n by m matrix and \mathbf{B} is a m by n matrix. By extension, if \mathbf{X} is a n by n square matrix then

$$\begin{aligned} |\mathbf{X} + \mathbf{AB}| &= |\mathbf{X}||\mathbf{I}_n + \mathbf{X}^{-1}\mathbf{AB}| \\ &= |\mathbf{X}||\mathbf{I}_m + \mathbf{BX}^{-1}\mathbf{A}| \end{aligned}$$

Similarly, if

$$\begin{aligned} |\mathbf{V}| &= |\mathbf{W}\mathbf{W}'\sigma_k^2 + \mathbf{R}| \\ &= |\mathbf{R}||\mathbf{I} + \mathbf{R}^{-1}\mathbf{W}\mathbf{W}'\sigma_k^2| \\ &= |\mathbf{R}||\mathbf{I} + \mathbf{W}'\mathbf{R}^{-1}\mathbf{W}\sigma_k^2| \end{aligned}$$

PART B:

Proof that $\mathbf{V}\mathbf{V}^{-1} = \mathbf{I}$ [following 27]:

Let

$$\mathbf{Q} = [\mathbf{W}'_j\mathbf{R}^{-1}\mathbf{W}_j + \sigma_k^{-2}]^{-1}$$

$\mathbf{V}\mathbf{V}^{-1}$

$$\begin{aligned} &= [\mathbf{R} + \mathbf{W}_j\mathbf{W}'_j\sigma_k^2] [\mathbf{R}^{-1} + \mathbf{R}^{-1}\mathbf{W}_j\mathbf{Q}\mathbf{W}'_j\mathbf{R}^{-1}] \\ &= \mathbf{I} + \mathbf{W}_j\mathbf{W}'_j\mathbf{R}^{-1}\sigma_k^2 - \mathbf{W}_j\mathbf{Q}\mathbf{W}'_j\mathbf{R}^{-1} - \mathbf{W}_j\mathbf{W}'_j\mathbf{R}^{-1}\mathbf{W}_j\mathbf{Q}\mathbf{W}'_j\mathbf{R}^{-1}\sigma_k^2 \\ &= \mathbf{I} + \mathbf{W}_j\mathbf{W}'_j\mathbf{R}^{-1}\sigma_k^2 - \mathbf{W}_j[\mathbf{I} + \mathbf{W}'_j\mathbf{R}^{-1}\mathbf{W}_j\sigma_k^2]\mathbf{Q}\mathbf{W}'_j\mathbf{R}^{-1} \\ &= \mathbf{I} + \mathbf{W}_j\mathbf{W}'_j\mathbf{R}^{-1}\sigma_k^2 - \mathbf{W}_j\sigma_k^2[\sigma_k^{-2} + \mathbf{W}'_j\mathbf{R}^{-1}\mathbf{W}_j]\mathbf{Q}\mathbf{W}'_j\mathbf{R}^{-1} \\ &= \mathbf{I} + \mathbf{W}_j\mathbf{W}'_j\mathbf{R}^{-1}\sigma_k^2 - \mathbf{W}_j\mathbf{Q}^{-1}\mathbf{Q}\mathbf{W}'_j\mathbf{R}^{-1} \\ &= \mathbf{I} \end{aligned}$$