An Equivalent (animal) Model for Genomic Prediction

More loci than animals

Allelic effects – but for selection we are more interested in animal (not allelic) merit

$$\mathbf{y} = \mathbf{1}\mu + \sum_{i=1}^{i=ploci} \mathbf{M}_i \mathbf{a}_i + \mathbf{e}$$

$$\mathbf{y} = \mathbf{1}\mu + \mathbf{I}\left\{ \sum_{i=1}^{i=ploci} \mathbf{M}_i \mathbf{a}_i \right\} + \mathbf{e}$$

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

Order of MME is number of fixed effects plus number of animals
Consider the implications for 100-1,000 animals with 50,000 loci

Mixed Model Equations

$$\mathbf{y} = \mathbf{1}'\mu + \mathbf{Zu} + \mathbf{e}$$

$$\begin{bmatrix} \mathrm{N} & \mathbf{1'Z} \\ \mathbf{Z'1} & \mathbf{Z'Z} + \sigma_e^2\mathbf{G}^{\text{-}\mathbf{1}} \end{bmatrix}\begin{bmatrix} \hat{\mu} \\ \hat{\mathbf{u}} \end{bmatrix} = \begin{bmatrix} \mathbf{1'y} \\ \mathbf{Z'y} \end{bmatrix}, \textit{ for full rank } \mathbf{G} = \mathrm{var}(\mathbf{u})$$

$$\mathbf{y} = \mathbf{1}'\mu + \mathbf{I}\sum \mathbf{M}_i\mathbf{a}_i + \mathbf{e}$$

$$\begin{bmatrix} \mathrm{N} & \mathbf{1}' \\ \mathbf{1} & \mathbf{I} + \sigma_e^2\left[\mathrm{var}\left(\sum \mathbf{M}_i\mathbf{a}_i\right)\right]^{-1} \end{bmatrix}\begin{bmatrix} \hat{\mu} \\ \widehat{\sum \mathbf{M}_i\mathbf{a}_i} \end{bmatrix} = \begin{bmatrix} \mathbf{1'y} \\ \mathbf{y} \end{bmatrix}$$

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Mixed Model Equations

$$\mathbf{y} = \mathbf{1}'\mu + \mathbf{I}\sum \mathbf{M}_i\mathbf{a}_i + \mathbf{e}$$

$$\begin{bmatrix} \mathrm{N} & \mathbf{1}' \\ \mathbf{1} & \mathbf{I} + \sigma_e^2\left[\mathrm{var}\left(\sum \mathbf{M}_i\mathbf{a}_i\right)\right]^{-1} \end{bmatrix} \begin{bmatrix} \hat{\mu} \\ \widehat{\sum \mathbf{M}_i\mathbf{a}_i} \end{bmatrix} = \begin{bmatrix} \mathbf{1'y} \\ \mathbf{y} \end{bmatrix}$$

$$\mathrm{var}\left(\sum \mathbf{M}_i\mathbf{a}_i\right) = \sum \mathrm{var}\left\{\mathbf{M}_i\mathbf{a}_i\right\} = \sum \mathbf{M_i A_i M_i'} = \sum \mathbf{M_i M_i'}\sigma_{a\mathbf{i}}^2 = like\ \mathbf{A}\sigma_g^2$$

numerator relationship matrix=**A**

$$\begin{bmatrix} \mathrm{N} & \mathbf{1}' \\ \mathbf{1} & \mathbf{I} + \sigma_e^2\left[\sum \mathbf{M_i M_i'}\sigma_{a\mathbf{i}}^2\right]^{-1} \end{bmatrix} \begin{bmatrix} \hat{\mu} \\ \widehat{\sum \mathbf{M}_i\mathbf{a}_i} \end{bmatrix} = \begin{bmatrix} \mathbf{1'y} \\ \mathbf{y} \end{bmatrix}$$

GBLUP

- If the variance parameters are assumed known and the inverse of the genomic relationship matrix is multiplied by (known) λ, the system is known as GBLUP, as opposed to conventional pedigree or PBLUP
  - It is effectively weighting all the loci equally
  - It is similar to BayesC0 except that in that method we estimate the variance components after including a prior distribution for them

