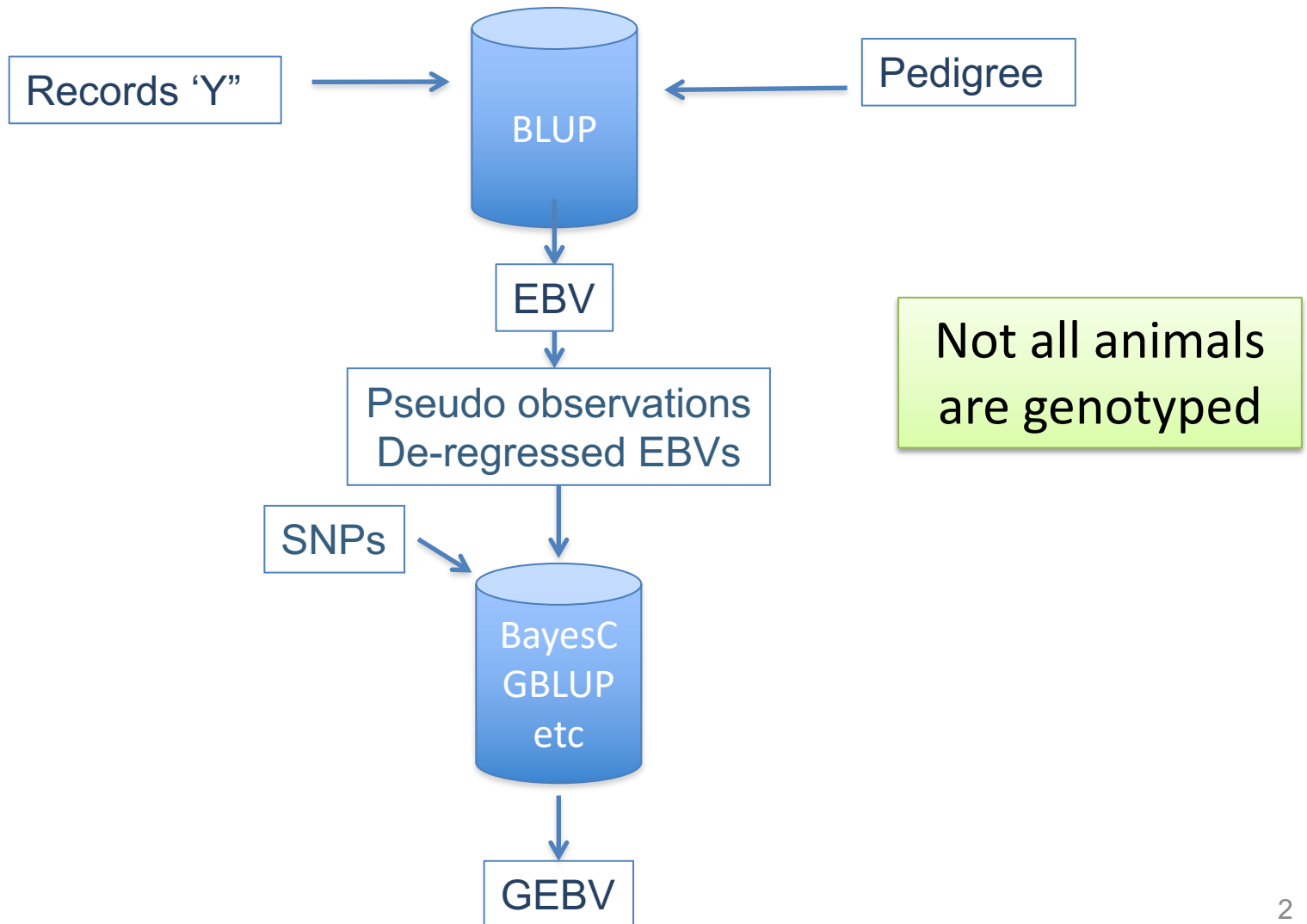


# Single Step GBLUP

# Multiple-step Genomic evaluation



# Genomic evaluation

- Estimate effect of all SNPs in the genome:

$$\begin{pmatrix} 2 \\ 12 \\ 8 \\ 6.2 \end{pmatrix} = \begin{pmatrix} -1 & 0 \\ 1 & -1 \\ 0 & -1 \\ -1 & -1 \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \begin{pmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \end{pmatrix}$$

