# A relationship matrix combining pedigree and markers when some individuals are not genotyped <br> Andres Legarra 

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## A RELATIONSHIP MATRIX COMBINING PEDIGREE AND MARKERS (WHEN SOME INDIVIDUALS ARE NOT GENOTYPED)

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## Thanks

- Organisers for organizing everything \& inviting me
- Projects GenSSeq and X-Gen (INRA)
- Work that I have been doing primarily with I Misztal (UGA, US), I Aguilar (INIA, Uruguay) and many other people
- Other group led by OF Christensen (University of Aarhus, DK) developed the theory in parallel
- with fruitful cross-fecundation


## Example

- Pedigree; grey is genotyped
- Numbers are records of a quantitative trait (e.g. weight)
- Can't easily assign a record to a genotyped individual



## Plan

- Intro: pedigree \& genomic relationship, why we need them
- Derivation of a joint matrix H
- Compatibility of genomic and pedigree relationships


## Pedigree relationships: A

- Additive relationships= $2^{*}$ (kinships or coancestries)
- $A_{i j}=2 \phi_{i j}$
- Pedigrees describe how genes are potentially transmitted
- Systematic "tabular" rules to compute any $A_{i j}$ (Emik \& Terrill 1947)
- The whole array of $A_{i j}$ is disposed in a matrix $\boldsymbol{A}$.
- $\boldsymbol{A}^{-1}$ is very sparse and easy to create(Henderson 1976)
- Extraordinary development of whole-pedigree methods in livestock genetics


## Genomic (or molecular) relationships: G

- The predecessors are poorly known
- Li and Horvitz 1953, Cockerham 1969, Ritland 1996, Caballero \& Toro 2002, VanRaden 2008 and many others
- Genomes are of finite size
- Some sib pairs are more equal than others (Hill \& Weir 2011, etc)
- Pedigree relationships are not "fair"


## Genomic (or molecular) relationships: G

- If we could see genes then we could just count
- Instead of genes, we see markers, which are not genes
- Markers are stretches of DNA that can be accurately read across individuals
- Biallelic SNP markers are used right now (e.g. A/a). Many of them: 50,000 to 800,000 / individual



## VanRaden genomic relationships

- (VanRaden, 2008, more known as Yang et al., 2010)
- Crossproduct across numerically coded genotypes
- $G_{i j}=\frac{z_{i} z_{j}}{2 \sum p_{k} q_{k}}$
- $z_{i}$ : vector of $n$ elements
- with standardized genotypes as $\{0,1,2\}-2 p_{k}$ for genotypes $\{A A, A a, a a\}$ at locus $k=1, n$
- $p_{k}$ : across-population frequency of $\{a\}$ at locus $k$
- Whole-population $\boldsymbol{G}=\boldsymbol{Z D} \boldsymbol{Z}^{\prime}$
- Semipositive definite, not easy to invert


## Genomic and pedigree relationships

- Pedigree (A) are estimated IBD relationships, assuming « unrelated» founders
- Genomic (G) are Identical by state (IBS) relationships, corrected to be in IBD scale (see later)
- Genomic relationships are similar to pedigree relationships but more accurate
- If pedigree correct, typically crude $\operatorname{sd}(\boldsymbol{G}-\boldsymbol{A}) \approx 0,04$
and $\operatorname{cor}(\boldsymbol{A}, \boldsymbol{G}) \approx 0,80$


## Applications

- Most applications come from the model
- $\boldsymbol{y}=\boldsymbol{X b}+\boldsymbol{W} \boldsymbol{u}+\boldsymbol{e}$
- Phenotype $=$ environmental effects + genetic value + residual
- Assuming
$\cdot \operatorname{Var}(\boldsymbol{u})=\boldsymbol{A} \sigma_{u}^{2} \quad$ Relationships
- $\operatorname{Var}(\boldsymbol{u})=\boldsymbol{G} \sigma_{u}^{2}$ 」
- $\operatorname{Var}(\boldsymbol{e})=\boldsymbol{R} \longrightarrow$ Typically simple structure
- In (G)BLUP equations we use relationships:

