## Pedigree-based mixed linear models

## The Prediction Problem

Model Equation

$$
\mathbf{y}=\mathbf{X b}+\mathbf{Z u}+\mathbf{e}
$$

Other aspects of the model
First moments $\mathbf{E}[\mathbf{u}]=\mathbf{0}, \mathbf{E}[\mathbf{e}]=\mathbf{0}$, therefore $\mathbf{E}[\mathbf{y}]=\mathbf{X b}$
Second moments $\operatorname{var}[\mathbf{u}]=\mathbf{G}, \operatorname{var}[\mathrm{e}]=\mathbf{R}, \boldsymbol{\operatorname { c o v }}\left[\mathbf{u}, \mathrm{e}^{\prime}\right]=\mathbf{0}$
Distributional Assumptions e.g. u, e $\sim$ MVN
Want to predict $\mathbf{u}$ or linear functions like $\mathbf{k}^{\prime} \mathbf{u}$

## Original Solution

Generalized Least Squares (GLS)
For estimable $\mathbf{q}^{\prime} \mathbf{b}, \mathbf{q}^{\prime} \hat{\mathbf{b}}^{\mathbf{0}}$ is BLUE (Best Linear Unbiased Estimator)
where $\hat{\mathbf{b}}^{\mathbf{0}}=\left(\mathbf{X}^{\prime} \mathbf{V}^{-1} \mathbf{X}\right)^{-} \mathbf{X}^{\prime} \mathbf{V}^{-1} \mathbf{y} \quad$ for $\mathbf{V}=\mathbf{Z} \mathbf{G Z} \mathbf{Z}^{\prime}+\mathbf{R}$
then $\hat{\mathbf{u}}=\mathbf{G} \mathbf{Z}^{\prime} \mathbf{V}^{-1}\left(\mathbf{y}-\mathbf{X} \hat{\mathbf{b}}^{\mathbf{0}}\right)$, is BLUP (BLU Predictor)
(same as Selection Index/BLP except $\left(\mathbf{y}-\mathbf{X} \hat{\mathbf{b}}^{0}\right)$ in place of $(\mathbf{y}-\mathbf{X b})$ obtained by exploiting (genetic) covariances between animals In traditional animal breeding practice
$\mathbf{G}$ is large and dense and determined by $\mathbf{A}$ the numerator relp matrix
$\mathbf{V}$ is too big to compute $\mathbf{X}^{\prime} \mathbf{V}^{-1}$

## BLP vs GLS BLUP

$\mathbf{y}=\mathbf{X} \beta+\mathbf{Z u}+\mathbf{e}$
$\mathbf{y}-\mathbf{X} \beta=\mathbf{Z u}+\mathbf{e}$, a fully random model
Selection Index Equations $\mathbf{P b}=\mathbf{G v}$
$\mathbf{b}=\mathbf{P}^{-1} \mathbf{G} \mathbf{v}$, defines the best linear function to predict $\mathbf{u}$ the "weights" are the same for every animal with the same sources of information (ie same traits observed)
$\mathrm{BLP} \hat{\mathbf{u}}=\mathbf{b}^{\prime}(\mathbf{y}-\mathbf{X} \beta)=\mathbf{v G P} \mathbf{P}^{\mathbf{- 1}}(\mathbf{y}-\mathbf{X} \beta)$
cf $\quad$ GLS BLUP $\hat{\mathbf{u}}=\mathbf{G Z}^{\prime} \mathbf{V}^{-1}\left(\mathbf{y}-\mathbf{X} \hat{\beta}^{0}\right)$

## Henderson's Contributions One

Developed methods to compute $\mathbf{G}$ and $\mathbf{R}$ from field data
Henderson's Method I (not his!), II and III Including circumstances that involved selection