BayesA, BayesB,  
BLUP-SNP, etc

Records

Genotypes

Marker  
effects

# Genomic evaluation

- What about records?

$$\begin{pmatrix} 2 \\ 12 \\ 8 \\ 6.2 \end{pmatrix} = \begin{pmatrix} -1 & 0 \\ 1 & -1 \\ 0 & -1 \\ -1 & -1 \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \end{pmatrix} + \begin{pmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \end{pmatrix}$$

**Records**

Genotypes

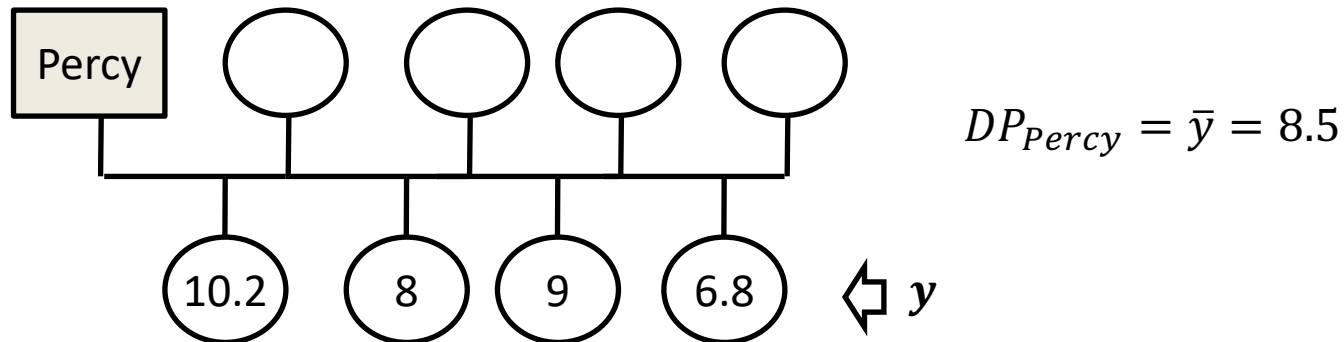
Marker effects

# Genomic evaluation

- What about records?
- We genotype key animals (breeding males and maybe females)
  - They may *not* have phenotype on their own
  - They also have progenies who could have phenotype but could not have genotype
- “Project” family phenotypes on genotyped animals
  - Deregressed Proofs, DYD, etc.
  - Let’s call this “DP”
- More easy said than done

# What about records ?

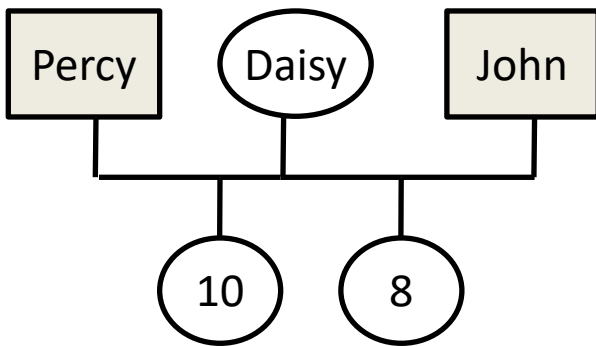
- Typical in dairy cattle: the male is “assigned” the performance of the daughters
- Similar to a sire model



- But to achieve more accuracy and to avoid selection bias, we need to correct for the dams' EBV and for the fixed effects
  - This is what we do in DEREGRESSION
- And corrections contain errors which pass on to deregressed proofs

# What about records ?

- Assume that Daisy EBV is overestimated as 6.4 (true BV is 4)