$$
\left(\begin{array}{cc}
\boldsymbol{X}^{\prime} \boldsymbol{R}^{-1} \boldsymbol{X} & \boldsymbol{X}^{\prime} \boldsymbol{R}^{-1} \boldsymbol{W} \\
\boldsymbol{W}^{\prime} \boldsymbol{R}^{-1} \boldsymbol{W} & \boldsymbol{W}^{\prime} \boldsymbol{R}^{-1} \boldsymbol{W}+\operatorname{Var}(\boldsymbol{u})^{-1}
\end{array}\right)\binom{\widehat{b}}{\widehat{\boldsymbol{u}}}=\binom{\boldsymbol{X}^{\prime} \boldsymbol{R}^{-1} \boldsymbol{y}}{\boldsymbol{W}^{\prime} \boldsymbol{R}^{-1} \boldsymbol{y}}
$$

$\cdot \operatorname{Var}(\boldsymbol{u})^{-1}=\boldsymbol{G}^{-1} \sigma_{u}^{-2}$ or perhaps $\operatorname{Var}(\boldsymbol{u})^{-1}=\boldsymbol{A}^{-1} \sigma_{u}^{-2}$

## Genomic predictions and Pedigree predictions

- Relationships can be obtained from pedigree (pedigree relationships) or from markers (genomic relationships)
- We expect markers to be better than pedigree because they are more "real" but they are expensive... (40-150 \$ / individual)
- We expect Artificial Selection based on markers ("Genomic Selection") to be more efficient than based on pedigree


## Genomic predictions and Pedigree predictions

- genomic predictions are 10-25\% more accurate than pedigree predictions in terms of cross-validation $R^{2}$
- e.g. VanRaden et al. 2009 (dairy cattle)

Table 2. Coefficients of determination $\left(R^{2} \times 100\right)$ for 2008 daughter $d$

| Trait | pedigree | genomic |
| :--- | :---: | :---: |
| Net merit | 11 | 28 |
| Milk yield | 28 | 47 |
| Fat yield | 15 | 42 |
| Protein yield | 27 | 47 |
| Fat percentage | 25 | 55 |
| Protein percentage | 28 | 51 |
| Productive life | 17 | 26 |
| SCS | 23 | 37 |
|  | VanRaden et al J. Dairy Sci. 92:16-24 |  |

- Similar results in sheep, pigs, chicken and goats (and plants)


## Pedigrees in livestock genetics

- They are deep and connect most animals
- From 100,000's to 1,000,000's
- However, only some animals are genotyped
- Important animals such as bulls, also recent animals
- MANY animals are ungenotyped (perhaps 99\%)
- This makes us unhappy
- A spans all animals but has no marker information and is less precise
- $\mathbf{G}$ is more precise but does not include all animals
- So far, we use horrible procedures for precorrection


## Example

- Grey is genotyped
- Numbers are records (e.g. weight)
- Can't easily assign a record to a genotyped individual



## Plan

- Intro: pedigree \& genomic relationship, why we need them
- Derivation of a joint matrix H
- Compatibility of genomic and pedigree relationships
- Things would be simple if we had genomic relationships for everyone (Legarra et al., 2009)
- Things would be simple if we could add genotypes for all animals (Christensen et al., 2010)
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## Single Step as a missing data problem

- We can see genotype as a missing data problem (Christensen \& Lund, 2010)
- Use the prediction and the distribution of the prediction


## Missing data

## Fill-in missing data: data augmentation

- « data augmentation refers to a scheme of augmenting the observed data so as to make it more easy to analyze " (Tanner \& Wong, 1987)
- Augmenting = adding genotypes
- Imputing algorithms work from low to high density markers
- For animals nongenotyped (at all), they may give a point estimate based on most likely genotype
-Why is this bad?