## Henderson's Contributions Two

Invented the Mixed Model Equations
$\left[\begin{array}{cc}\mathbf{X}^{\prime} \mathbf{R}^{-1} \mathbf{X} & \mathbf{X}^{\prime} \mathbf{R}^{-1} \mathbf{Z} \\ \mathbf{Z}^{\prime} \mathbf{R}^{-1} \mathbf{X} & \mathbf{Z}^{\prime} \mathbf{R}^{-1} \mathbf{Z}+\mathbf{G}^{-1}\end{array}\right]\left[\begin{array}{c}\hat{\mathbf{b}}^{\mathbf{0}} \\ \hat{\mathbf{u}}\end{array}\right]=\left[\begin{array}{c}\mathbf{X}^{\prime} \mathbf{R}^{-1} \mathbf{y} \\ \mathbf{Z}^{\prime} \mathbf{R}^{-1} \mathbf{y}\end{array}\right]$, for full rank $\mathbf{G}$
and jointly showed $\mathbf{k}^{\prime} \hat{\mathbf{b}}^{\mathbf{0}}$ and $\hat{\mathbf{u}}$ were BLUE and BLUP
Computationally tractable if $\mathbf{G}$ and $\mathbf{R}$ assumed diagonal or block-diagonal (eg sire model with relationships ignored)
(Order 40 matrix takes weeks to invert by hand)
MME typically sparse in national animal evaluation

## Example NRM or A matrix



|  | Offspring $_{1}$ | Offspring $_{2}$ | Offspring $_{3}$ | Offspring $_{4}$ |
| :--- | :---: | :---: | :---: | :---: |
| Offspring $_{1}$ | 1 | $1 / 2$ | 0 | 0 |
| Offspring $_{2}$ | $1 / 2$ | 1 | 0 | 0 |
| Offspring $_{3}$ | 0 | 0 | 1 | $1 / 4$ |
| Offspring $_{4}$ | 0 | 0 | $1 / 4$ | 1 |

Sires and dams unrelated and non-inbred Simple calculation of $\mathbf{A}_{\mathbf{p}}{ }^{-1}$ requires including all ancestors and would result in a matrix of order 7 not 4

## $\mathbf{A}^{-1}$ matrix (animal model)



Ancestors w/out records are fitted for simple $\mathbf{A}^{-1}$ structure

## Henderson's Contributions Three

Invented an algorithm to directly form $\mathbf{A}^{-1}$ from a pedigree list Then $\mathbf{G}^{-1}$ can be formed as a scalar product or kronecker product
define $d$ to be "mendelian" sampling variance
$d=(1,3 / 4,1 / 2)$ for 0,1 or 2 parents known
define $\mathbf{s}^{\prime}=(-1 / 2,-1 / 2,1)$ to represent sire (if known), dam (if known) and individual equations
accumulate $\mathbf{s} d^{-1} \mathbf{s}$ ' in the sire, dam and individual rows/columns
for every trio of animals in the pedigree list

## Consequence of $\mathbf{A}^{-1}$ structure

|  | sire $d a m$ $i$ <br> Accumulate for each animal sire  <br>  dam  <br> $i$  $\left[\begin{array}{ccc}0.25 & 0.25 & -0.5 \\ 0.25 & 0.25 & -0.5 \\ -0.5 & -0.5 & 1\end{array}\right] d^{-1}$ |
| :---: | :---: |

When both parents are known
Nonparents (ie terminal offspring)
Own equation (ie row) has 2 on diagonal, -1 in sire column -1 in dam column
Parent with one offspring
Own equation has $2+1 / 2$ on diagonal, -1 in sire and dam columns in addition to $-1 / 2$ in the column of its mate, -1 in column of offspring

Parent with many offspring to different mates
accumulates a large diagonal element, many small negative offdiagonals

## Consider rearranging the MME

In general,
$\left[\begin{array}{ll}\mathbf{Z}^{\prime} \mathbf{R}^{-1} \mathbf{X} & \mathbf{Z}^{\prime} \mathbf{R}^{-1} \mathbf{Z}+\mathbf{G}^{-1}\end{array}\right]\left[\begin{array}{c}\hat{\mathbf{b}}^{0} \\ \hat{\mathbf{u}}\end{array}\right]=\left[\begin{array}{l}\left.\mathbf{Z}^{\prime} \mathbf{R}^{-1} \mathbf{y}\right]\end{array}\right.$
or equivalently $\left[\mathbf{Z}^{\prime} \mathbf{R}^{-1} \mathbf{Z}+\mathbf{G}^{-1}\right][\hat{\mathbf{u}}]=\left[\mathbf{Z}^{\prime} \mathbf{R}^{-1}\left(\mathbf{y}-\mathbf{X} \hat{\mathbf{b}}^{0}\right)\right]$
Single trait animal model $\mathbf{R}=\mathbf{I} \sigma_{e}^{2}, \quad \mathbf{G}=\mathbf{A} \sigma_{g}^{2}, \quad \mathbf{G}^{-1}=\mathbf{A}^{-1} \sigma_{g}^{-2}$
or multiplying $\sigma_{e}^{2},\left[\mathbf{Z}^{\prime} \mathbf{Z}+\lambda \mathbf{A}^{-1}\right][\hat{\mathbf{u}}]=\left[\mathbf{Z}^{\prime}\left(\mathbf{y}-\mathbf{X} \hat{\mathbf{b}}^{0}\right)\right]$, with $\lambda=\sigma_{e}^{2} / \sigma_{g}^{2}$