Lack of Equivalence

- The GBLUP and Marker Effects Models (MEM) such as BayesC0 with high df for the prior variances will give the same EBV for the genotyped animals
  - This is true regardless of
    - whether the models fit the A allele at every locus, the B allele at every locus, or both alleles at every locus
    - how the alleles are centered (coded 0,1,2 or -1,0,1 etc)
  - However, the PEV (and reliability) for GBLUP are not invariant to these alternative models

Genomic Analysis Combining Genotyped and Non-Genotyped Individuals

Why a Combined Analysis?

- To exploit all the available phenotypic data in GWAS and genomic prediction
  - Not just the records on genotyped individuals
  - Account for preselection of genotyped individuals
- To ensure that genomic predictions include all available information
- To avoid approximations required in multi-step analyses (that lead to double-counting)

Multi-step Genomic Prediction Analysis

- Mixed model evaluation using all phenotypes and pedigree information to generate EBV and R^2
- Deregression of EBV on genotyped individuals using EBV and R^2 of trios of every genotyped individual, its sire and its dam
- Weighted multiple regression analysis of deregressed EBV to estimate SNP effects
- Genomic prediction DGV of genotyped individuals
- Pedigree prediction of DGV for nongenotyped
- Selection Index blending of DGV & EBV for GE-EBV

Pedigree Prediction

$$\begin{bmatrix} y_n \\ y_g \end{bmatrix} = \begin{bmatrix} X_n \\ X_g \end{bmatrix} b + \begin{bmatrix} Z_n & 0 \\ 0 & Z_g \end{bmatrix} \begin{bmatrix} u_n \\ u_g \end{bmatrix} + \begin{bmatrix} e_n \\ e_g \end{bmatrix}$$

with

$$var \begin{bmatrix} u_n \\ u_g \end{bmatrix} = \begin{bmatrix} A_{nn} & A_{ng} \\ A_{gn} & A_{gg} \end{bmatrix} \sigma_a^2$$

Where ***A*** is the numerator relationship matrix (from pedigree) with subscripts n=non-genotyped & g=genotyped

Nejati-Javaremi et al (1997)

$$Replace\ A\ with\ G = \sum_{i=1}^{i=\#loci} \sum_{j=1}^{j=\#alleles} m_{ij} m_{ij}'\ for\ genotyped$$

Various other authors expanded this
with various approaches to center the marker covariates
to create a Genomic Relationship Matrix

Fitting G^{-1} in the mixed model equations
is known as GBLUP
and gives the same estimates
of genomic merit as MHG “BLUP”

Genotyped Animals

$$y_g = X_g b + Z_g u_g + e_g$$

Meuwissen, Hayes & Goddard (2001)

$$with\, u_g = M_g \alpha = \sum_{j=1}^{j=\#loci} m_j \alpha_j \delta_j$$

$$\alpha_j = substitution\, effect$$

$$\delta_j = (0,1)\, indicator\; variable$$

Bayesian Alphabet

$$\delta_j = 1, \;\; \sigma^2_{\alpha_j} = (\mathit{known})\, \sigma^2_{\alpha}\; \mathit{was}\; "\mathit{BLUP}"$$

$$\delta_j = 1, \;\; \sigma^2_{\alpha_j} = (\mathit{unknown})\, \sigma^2_{\alpha_j}\; \mathit{was}\; \mathit{BayesA}$$

$$\left[\begin{array}{l} \delta_j = 0\; \mathit{with}\; \mathit{known}\; \mathit{probability} = \pi \\ \sigma^2_{\alpha_j} = (\mathit{unknown})\, \sigma^2_{\alpha_j}\; \mathit{was}\; \mathit{BayesB} \end{array}\right.$$