## Problem with point estimates of genotypes

- Imagine a major gene

- Point estimate of genotype of the descendants: "Aa"
- Clearly, based on $\boldsymbol{y}$ there is Mendelian segregation where one descendant received "AA" and the other "aa"
- There is variation of true genotype around the point estimate of the genotype
- If we do not consider this variation we consider the offspring as identical twins


## Augmenting genotypes

- Gengler et al. (2007) conceived an algebraic way to deal with these point estimates (== to McPeek et al. 2004)
- Christensen \& Lund (2010) showed how to take the variation into account
- Genotype of descendants = half their parents + Mendelian sampling

$\left\{\begin{array}{c}\text { AA with probability } 1 / 2 \\ \text { Aa with probability } 1 / 2\end{array}\right.$
$\mathrm{E}($ Genotype $)=\frac{3}{2} " A^{"}+\frac{1}{2} " a^{\prime \prime}$

Variance(Genotype) $=\frac{1}{4}$ "A" $+\frac{1}{4}$ " $a "$

## Augmenting genotypes

Genotype $=\frac{3}{2}{ }^{\prime \prime} A^{\prime \prime}+\frac{1}{2} "^{\prime \prime} a^{\prime}$
Variance(Genotype) $=\frac{1}{4}$ "A" $+\frac{1}{4}$ " $a "$

- Yes this is weird but it allows linear and algebraic treatment of an almost impossible problem
- You can see it as a linear simplification of a superpolynomial problem
- This allows using the classical machinery of animal breeding (relationships and matrix algebra)


## Inferring genotypes

- Gengler's gene content prediction (2007)
- Linear approximation to the imputation problem

This method can be applied to any member of a pedigree and generalized to a set of individuals

$\hat{\mathbf{z}}_{\text {non genotyped }}=E\left(\mathbf{z}_{\text {non genotyped }} \mid \mathbf{z}_{\text {genotyped }}\right)=\mathbf{A}_{1,2} \mathbf{A}_{2,2}^{-1}\left(\mathbf{z}_{\text {genotyped }}-\mathbf{2} p\right)$
$\operatorname{Var}\left(\hat{\mathbf{z}}_{\text {non genotyped }}\right)=\operatorname{Var}\left(\mathbf{z}_{\text {non genotyped }} \mid \mathbf{z}_{\text {genotyped }}\right)=\left(\mathbf{A}_{1,1}-\mathbf{A}_{1,2} \mathbf{A}_{2,2}^{-1} \mathbf{A}_{2,1}\right) 2 p q$
non genotyped
Let $\quad \mathbf{A}=\overbrace{\left[\begin{array}{ll}\mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \underbrace{}_{\text {genotyped }} \\ \mathbf{A}_{22}\end{array}\right]}$

Christensen \& Lund key idea:
$\boldsymbol{u}=\binom{\boldsymbol{u}_{\boldsymbol{n} g}}{\boldsymbol{u}_{g}}=\binom{\boldsymbol{Z}_{\boldsymbol{n} g}}{\boldsymbol{Z}_{g}} \boldsymbol{a}$
$n g:$ « non genotyped » $g:$ « genotyped»

Chistensen \& Lund use $\operatorname{Var}(A)=E(\operatorname{Var}(A \mid B))+\operatorname{Var}(E(A \mid B))$ to consider the prediction of the genotype and its variance

$$
\begin{gathered}
\operatorname{Var}(\boldsymbol{u})=\binom{\widehat{\boldsymbol{Z}}_{n g}}{\boldsymbol{Z}_{g}} \operatorname{Var}(\boldsymbol{a})\left(\begin{array}{ll}
\widehat{\mathbf{Z}}_{n g} & \boldsymbol{Z}_{g}^{\prime}
\end{array}\right)+\left(\begin{array}{ccc}
\operatorname{Var}\left(\widehat{\mathbf{Z}}_{n g}\right) & \mathbf{0} \\
\mathbf{0} & \mathbf{0}
\end{array}\right) \operatorname{Var}(\boldsymbol{a}) \\
\operatorname{Var}\left(\mathbf{Z}_{n g} \mid \boldsymbol{Z}_{n g}\right) \\
\underbrace{}_{\text {Resulting in: }} \boldsymbol{Z}_{g})
\end{gathered}
$$