## Consider the MME for a nonparent

$$
\left[\mathbf{Z}^{\prime} \mathbf{Z}+\lambda \mathbf{A}^{-1}\right][\hat{\mathbf{u}}]=\left[\mathbf{Z}^{\prime}\left(\mathbf{y}-\mathbf{X} \hat{\mathbf{b}}^{0}\right)\right]
$$

Nonparent animal with one record

$$
\begin{aligned}
(1+2 \lambda) & \hat{u}_{\text {animal }}-\lambda \hat{u}_{\text {sire }}-\lambda \hat{u}_{\text {dam }}=\text { adjusted } y \\
\hat{u}_{\text {animal }} & =\frac{2 \lambda\left(\hat{u}_{\text {sire }}+\hat{u}_{\text {dam }}\right)}{(1+2 \lambda) 2}+\frac{(\text { adjusted_ } y)}{(1+2 \lambda)} \\
& =(1-w) P A+w\left(\text { adjusted }_{-} y\right) \text { for } w=\frac{1}{(1+2 \lambda)}
\end{aligned}
$$

## Consider the MME for a nonparent

$\hat{u}_{\text {animal }}=(1-w) P A+w\left(\right.$ adjusted $\left._{-} y\right)$ for $w=\frac{1}{(1+2 \lambda)}$
$\lambda=\frac{1-h^{2}}{h^{2}}$ so for $h^{2}=1, \lambda=0, w=1$, (no shrinkage)
for $h^{2}=$ low, $\lambda=$ big, $w=$ small, $($ shrink the deviation $)$
Two sources of BV information are pooled
The parent average PA
The individual prediction (shrunk deviation) with heritability influencing shrinkage

## Consider the MME for a nonparent

$$
\left[\mathbf{Z} \mathbf{Z}+\lambda \mathbf{A}^{-1}\right][\hat{\mathbf{u}}]=\left[\mathbf{Z}\left(\mathbf{y}-\mathbf{X} \hat{\mathbf{b}}^{0}\right)\right]
$$

Nonparent animal with one record
$\hat{u}_{\text {animal }}=(1-w) P A+w($ adjusted_y $)$
Nonparent animal with no record
$2 \lambda \hat{u}_{\text {animal }}-\lambda \hat{u}_{\text {sire }}-\lambda \hat{u}_{\text {dam }}=0$
$\hat{u}_{\text {animal }}=\frac{\lambda\left(\hat{u}_{\text {sire }}+\hat{u}_{\text {dam }}\right)}{\lambda 2}=\frac{\left(\hat{u}_{\text {sire }}+\hat{u}_{\text {dam }}\right)}{2}=P A$

## Reliability of nonparents

Property of BLP/BLUP is $\operatorname{cov}(u, \hat{u})=\operatorname{var}(\hat{u})$ so $\mathrm{r}^{2}=\frac{\operatorname{var}(\hat{u})}{\operatorname{var}(u)}$
but $\hat{u}_{\text {nonparent }}=\frac{\hat{u}_{\text {sire }}}{2}+\frac{\hat{u}_{\text {dam }}}{2}$, for nonparent without a record
so $\mathrm{r}_{\text {nonparent }}^{2}=\frac{r_{\text {sire }}^{2}}{4}+\frac{r_{\text {dam }}^{2}}{4} \leq \frac{1}{2}$
Finally $\Delta G=\frac{i r_{\text {nonparent }} \sigma_{g}}{L}$, limiting selection response when candidates at puberty lack phenotypic information