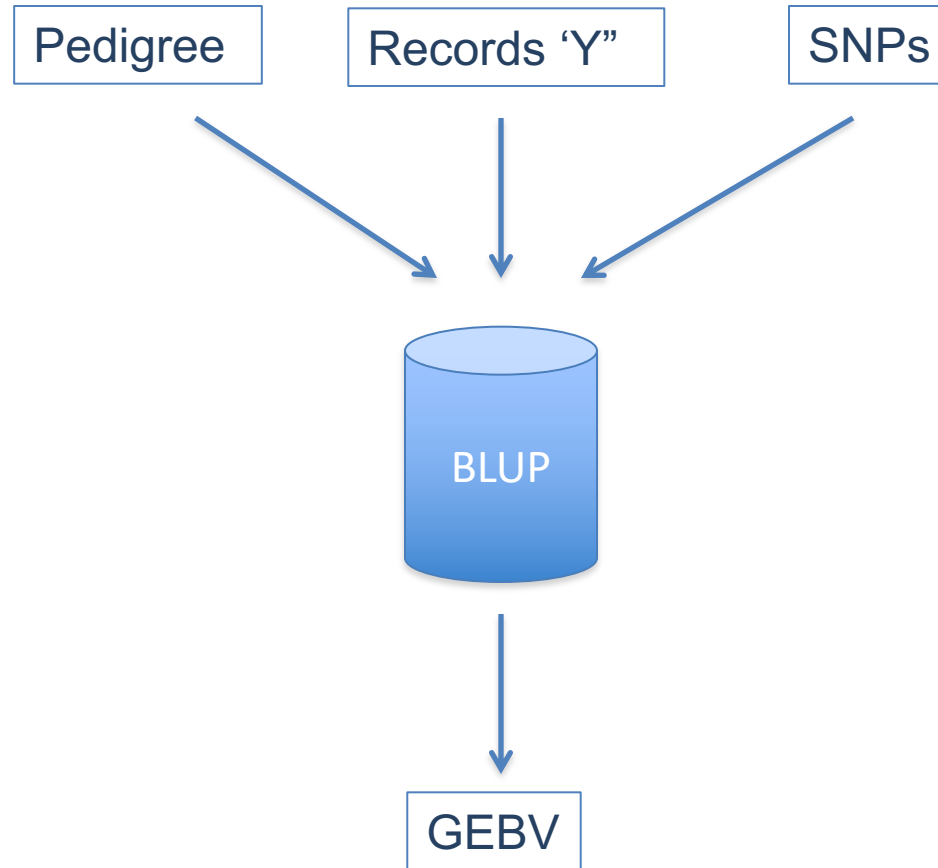
$$DP_{Percy} = 10 - 3.2 = 6.8$$

$$DP_{John} = 8 - 3.2 = 4.8$$

- Now both Percy and John are biased downwards !!
- Sometimes Daisy will be biased upwards and sometimes downwards
- Thus, the deregressed proofs of Percy and John will have a residual covariance
- This covariance is always ignored in practice
- The same problem exists when we correct by effects such as herd

# Single-Step Genomic Evaluation

Aguilar et al., 2010



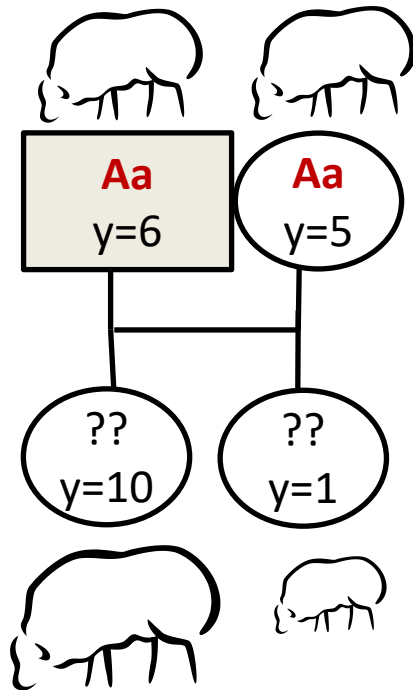


# Expand information

- We can do ONE evaluation if we “augment” information generating either
  - genotypes for all animals
  - **G** matrix for all animals
- Imputing algorithms (Beagle, Fimpute, AlphaImpute, etc.) are conceived to impute from low to high density
- For nongenotyped animals, they *may* give a point estimate of the genotype
- Why is this bad?