## Covariances of all animals

Legarra et al. 2009; Aguilar et al., 2010; Christensen \& Lund, 2010

$$
\begin{aligned}
\operatorname{Var}\binom{\mathbf{u}_{1}}{\mathbf{u}_{2}}=\mathbf{H}=\left[\begin{array}{ll}
\mathbf{H}_{11} & \mathbf{H}_{12} \\
\mathbf{H}_{21} & \mathbf{H}_{22}
\end{array}\right]= & \overbrace{\text { non genotyped }}^{\text {no }} \\
& {\left[\begin{array}{cc}
\mathbf{A}_{11}-\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21}+\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{G A}_{22}^{-1} \mathbf{A}_{21} & \mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{G} \\
\mathbf{G A}_{22}^{-1} \mathbf{A}_{21}
\end{array}\right] }
\end{aligned}
$$

non genotyped
Let $\quad \mathbf{A}=\overbrace{\left[\begin{array}{ll}\mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \underbrace{\mathbf{A}_{22}}\end{array}\right]}$

## Covariances of all animals

$$
\operatorname{Var}\binom{\mathbf{u}_{1}}{\mathbf{u}_{2}}=\mathbf{H}=\left[\begin{array}{ll}
\mathbf{H}_{11} & \mathbf{H}_{12} \\
\mathbf{H}_{21} & \mathbf{H}_{22}
\end{array}\right]=
$$

$$
\begin{gathered}
\text { This is the variance of prediction } \\
\text { of genotypes from genotyped to } \\
\text { non-genotyped }
\end{gathered}
$$


$\operatorname{Var}\binom{\mathbf{u}_{1}}{\mathbf{u}_{2}}=\mathbf{H}=\left[\begin{array}{ll}\mathbf{H}_{11} & \mathbf{H}_{12} \\ \mathbf{H}_{21} & \mathbf{H}_{22}\end{array}\right]=$

$$
\left[\begin{array}{cc}
\mathbf{A}_{11}-\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21}+\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{G} \mathbf{A}_{22}^{-1} \mathbf{A}_{21} & \mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{G} \\
\mathbf{G A}_{22}^{-1} \mathbf{A}_{21} & \mathbf{G}
\end{array}\right]
$$

- Incredibly: $\mathbf{H}^{\mathbf{- 1}}$ is very simple:

Inverse of the regular pedigree relationship matrix


- Things would be simple if we had genomic relationships for everyone (Legarra et al., 2009)
- Things would be simple if we could add genotypes for all animals (Christensen et al., 2010)


## Overall modification

- Look at A as a « prior » (pedigree) relationship and to G as an « observed» (genomic) relationship
- $\mathbf{G}$ is observed for some individuals only, whose « a priori » (pedigree) relationship matrix was $\mathbf{A}_{22}$
- Try to construct a « posterior » relationship matrix


## Joint distributions

Unconditional distribution of genetic values of Genotyped individuals

$$
p\left(\mathbf{u}_{2}\right)=N(\mathbf{0}, \mathbf{G}) \text { and } \longrightarrow \text { After seeing their genotypes ! }
$$

Conditional distribution of Non-Genotyped individuals

$$
p\left(\mathbf{u}_{1} \mid \mathbf{u}_{2}\right)=N\left(\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{u}_{2}, \mathbf{A}_{11}-\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21}\right)
$$

Because they have no
$p\left(\mathbf{u}_{1}, \mathbf{u}_{2}\right)=p\left(\mathbf{u}_{2}\right) p\left(\mathbf{u}_{1} \mid \mathbf{u}_{2}\right)$ genotypes, this depends only on pedigree

Joint distribution

## Joint distributions

$p\left(\mathbf{u}_{1}, \mathbf{u}_{2}\right)=p\left(\mathbf{u}_{1}, \mid \mathbf{u}_{2}\right) p\left(\mathbf{u}_{2}\right)$

$$
=p\left(\mathbf{u}_{1} \mid \mathbf{u}_{2}\right) p\left(\mathbf{u}_{2}\right)
$$

$$
\propto \exp \left[-0.5\left(\mathbf{u}_{1}-\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{u}_{2}\right)^{\prime} \mathbf{A}^{11}\left(\mathbf{u}_{1}-\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{u}_{2}\right)\right] \exp \left[-0.5 \mathbf{u}_{2}^{\prime} \mathbf{G}^{-1} \mathbf{u}_{2}\right]
$$

$$
=\exp \left(-0.5\left[\begin{array}{ll}
\mathbf{u}_{1}^{\prime} & \mathbf{u}_{2}^{\prime}
\end{array}\right]\left[\begin{array}{lc}
\mathbf{A}^{11} & \mathbf{A}^{12} \\
\mathbf{A}^{21} & \mathbf{G}^{-1}+\mathbf{A}^{22}-\mathbf{A}_{22}^{-1}
\end{array}\right]\left[\begin{array}{l}
\mathbf{u}_{1} \\
\mathbf{u}_{2}
\end{array}\right]\right) .
$$