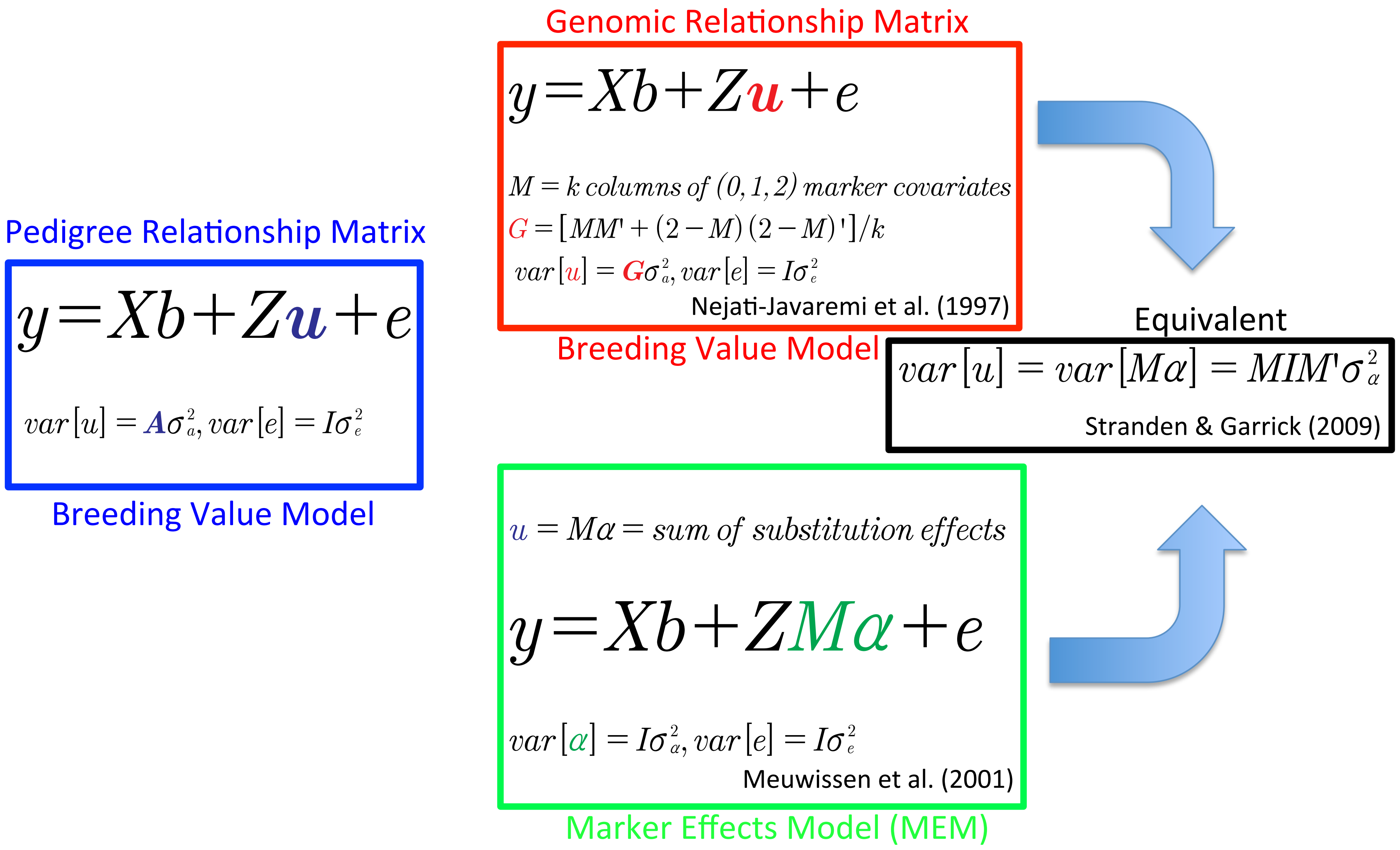
Meuwissen, Hayes & Goddard (2001)

$$\delta_j = 0\; \mathit{with}\, (\mathit{un})\, \mathit{known}\; \mathit{probability} = \pi$$

$$\sigma^2_{\alpha_j} = (\mathit{unknown})\, \sigma^2_{\alpha}\; \mathit{was}\; \mathit{BayesC}\; \mathit{or}\; (\mathit{BayesC}\pi)$$