# Problem with point estimates of genotypes

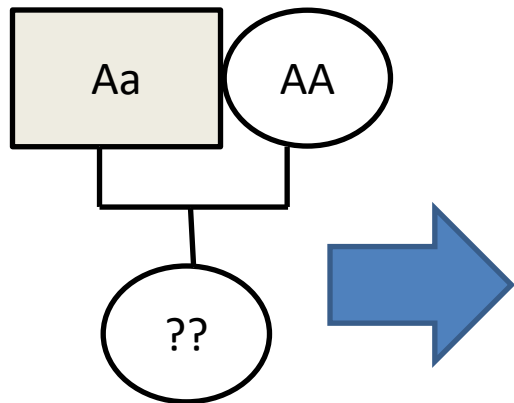
- Imagine a major gene



- Point estimate of genotype of the descendants: “Aa”
- Clearly, based on  $y$  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
- Christensen & Lund (2010) showed how to take the variation into account
- Genotype of descendants = half their parents + Mendelian sampling



{ AA with probability  $\frac{1}{2}$   
Aa with probability  $\frac{1}{2}$

$$\text{Prediction of Genotype} = \frac{3}{2} "A" + \frac{1}{2} "a"$$

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

# Missing data

Fill-in missing data: data augmentation

- Augmenting = adding genotypes
- But we need to account for the fact that these are « guesses »

# 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 (if not the procedure does not work)



$$\text{Let } \mathbf{A} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{bmatrix}$$

*non genotyped* *genotyped*

# Inferring genotypes

- There is Gengler's gene content prediction J. Dairy Sci. 91:1652
  - Linear approximation to the imputation problem
    - This method can be applied to any member of a pedigree
- Using centered gene content:

$$\hat{\mathbf{Z}}_1 = \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{Z}_2$$

- Christensen and Lund realized that

$$Var(\hat{\mathbf{Z}}_1|\mathbf{Z}_2) = (\mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21})\mathbf{V}$$

where  $\mathbf{V}$  contains  $2p_kq_k$  in the diagonal



# Inferring genotypes

- Instead of working with individual SNP effects, we will define
  - $\mathbf{u} = \mathbf{Z}\mathbf{a}$
  - i.e., the genetic value is the sum of SNP effects
  - We're not really interested in  $\mathbf{a}$  themselves but in  $\mathbf{u}$  (we know from GBLUP that we can jump from one to the other)
  - Moreover, we're interested in the distribution of  $\mathbf{u}$ 's, so that we can compute their covariances and put them into the MME

## Christensen & Lund key idea:

$$\mathbf{u} = \begin{pmatrix} \mathbf{u}_2 \\ \mathbf{u}_1 \end{pmatrix} = \begin{pmatrix} \mathbf{Z}_2 \\ \mathbf{Z}_1 \end{pmatrix} \mathbf{a}$$

Breeding values

SNP effects

1= « non genotyped »  
2= « genotyped »

Re-create GBLUP...

Christensen & Lund use  $Var(\mathbf{a}) = E(Var(\mathbf{a}|\mathbf{B})) + Var(E(\mathbf{a}|\mathbf{B}))$  to consider the prediction of the genotype and its variance

$$Var(\mathbf{u}) = \begin{pmatrix} \mathbf{Z}_2 \\ \hat{\mathbf{Z}}_1 \end{pmatrix} Var(\mathbf{a}) \begin{pmatrix} \mathbf{Z}_2' & \hat{\mathbf{Z}}_1' \end{pmatrix} + \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & Var(\hat{\mathbf{Z}}_1) \end{pmatrix} Var(\mathbf{a})$$

$E(\mathbf{Z}_1|\mathbf{Z}_2)$

$1/2 \sum p_i q_i$

$Var(\mathbf{Z}_1|\mathbf{Z}_2)$

Using Gengler's results

Resulting in:



# Covariances of all animals

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

$$\text{Var} \begin{pmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{pmatrix} = \mathbf{H} = \begin{bmatrix} \mathbf{H}_{11} & \mathbf{H}_{12} \\ \mathbf{H}_{21} & \mathbf{H}_{22} \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} + \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G} \\ \mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{G} \end{bmatrix}}_{\text{genotyped}}$$