...for those inclined to algebra

## Covariances of all animals

Legarra et al. 2009; Aguilar et al., 2010; Christensen \& Lund, 2010

$$
\begin{aligned}
\operatorname{Var}\binom{\mathbf{u}_{1}}{\mathbf{u}_{2}}=\mathbf{H}=\left[\begin{array}{ll}
\mathbf{H}_{11} & \mathbf{H}_{12} \\
\mathbf{H}_{21} & \mathbf{H}_{22}
\end{array}\right] & =\overbrace{\left[\begin{array}{cc}
\mathbf{A}_{11}-\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21}+\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{G} \mathbf{A}_{22}^{-1} \mathbf{A}_{21} \\
\mathbf{G A}_{22}^{-1} \mathbf{A}_{21} & \text { non genotyped } \\
\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{G} \\
\mathbf{G}
\end{array}\right]}
\end{aligned}
$$

Exactly same results...

## Overall modification: example



Figure 1. Example pedigree. Genotyped animals are in bold.

## Overall modification: example

Table 1. Numerator relationship matrix A for the pedigree in Figure $1^{1}$

| 1.00 |  |  |  |  |  |  |  | 0.50 |  |  |  | 0.25 |  |  | 0.13 | 0.13 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 1.00 |  |  |  |  |  |  | 0.50 |  |  |  | 0.25 |  |  | 0.13 | 0.13 |
|  |  | 1.00 |  |  |  |  |  |  | 0.50 |  |  | 0.25 |  |  | 0.13 | 0.13 |
|  |  |  | 1.00 |  |  |  |  |  | 0.50 |  |  | 0.25 |  | 0.50 | 0.38 | 0.13 |
|  |  |  |  | 1.00 |  |  |  |  |  | 0.50 |  |  | 0.25 | 0.25 | 0.13 | 0.13 |
|  |  |  |  |  | 1.00 |  |  |  |  | 0.50 |  |  | 0.25 | 0.25 | 0.13 | 0.13 |
|  |  |  |  |  |  | 1.00 |  |  |  |  | 0.50 |  | 0.25 |  |  | 0.13 |
|  |  |  |  |  |  |  | 1.00 |  |  |  |  |  | 0.25 |  |  | 0.13 |
| 0.50 | 0.50 |  |  |  |  |  |  | 1.00 |  |  |  | 0.50 |  |  | 0.25 | 0.25 |
|  |  | 0.50 | 0.50 |  |  |  |  |  | 1.00 |  |  | 0.50 |  | 0.25 | 0.38 | 0.25 |
|  |  |  |  | 0.50 | 0.50 |  |  |  |  | 1.00 |  |  | 0.50 | 0.50 | 0.25 | 0.25 |
|  |  |  |  |  |  | 0.50 | 0.50 |  |  |  | 1.00 |  | 0.50 |  |  | 0.25 |
| 0.25 | 0.25 | 0.25 | 0.25 |  |  |  |  |  |  |  |  | 1.00 |  | 0.13 | 0.56 | 0.50 |
|  |  |  |  | 0.25 | 0.25 | 0.25 | 0.25 |  |  | 0.50 | 0.50 |  | 1.00 | 0.25 | 0.13 | 0.50 |
|  |  |  | 0.50 | 0.25 | 0.25 |  |  |  | 0.25 | 0.50 |  | 0.13 | 0.25 | 1.00 | 0.56 | 0.19 |
| 0.13 | 0.13 | 0.13 | 0.38 | 0.13 | 0.13 |  |  | 0.25 | 0.38 | 0.25 |  | 0.56 | 0.13 | 0.56 | 1.06 | 0.34 |
| 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.13 | 0.25 | 0.25 | 0.25 | 0.25 | 0.50 | 0.50 | 0.19 | 0.34 | 1.00 |

[^0]This is the regular relationship matrix. Assume now that animals 9 to 12 have a genomic relationship of 0.7