Kizilkaya et al (2010); Habier et al (2011)

Evolution of “The Model”



Pedigree Relationship Matrix

$$y = Xb + Zu + e$$

$$var[u] = A\sigma_a^2, var[e] = I\sigma_e^2$$

Breeding Value Model

Genomic Relationship Matrix

$$y = Xb + Zu + e$$

$$M = k\ columns\ of\ (0,1,2)\ marker\ covariates$$

$$G = [MM' + (2-M)(2-M)']/k$$

$$var[u] = G\sigma_a^2, var[e] = I\sigma_e^2$$

Nejati-Javaremi et al. (1997)

Breeding Value Model

Equivalent

$$var[u] = var[M\alpha] = MIM'\sigma_\alpha^2$$

Stranden & Garrick (2009)

$$u = M\alpha = sum\ of\ substitution\ effects$$

$$y = Xb + ZM\alpha + e$$

$$var[\alpha] = I\sigma_\alpha^2, var[e] = I\sigma_e^2$$

Meuwissen et al. (2001)

Marker Effects Model (MEM)

What to do with the non-genotyped?

Known as Single-Step “First Attempt”

$$var\begin{bmatrix} u_n \\ u_g \end{bmatrix} = \begin{bmatrix} A_{nn} & A_{ng} \\ A_{gn} & G_{gg} \end{bmatrix} \sigma_a^2$$

Just replace that part of the numerator relationship matrix with genomic relationships

Then need a “brute-force” inversion of the var-cov matrix

Misztal et al (2009)

What to do with the non-genotyped?

Known as Single-Step “Second Attempt” (with brute force inverse)

$$H = var\begin{bmatrix} u_n \\ u_g \end{bmatrix}\sigma_a^{-2} = \begin{bmatrix} A_{nn} + A_{ng}A_{gg}^{-1}G_{gg}A_{gg}^{-1}A_{gn} & A_{ng}A_{gg}^{-1}G_{gg} \\ G_{gg}A_{gg}^{-1}A_{gn} & G_{gg} \end{bmatrix}$$

Legarra et al (2009)

Then with recognition of its simply structured inverse

$$H^{-1} = A^{-1} + \begin{bmatrix} 0 & 0 \\ 0 & G_{gg}^{-1} - A_{gg}^{-1} \end{bmatrix}$$

Aguilar et al (2010)

Offering programming appeal by simply replacing A^{-1} in MME by H^{-1} known as Single-Step GBLUP and variants of which are widely used

What’s wrong with Single-Step GBLUP?

- When there are less loci than genotyped individuals, G is singular
- When there are more loci than genotyped individuals, G is singular if locus covariates are centered by allele frequency

  (since G=MM’ and M’1=0 then G1=0)
- These problems can be overcome by adhoc regression of **G** towards **A**

What’s wrong with Single-Step GBLUP?

- The var-cov matrix involves a blending of **A** and **G** requiring that they represent the same “base”
  - The base in **A** is the pedigree founders but the allele frequencies are not usually known in that population
- It is not clear what to use to center locus covariates in populations of mixed breeds, or populations with variable breed percentages

What's wrong with Single-Step GBLUP?

- Its predictive ability can be improved by introducing another ad hoc constant κ whose optimal value can be found by trial and error

$$H^{-1} = A^{-1} + \begin{bmatrix} 0 & 0 \\ 0 & \varkappa\left(G_{gg}^{-1} - A_{gg}^{-1}\right) \end{bmatrix}$$

What’s wrong with Single-Step GBLUP?

- It requires brute force inversion of 2 matrices whose order is the number of genotyped individuals (ie **G** and $\mathbf{A}_{gg}$)
  - The inversion effort increase rapidly with number of genotyped individuals
  - Inversion is impractical beyond say 100,000 individuals

What's wrong with Single-Step GBLUP?