*non genotyped*

Let  $\mathbf{A} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} \\ \mathbf{A}_{21} & \mathbf{A}_{22} \end{bmatrix}$

*non genotyped*

# Covariances of all animals

$$\text{Var} \begin{pmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{pmatrix} = \mathbf{H} = \begin{bmatrix} \mathbf{H}_{11} & \mathbf{H}_{12} \\ \mathbf{H}_{21} & \mathbf{H}_{22} \end{bmatrix} = \left[ \begin{array}{c|c} \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} + \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G} \\ \hline \mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{G} \end{array} \right]$$

This is the variance of prediction of genotypes *from* genotyped *to* non-genotyped

This is the error in the prediction

The prediction « generates » a covariance

$\mathbf{G}$  comes from genotypes

$$Var\begin{pmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{pmatrix} = \mathbf{H} = \begin{bmatrix} \mathbf{H}_{11} & \mathbf{H}_{12} \\ \mathbf{H}_{21} & \mathbf{H}_{22} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} + \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G} \\ \mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{G} \end{bmatrix}$$

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

$$\mathbf{H}^{-1} = \mathbf{A}^{-1} + \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^{-1} - \mathbf{A}_{22}^{-1} \end{bmatrix}$$

...and avoiding « double counting »

Inverse of the regular pedigree relationship matrix

Correcting for genomic 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)

# Overall modification

- Look at **A** as a « prior » relationship and to **G** as an « observed » relationship
  - **G** is observed for some individuals only, whose « a priori » relationship matrix was **A**<sub>22</sub>
- Try to construct a « posterior » relationship matrix

# Joint distributions

Unconditional distribution of genetic values of Genotyped individuals

$$p(\mathbf{u}_2) = N(\mathbf{0}, \mathbf{G}) \text{ and}$$

After seeing their genotypes !

Conditional distribution of Non-Genotyped individuals

$$p(\mathbf{u}_1 | \mathbf{u}_2) = N(\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{u}_2, \mathbf{A}_{11} - \mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21})$$

Because they have no genotypes, this depends only on pedigree

$$p(\mathbf{u}_1, \mathbf{u}_2) = p(\mathbf{u}_2) p(\mathbf{u}_1 | \mathbf{u}_2)$$

**Joint distribution**

# Joint distributions

$$p(\mathbf{u}_1, \mathbf{u}_2) = p(\mathbf{u}_1 | \mathbf{u}_2) p(\mathbf{u}_2)$$

$$= p(\mathbf{u}_1 | \mathbf{u}_2) p(\mathbf{u}_2)$$

prediction of non genotyped  
from genotyped

"Genomic"  
relationships

$$\propto \exp[-0.5(\mathbf{u}_1 - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{u}_2)' \mathbf{A}^{11}(\mathbf{u}_1 - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{u}_2)] \exp[-0.5\mathbf{u}_2' \mathbf{G}^{-1}\mathbf{u}_2]$$

$$= \exp \left( -0.5 \begin{bmatrix} \mathbf{u}_1' & \mathbf{u}_2' \end{bmatrix} \begin{bmatrix} \mathbf{A}^{11} & -\mathbf{A}^{11}\mathbf{A}_{12}\mathbf{A}_{22}^{-1} \\ -\mathbf{A}_{22}^{-1}\mathbf{A}_{21}\mathbf{A}^{11} & \mathbf{G}^{-1} + \mathbf{A}_{22}^{-1}\mathbf{A}_{21}\mathbf{A}^{11}\mathbf{A}_{12}\mathbf{A}_{22}^{-1} \end{bmatrix} \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{bmatrix} \right)$$

$$= \exp \left( -0.5 \begin{bmatrix} \mathbf{u}_1' & \mathbf{u}_2' \end{bmatrix} \begin{bmatrix} \mathbf{A}^{11} & \mathbf{A}^{12} \\ \mathbf{A}^{21} & \mathbf{G}^{-1} + \mathbf{A}^{22} - \mathbf{A}_{22}^{-1} \end{bmatrix} \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{bmatrix} \right).$$