## Overall modification: example

Table 3. Modified relationship matrix H including genomic information for genotyped animals and all relatives for the pedigree in Figure $1^{1}$


## Understanding H matrix

- It is a projection of $\mathbf{G}$ matrix on the rest of individuals "so that" $\mathbf{G}$ matrix makes sense
- e.g. parents of two animals related in G should be related in A
- It is a Bayesian updating of the pedigree matrix based on new information from genotypes
- The approximation of multivariate normality is good because we have many markers
- Typically
- $\mathbf{A}^{-1}$ in the millions but extremely sparse
- $\mathbf{G}$ and $\mathbf{A}_{22}$ in the thousands
- Leads to a very efficient method of genomic evaluation:
- Single Step GBLUP


## Single step GBLUP

Single Step = Your regular BLUP with small modifications
W: incidence matrix of animals on data

```
[\begin{array}{cc}{\mp@subsup{\mathbf{X}}{}{\prime}\mp@subsup{\mathbf{R}}{}{-1}\mathbf{X}}&{\mp@subsup{\mathbf{X}}{}{\prime}\mp@subsup{\mathbf{R}}{}{-1}\mathbf{W}}\\{\mp@subsup{\mathbf{WR}}{}{-1}\mathbf{X}}&{\mp@subsup{\mathbf{WR}}{}{-1}\mathbf{W}+\mp@subsup{\mathbf{H}}{}{-1}\mp@subsup{\sigma}{u}{-2}}\end{array}][\begin{array}{l}{\hat{\mathbf{b}}}\\{\hat{\mathbf{u}}}\end{array}]=[\begin{array}{c}{\mp@subsup{\mathbf{X}}{}{\prime}\mp@subsup{\mathbf{R}}{}{-1}\mathbf{y}}\\{\mp@subsup{\mathbf{WR}}{}{-1}\mathbf{y}}\end{array}]
```

$\mathbf{H}^{-1}=\mathbf{A}^{-1}+\lceil\mathbf{0}$

A: pedigree relationship matrix

This G could be any matrix describing « genomic» covariances of breeding values;
it does not restrict to VanRaden's (2008) GBLUP
$\mathbf{A}_{22}$ : pedigree matrix among genotyped individuals

## Single Step GBLUP

- Easy modification to a general purpose BLUP software
- Only changes: addition of $\boldsymbol{G}^{-1}$ and $\boldsymbol{A}_{22}^{-1}$
- Matrices $\boldsymbol{G}^{-1}$ and $\boldsymbol{A}_{22}^{-1}$ can be computed with external tools
- Can fit any model (probit, GxE,...)
- Simple extraction of SNP effects for prediction or (multimarker) GWAS:

$$
\widehat{\boldsymbol{a}}=\boldsymbol{Z}^{\prime} \boldsymbol{G}^{-1} \widehat{\boldsymbol{u}}_{2} / k
$$

## Some results in Pigs

- Christensen et al., 2012
- Joint two-trait analysis: daily gain (massively recorded) and feed efficiency (scarcely recorded)
- 2600 genotyped, 300,000 records
- Single Step increased accuracy by 0.10 in both traits compared to pedigree BLUP and reduced bias compared to simple GBLUP
- Lourenço et al., 2014, PIC data
- Litter size, fertility
- 2,000,000 animals in data, 5,000 animals genotyped
- Single Step increased accuracy by 0.10-0.20 compared to pedigree BLUP


## Single-Step Heat Stress GWAS

- Aguilar et al., unpublished
- Multiple-Trait Test-Day model heat tolerance
- $\sim 90$ millions records, $\sim 9$ millions pedigrees
- ~ 3,800 genotyped bulls
- Computing time
- Complete evaluation ~ 16 h Marker effects (after backsolving)




## Plan

- Intro: pedigree \& genomic relationship, why we need them
- Derivation of a joint matrix H
- Compatibility of genomic and pedigree relationships


## Compatibility of marker and pedigree relationships

- Populations evolve with time, but genotypes came years after pedigree started
- Genomic Predictions are shifted from Pedigree Predictions
- This makes them not directly comparable
- Underlying hypothesis of Christensen \& Lund (allelic frequencies constant across time) or Legarra et al. (average genetic value does not change) false
- This can be modelled in a quantitative framework