## An option to do better

## Solution

- We need a different representation of the covariance between relatives, that allows relatives other than parents to directly contribute to the prediction of nonparents without records
- The NRM or A-matrix is an expectation of relationships in the context of repeated sampling of the pedigree (conditional on pedigree)


## A-matrix

- Relationship with self is $1+\mathrm{F}$ (noninbred $\mathrm{F}=0$ )
- (Additive) relationship of $1 / 2$ between non-inbred full-sibs and between parents and non-inbred offspring
- Relationship of $1 / 4$ between non-inbred half-sibs and between grandparents and offspring
- But particular individuals can have greater or lesser values
- If we know their genotype we can compute relationships conditional on the chromosome regions they inherited


## Relationship matrix



## Relationship matrix



## G-inverse matrix

| A-inverse matrix |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\begin{array}{lllllll}3 & 2 & -1 & -1 & -1 & -1\end{array}$ | 3.5 | 2.5 | -1.25 | -1.25 | -1.25 | -1.25 |
| $\begin{array}{llllll}3 & 2 & -1 & -1 & -1 & -1 \\ 2 & 3 & -1 & -1 & -1 & -1\end{array}$ | 2.5 | 3.5 | -1.25 | -1.25 | -1.25 | -1.25 |
| $\begin{array}{lllllll}-1 & -1 & 2 & 0 & 0 & 0\end{array}$ | -1.25 | -1.25 | 2.1875 | -0.3125 | 0.3125 | 0.3125 |
| $\begin{array}{lllllll}-1 & -1 & 0 & 2 & 0 & 0\end{array}$ | -1.25 | -1.25 | -0.3125 | 2.1875 | 0.3125 | 0.3125 |
| $\begin{array}{lllllll}-1 & -1 & 0 & 0 & 2 & 0\end{array}$ | -1.25 | -1.25 | 0.3125 | 0.3125 | 2.1875 | -0.3125 |
| $\begin{array}{lllllll}-1 & -1 & 0 & 0 & 0 & 2\end{array}$ | -1.25 | -1.25 | 0.3125 | 0.3125 | -0.3125 | 2.1875 |

## Predict the last animal with no data

$$
\begin{gathered}
{\left[\begin{array}{cllll}
-1.25 \hat{u}_{\text {sire }} & -1.25 \hat{u}_{\text {dam }} & .3125 \hat{u}_{\text {sib1 }} & .3125 \hat{u}_{\text {sib2 }} & -.3125 \hat{u}_{\text {sib } 3} \\
2.1875 \hat{u}_{\text {candidate }}
\end{array}\right]=[0]} \\
\hat{u}_{\text {candidate }}=\frac{1.25\left(\hat{u}_{\text {sire }}+\hat{u}_{\text {dam }}\right)-0.3125\left(\hat{u}_{\text {sib } 1}+\hat{u}_{\text {sib2 }}\right)+0.3125 \hat{u}_{\text {sib } 3}}{2.1875}
\end{gathered}
$$

But to form G, we needed to know which loci/QTL contribute to variation in performance

## Some MME Results

$$
\left[\begin{array}{cc}
X^{\prime} X & X^{\prime} Z \\
Z^{\prime} X & Z^{\prime} Z+\lambda G^{-1}
\end{array}\right]^{-}=\left[\begin{array}{cc}
C^{11} & C^{12} \\
C^{21} & C^{22}
\end{array}\right]
$$

$\operatorname{var}(\mathbf{g})=\mathbf{G} \quad \operatorname{var}(\hat{\mathbf{g}})=\mathbf{G}-\mathbf{C}^{22} \quad \operatorname{var}(\hat{\mathbf{g}}-\mathbf{g})=\mathbf{C}^{22} \quad r_{8 \hat{\mathrm{~g}}}^{2}=\operatorname{var}(\hat{g}) / \operatorname{var}(g)$
$\operatorname{var}\left(\mathbf{k}^{\prime} \mathbf{g}\right)=\mathbf{k}^{\prime} \mathbf{G k} \quad \operatorname{var}\left(\mathbf{k}^{\prime} \hat{\mathbf{g}}\right)=\mathbf{k}^{\prime}\left(\mathbf{G}-\mathbf{C}^{\mathbf{2 2}}\right) \mathbf{k}$