...for those inclined to algebra

# Joint distributions

$$p(\mathbf{u}_2) = N(\mathbf{0}, \mathbf{G})$$

$$p(\mathbf{u}_1 | \mathbf{u}_2) = N(\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{u}_2, \mathbf{A}_{11} - \mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21})$$



# Joint distributions

$$p(\mathbf{u}_2) = N(\mathbf{0}, \mathbf{G}) \quad \longrightarrow \quad \text{Var}(\mathbf{u}_2) = \mathbf{G}$$

$$p(\mathbf{u}_1 | \mathbf{u}_2) = N(\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{u}_2, \mathbf{A}_{11} - \mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21})$$

# Joint distributions

$$p(\mathbf{u}_2) = N(\mathbf{0}, \mathbf{G}) \quad \longrightarrow \quad \text{Var}(\mathbf{u}_2) = \mathbf{G}$$

$$p(\mathbf{u}_1 | \mathbf{u}_2) = N\left(\underbrace{\mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{u}_2}_{\text{mean}}, \underbrace{\mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21}}_{\text{covariance}}\right)$$

$$\text{Var}(\mathbf{u}_1) = \underbrace{\mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21}}_{\text{from conditional cov}} + \underbrace{\mathbf{A}_{12}\mathbf{A}_{22}^{-1}}_{\text{from conditional mean}} \mathbf{G} \mathbf{A}_{22}^{-1} \mathbf{A}_{21}$$

because  $\text{Var}(\mathbf{Xt}) = \mathbf{X}\text{Var}(\mathbf{t})\mathbf{X}'$

# Joint distributions

$$p(\mathbf{u}_2) = N(\mathbf{0}, \mathbf{G}) \quad \longrightarrow \quad \text{Var}(\mathbf{u}_2) = \mathbf{G}$$

$$p(\mathbf{u}_1 | \mathbf{u}_2) = N\left(\underbrace{\mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{u}_2}_{\text{Cov}(\mathbf{u}_1, \mathbf{u}_2)}, \mathbf{A}_{11} - \mathbf{A}_{12} \mathbf{A}_{22}^{-1} \mathbf{A}_{21}\right)$$

$$\text{Cov}(\mathbf{u}_1, \mathbf{u}_2) = \underbrace{\mathbf{A}_{12} \mathbf{A}_{22}^{-1}}_{\text{Cov}(\mathbf{u}_1, \mathbf{u}_2)} \mathbf{G}$$

because  $\text{Cov}(\mathbf{X}\mathbf{t}, \mathbf{t}) = \mathbf{X}\text{Var}(\mathbf{t})$

# Covariances of all animals

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

$$\text{Var} \begin{pmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{pmatrix} = \mathbf{H} = \begin{bmatrix} \mathbf{H}_{11} & \mathbf{H}_{12} \\ \mathbf{H}_{21} & \mathbf{H}_{22} \end{bmatrix} = \underbrace{\begin{bmatrix} \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} + \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G} \\ \mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{G} \end{bmatrix}}_{\text{genotyped}}$$

$$\text{Var} \begin{pmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{pmatrix} = \mathbf{H} = \begin{bmatrix} \mathbf{H}_{11} & \mathbf{H}_{12} \\ \mathbf{H}_{21} & \mathbf{H}_{22} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{11} - \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} + \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{A}_{12}\mathbf{A}_{22}^{-1}\mathbf{G} \\ \mathbf{G}\mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{G} \end{bmatrix}$$

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

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Inverse of the regular pedigree relationship matrix

Correcting for genomic relationships...