- It is not computationally straightforward for extension to Single-Step BayesA
- It is not suitable for application of mixture models (BayesB, BayesC, BayesCπ)
  - But these models that provide variable selection are particularly appealing in fine-mapping applications such as with imputed NGS genotypes

Let’s revisit the basic idea

$$\begin{bmatrix} y_n \\ y_g \end{bmatrix} = \begin{bmatrix} X_n \\ X_g \end{bmatrix} b + \begin{bmatrix} Z_n & 0 \\ 0 & Z_g \end{bmatrix} \begin{bmatrix} u_n \\ u_g \end{bmatrix} + \begin{bmatrix} e_n \\ e_g \end{bmatrix}$$

$$with\; u_g = M_g \alpha \; for\; genotyped\; individuals$$

$$whereas\; u_n = \widehat{u_n} / u_g + \left(u_n - \widehat{u_n} / u_g \right) = \widehat{u_n} / u_g + \varepsilon_n$$

$$with\; \widehat{u_n} / u_g = A_{ng} A_{gg}^{-1} u_g$$

$$so\; u_n = A_{ng} A_{gg}^{-1} u_g + \left(u_n - A_{ng} A_{gg}^{-1} u_g \right)$$

Substituting these results gives

$$\begin{bmatrix} y_n \\ y_g \end{bmatrix} = \begin{bmatrix} X_n \\ X_g \end{bmatrix} b + \begin{bmatrix} Z_n & 0 \\ 0 & Z_g \end{bmatrix} \begin{bmatrix} u_n \\ u_g \end{bmatrix} + \begin{bmatrix} e_n \\ e_g \end{bmatrix}$$

$$= \begin{bmatrix} X_n \\ X_g \end{bmatrix} b + \begin{bmatrix} Z_n & 0 \\ 0 & Z_g \end{bmatrix} \begin{bmatrix} A_{ng} A_{gg}^{-1} M_g \alpha \\ M_g \alpha \end{bmatrix} + \begin{bmatrix} Z_n & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_n \\ 0 \end{bmatrix} + \begin{bmatrix} e_n \\ e_g \end{bmatrix}$$

$$= \begin{bmatrix} X_n \\ X_g \end{bmatrix} b + \begin{bmatrix} Z_n A_{ng} A_{gg}^{-1} M_g \\ Z_g M_g \end{bmatrix} \alpha + \begin{bmatrix} Z_n \\ 0 \end{bmatrix} \varepsilon_n + \begin{bmatrix} e_n \\ e_g \end{bmatrix}$$

Fernando et al (2014) GSE

With "Hybrid" Mixed Model Equations

$$\begin{bmatrix} X'X & X'ZM & X_n'Z_n \\ M'Z'X & M'Z'ZM+\phi & M_n'Z_n'Z_n \\ Z_n'X_n & Z_n'Z_nM_n & Z_n'Z_n+A^{nn}\lambda \end{bmatrix} \begin{bmatrix} b \\ \alpha \\ \varepsilon_n \end{bmatrix} = \begin{bmatrix} X'y \\ M'Z'y \\ Z_n'y_n \end{bmatrix}$$

$$where\ X=\begin{bmatrix} X_n \\ X_g \end{bmatrix}, Z=\begin{bmatrix} Z_n & 0 \\ 0 & Z_g \end{bmatrix}, M=\begin{bmatrix} M_n \\ M_g \end{bmatrix}=\begin{bmatrix} A_{ng}A_{gg}^{-1}M_g \\ M_g \end{bmatrix}, y=\begin{bmatrix} y_n \\ y_g \end{bmatrix}$$

$$with\ EBV\ given\ by$$

$$\widehat{u_g}=M_g\widehat{\alpha}$$

$$\widehat{u_n}=M_n\widehat{\alpha}+\widehat{\varepsilon}_n$$

NB Single-Step GBLUP
is a special case of the above
(but in this equivalent model no inversion is needed)

$$M_n=A_{ng}A_{gg}^{-1}M_g$$

If everyone is genotyped

$$\begin{bmatrix} X'X & X'ZM & X_n'Z_n \\ M'Z'X & M'Z'ZM+\phi & M_n'Z_n'Z_n \\ Z_n'X_n & Z_n'Z_nM_n & Z_n'Z_n+A^{nn}\lambda \end{bmatrix} \begin{bmatrix} b \\ \alpha \\ \varepsilon_n \end{bmatrix} = \begin{bmatrix} X'y \\ M'Z'y \\ Z_n'y_n \end{bmatrix}$$