## Compatibility of marker and pedigree relationships

$\boldsymbol{G}=\mathbf{Z Z} \mathbf{Z}^{\prime} / k$ or $\boldsymbol{G}=\mathbf{Z D Z} \mathbf{Z}^{\prime}$
Consider a model $\boldsymbol{y}=\mu+\boldsymbol{u}+\boldsymbol{e}, \operatorname{Var}(u)=\boldsymbol{G}$

- Adding or substracting constants from $\mathbf{G}$ shifts $\widehat{\boldsymbol{u}}$ by a constant absorbed by $\hat{\mu}$
- Multiplying $\mathbf{G}$ by a constant changes the genetic variance


## Compatibility of marker and pedigree relationships

- The population for which average $(\boldsymbol{u})=0$ and for which the genetic variance is defined is called the genetic base
- Founders of the pedigree in classical A
- Whole set of genotyped animals in most typical G
- Typically, genotyped animals come after pedigree starts
- e.g. Lacaune sheep pedigree go back to 1960 but genotypes start in 1995
- Drift (and selection) causes :
- Average genetic values "drift" (in particular in small populations)
- Genetic variance reduces


## Compatibility of marker and pedigree relationships

- Vitezica et al. (2011) and Christensen et al. (2012) provided an unbiased method that forces the same genetic base across $\mathbf{G}$ and $\mathbf{A}$ :
- $\boldsymbol{G}^{*}=a+b \boldsymbol{G}$
- $a$ accounts for old relationships among non genotyped ancestors
- $b$ accounts for reduction in the genetic variance
- $a$ and $b$ can be obtained equating average inbreeding and average relationships:

$$
\begin{gathered}
a+b \overline{\boldsymbol{G}}=\overline{\boldsymbol{A}}_{22} \\
a+b \overline{\operatorname{diag}(\boldsymbol{G})}=\overline{\left(\operatorname{diag}\left(\boldsymbol{A}_{\mathbf{2 2}}\right)\right)}
\end{gathered}
$$

In H-W $b=1-a / 2$ and this is Wright's fixation index (Powell et al., 2011):

$$
\left(1-\frac{G_{i j}^{*}}{2}\right)=\left(1-\frac{G_{i j}}{2}\right)\left(1-\frac{\left(\bar{A}_{22}-\bar{G}\right)}{2}\right)
$$

## Christensen, 2012

- Christensen (2012) suggests fitting $\mathbf{A}$ to $\mathbf{G}$ instead of the opposite
- Ancestral relationships that can be seen in $\mathbf{G}$ go undetected in A
- Christensen analitically integrates out $p_{i}$ (=allele frequencies) in a model that
- uses $p=0.5$ as reference in ALL loci
- uses a relationship matrix $\mathbf{A}^{\gamma}$ with related founders


## Relationship across founders

Classically we assume

$$
\boldsymbol{A}=\left(\begin{array}{llll}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{array}\right)
$$

- Christensen changes this into:

$$
\mathbf{A}^{\gamma}=\left(\begin{array}{cccc}
1+\frac{\gamma}{2} & \gamma & \gamma & \gamma \\
\gamma & 1+\frac{\gamma}{2} & \gamma & \gamma \\
\gamma & \gamma & 1+\frac{\gamma}{2} & \gamma \\
\gamma & \gamma & \gamma & 1+\frac{\gamma}{2}
\end{array}\right)
$$

He was unaware of Jacquard (1974) who posited this structure

## Conclusions

- We have a rather good theory on mixing pedigree and genomic relationships for a single population
- This theory is useful for genomic predictions and for GWAS in complex scenarios such as livestock
- The associated computational methods are quite efficient
- BUT
- It is sensible to pedigree or genotyping mistakes (label switching)
- Compatibility needs a reasonable data set (representative samples)


## TODO list

- Extend to multiple origins (=crosses of lines or breeds)
- Include linkage among markers (useful ?)
- Improve computational algorithms
- Understand those differences between realized (G) and expected (A) relationships, in order to come up with a comprehensive theory