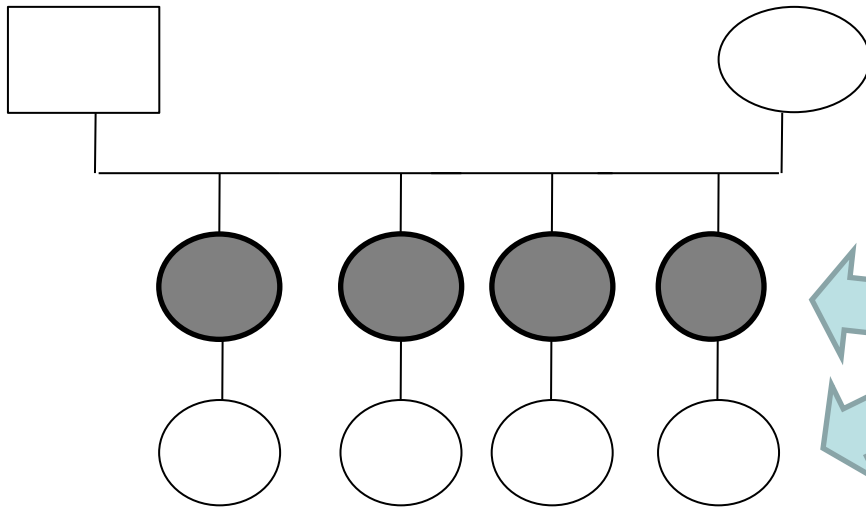


# Understanding H matrix

- It is a projection of **G** matrix on the rest of individuals “so that” **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
  - **A**<sup>-1</sup> in the millions but extremely sparse
  - **G** and **A**<sub>22</sub> in the thousands
  - Leads to a very efficient method of genomic evaluation:
    - Single Step GBLUP

# Examples on H matrix

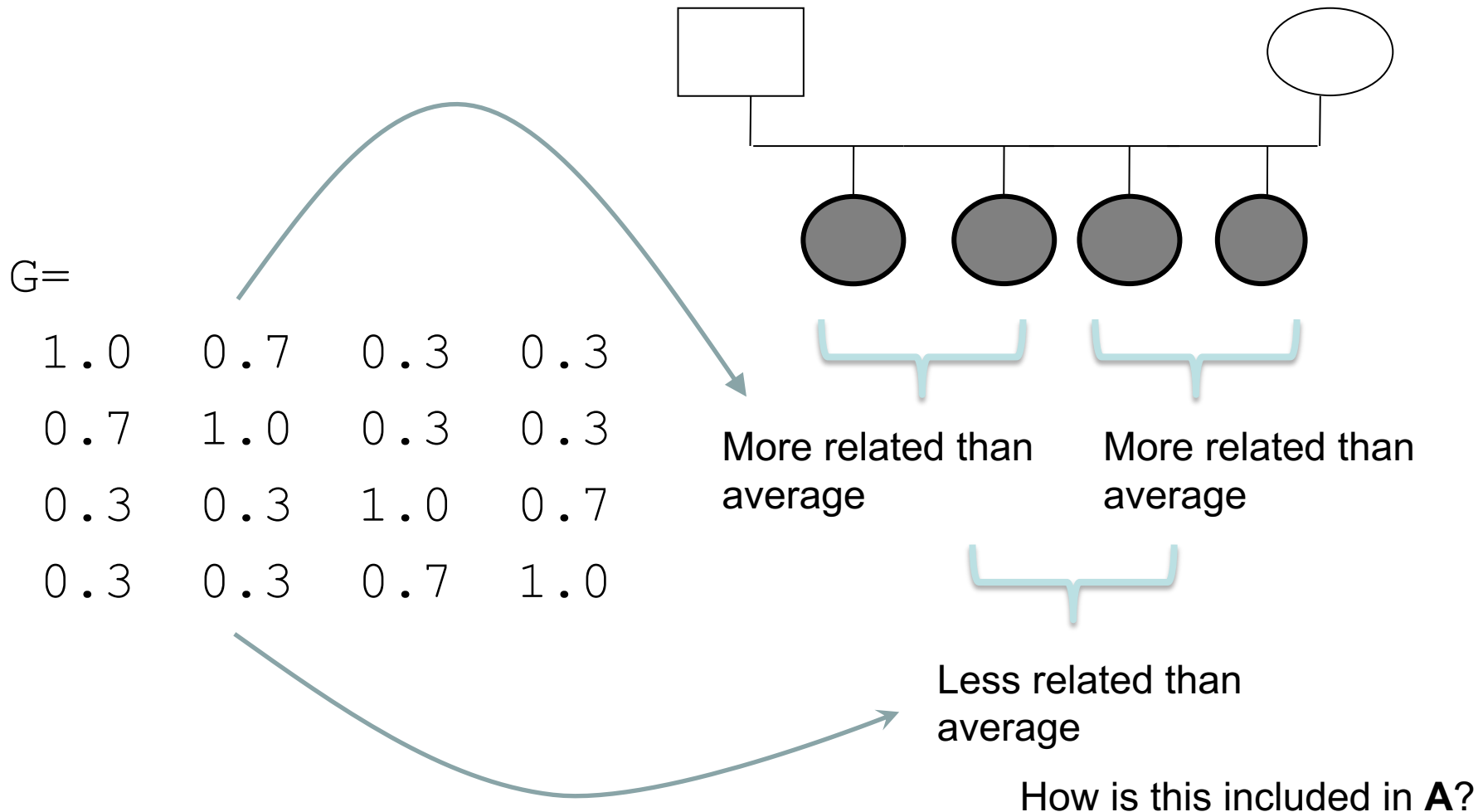
- Consider 4 full-sibs with one progeny each