These are the MME that form the basis of BayesA, BayesB, BayesC etc

If no one is genotyped

$$\begin{bmatrix} X'X & X'ZM & X_n'Z_n \\ M'Z'X & M'Z'ZM+\phi & M_n'Z_n'Z_n \\ Z_n'X_n & Z_n'Z_nM_n & Z_n'Z_n+A^{nn}\lambda \end{bmatrix} \begin{bmatrix} b \\ \alpha \\ \varepsilon_n \end{bmatrix} = \begin{bmatrix} X'y \\ M'Z'y \\ Z_n'y_n \end{bmatrix}$$

These MME form the basis of traditional pedigree-based BLUP

Invariant to Covariate Centering

$$Genotyped$$

$$y_g = \mathbf{1}\mu + X_g b + Z_g M_g \alpha + e_g$$

$$= \mathbf{1}\mu + X_g b + Z_g \mathbf{1} c'\alpha + Z_g (M_g - 1c')\alpha + e_g$$

$$define \;\; t = c'\alpha$$

$$y_g = \mathbf{1}(\mu + t) + X_g b + Z_g (M_g - 1c')\alpha + e_g$$

$$= \mathbf{1}\mu^* + X_g b + Z_g M_g^c \alpha + e_g$$

……when all animals genotyped (BayesA, BayesB etc)

But non-genotyped NOT invariant

$$
\begin{aligned}
&Non-genotyped\\
&y_n = \mathbf{1}\mu + X_n b + Z_n A_{ng} A_{gg}^{-1} M_g \alpha + Z_n \boldsymbol{\varepsilon}_n + e_n\\
&\quad = \mathbf{1}\mu + X_n b + Z_n A_{ng} A_{gg}^{-1} \mathbf{1} c'\alpha + Z_n A_{ng} A_{gg}^{-1} (M_g - 1c')\alpha + Z_n \boldsymbol{\varepsilon}_n + e_n\\
&\quad = \mathbf{1}\mu + X_n b + Z_n A_{ng} A_{gg}^{-1} \mathbf{1} t + Z_n A_{ng} A_{gg}^{-1} M_g^c \alpha + Z_n \boldsymbol{\varepsilon}_n + e_n
\end{aligned}
$$

So combined analysis of genotyped and non-genotype animals need to include a covariate for *t* if there is arbitrary centering (unless t = 0)

Computational Aspects

- It is easy to compute $A_{ng}A_{gg}^{-1}M_g$
  - And this can be done in parallel
- The computing becomes easier (rather than more difficult or impossible) as more individuals are genotyped
- Readily caters for variable selection or mixture models (eg BayesB, BayesC)
- We believe this formulation is readily extended to multi-breed and multi-trait settings
- In an MCMC framework can provide PEV

Summary

- Genomic prediction is an immature technology
- Much effort is required to extend algorithms and to develop parallel computing procedures to implement the full range of multi-breed, multi-trait, maternal effects and other models that have been routinely applied to large-scale animal prediction in recent decades

Prediction of BVs

$$
\begin{aligned}
& with\, EBV\; given\, by \\
& \widehat{u_g} = M_g \widehat{\alpha} \\
& \widehat{u_n} = M_n \widehat{\alpha} + \widehat{\varepsilon_n} \\
& or, with\, M_n = A_{ng} A_{gg}^{-1} M_g \\
& \widehat{u_n} = A_{ng} A_{gg}^{-1} M_g \widehat{\alpha} + \widehat{\varepsilon_n} \\
& \quad\; = A_{ng} A_{gg}^{-1} \widehat{u_g} + \widehat{\varepsilon_n}
\end{aligned}
$$