Aguilar, I., I. Misztal, D. L. Johnson, A. Legarra, S. Tsuruta et al., 2010 Hot topic: a unified approach to utilize phenotypic, full pedigree, and genomic information for genetic evaluation of Holstein final score. J Dairy Sci 93: 743-752.
Aguilar, I., I. Misztal, A. Legarra and S. Tsuruta, 2011 Efficient computations of genomic relationship matrix and other matrices used in the single-step evaluation. Journal of Animal Breeding and Genetics 128: 422-428.
Emik, L. O., and C. E. Terrill, 1949 Systematic procedures for calculating inbreeding coefficients. J Hered 40: 51-55.
LI, C. C., and D. G. HORVITZ, 1953 Some methods of estimating the inbreeding coefficient. Am J Hum Genet 5: 107-117.
Cockerham, C. C., 1969 Variance of gene frequencies. Evolution 23: 72-84.
Ritland, K., 1996 Estimators for pairwise relatedness and individual inbreeding coefficients. Genetical research 67: 175-185.
Caballero, A., and M. A. Toro, 2002 Analysis of genetic diversity for the management of conserved subdivided populations. Conservation genetics 3: 289.
VanRaden, P. M., 2008 Efficient Methods to Compute Genomic Predictions. J. Dairy Sci. 91: 4414-4423.
Hill, W. G., and B. S. Weir, 2011 Variation in actual relationship as a consequence of Mendelian sampling and linkage. Genet Res (Camb): 118.

Yang, J., B. Benyamin, B. P. McEvoy, S. Gordon, A. K. Henders et al., 2010 Common SNPs explain a large proportion of the heritability for human height. Nat Genet 42: 565-569.
VanRaden, P. M., C. P. V. Tassell, G. R. Wiggans, T. S. Sonstegard, R. D. Schnabel et al., 2009 Invited review: reliability of genomic predictions for North American Holstein bulls. J Dairy Sci 92: 16-24.
Legarra, A., I. Aguilar and I. Misztal, 2009 A relationship matrix including full pedigree and genomic information. J Dairy Sci 92: 4656-4663. Christensen, O. F., and M. S. Lund, 2010 Genomic prediction when some animals are not genotyped. Genet Sel Evol 42: 2.
Tanner, M. A., and W. H. Wong, 1987 The calculation of posterior distributions by data augmentation. Journal of the American Statistical Association 82: 528-540.
Gengler, N., P. Mayeres and M. Szydlowski, 2007 A simple method to approximate gene content in large pedigree populations: application to the myostatin gene in dual-purpose Belgian Blue cattle. animal 1: 21-28.
McPeek, M. S., X. Wu and C. Ober, 2004 Best linear unbiased allele-frequency estimation in complex pedigrees. Biometrics 60: 359-367. Christensen, O. F., 2012 Compatibility of pedigree-based and marker-based relationship matrices for single-step genetic evaluation. GENETICS SELECTION EVOLUTION 44: 37.
Lourenco, D., I. Misztal, S. Tsuruta, I. Aguilar, T. Lawlor et al., 2014 Are evaluations on young genotyped animals benefiting from the past generations? Journal of Dairy Science 97: 3930-3942.
Chen, C., I. Misztal, I. Aguilar, S. Tsuruta, S. Aggrey et al., 2011 Genome-wide marker-assisted selection combining all pedigree phenotypic information with genotypic data in one step: An example using broiler chickens. Journal of Animal Science 89: 23-28.
Vitezica, Z., I. Aguilar, I. Misztal and A. Legarra, 2011 Bias in genomic predictions for populations under selection. Genetics Research: In press.
Christensen, O. F., 2012 Compatibility of pedigree-based and marker-based relationship matrices for single-step genetic evaluation. GENETICS SELECTION EVOLUTION 44: 37.
Jacquard, A., 1970 Genetic structures of populations. Structures genetiques des populations.

## General review:

Legarra, A., O. F. Christensen, I. Aguilar and I. Misztal, 2014 Single Step, A General Approach For Genomic Selection. Livestock Science.


[^0]:    ${ }^{1}$ Cells with 0 are empty to show the pattern. Coefficients for genotyped animals are in bold. Matrix $\mathbf{A}_{\mathrm{g}}$ is obtained by setting the out-of-diagonal coefficients of genotyped animals to 0.7 .