- With pedigree, sibs are related by 0.5
- their offspring are cousins with a relationship of 0.125
- The 0.5 assumes infinite unlinked loci, with actual genomes relationship varies:  $0.5 \pm 0.05$



- Pedigree; grey is genotyped



# Classical A (pedigree)

1.00	0.00	0.50	0.50	0.50	0.50	0.25	0.25	0.25	0.25
0.00	1.00	0.50	0.50	0.50	0.50	0.25	0.25	0.25	0.25
0.50	0.50	1.00	0.50	0.50	0.50	0.50	0.25	0.25	0.25
0.50	0.50	0.50	1.00	0.50	0.50	0.25	0.50	0.25	0.25
0.50	0.50	0.50	0.50	1.00	0.50	0.25	0.25	0.50	0.25
0.50	0.50	0.50	0.50	0.50	1.00	0.25	0.25	0.25	0.50
0.25	0.25	0.50	0.25	0.25	0.25	1.00	0.12	0.12	0.12
0.25	0.25	0.25	0.50	0.25	0.25	0.12	1.00	0.12	0.12
0.25	0.25	0.25	0.25	0.50	0.25	0.12	0.12	1.00	0.12
0.25	0.25	0.25	0.25	0.25	0.50	0.12	0.12	0.12	1.00

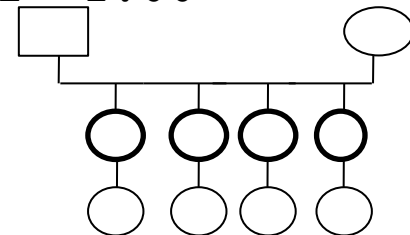


Full-sibs is 0.50



Cousins is 0.125

Uncle-nephew is 0.25



# H (pedigree + markers)

1.00	0.00	0.50	0.50	0.50	0.50	0.25	0.25	0.25	0.25
0.00	1.00	0.50	0.50	0.50	0.50	0.25	0.25	0.25	0.25
0.50	0.50	1.00	0.70	0.30	0.30	0.50	0.35	0.15	0.15
0.50	0.50	0.70	1.00	0.30	0.30	0.35	0.50	0.15	0.15
0.50	0.50	0.30	0.30	1.00	0.70	0.15	0.15	0.50	0.35
0.50	0.50	0.30	0.30	0.70	1.00	0.15	0.15	0.35	0.50
0.25	0.25	0.50	0.35	0.15	0.15	1.00	0.17	0.07	0.07
0.25	0.25	0.35	0.50	0.15	0.15	0.17	1.00	0.07	0.07
0.25	0.25	0.15	0.15	0.50	0.35	0.07	0.07	1.00	0.17
0.25	0.25	0.15	0.15	0.35	0.50	0.07	0.07	0.17	1.00

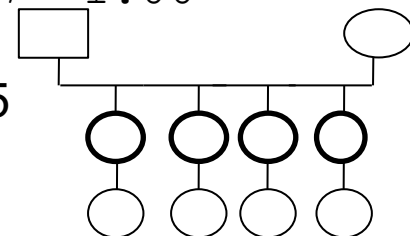


Full-sibs is  $0.70 - 0.30$

Uncle-nephew is  $0.35 - 0.15$



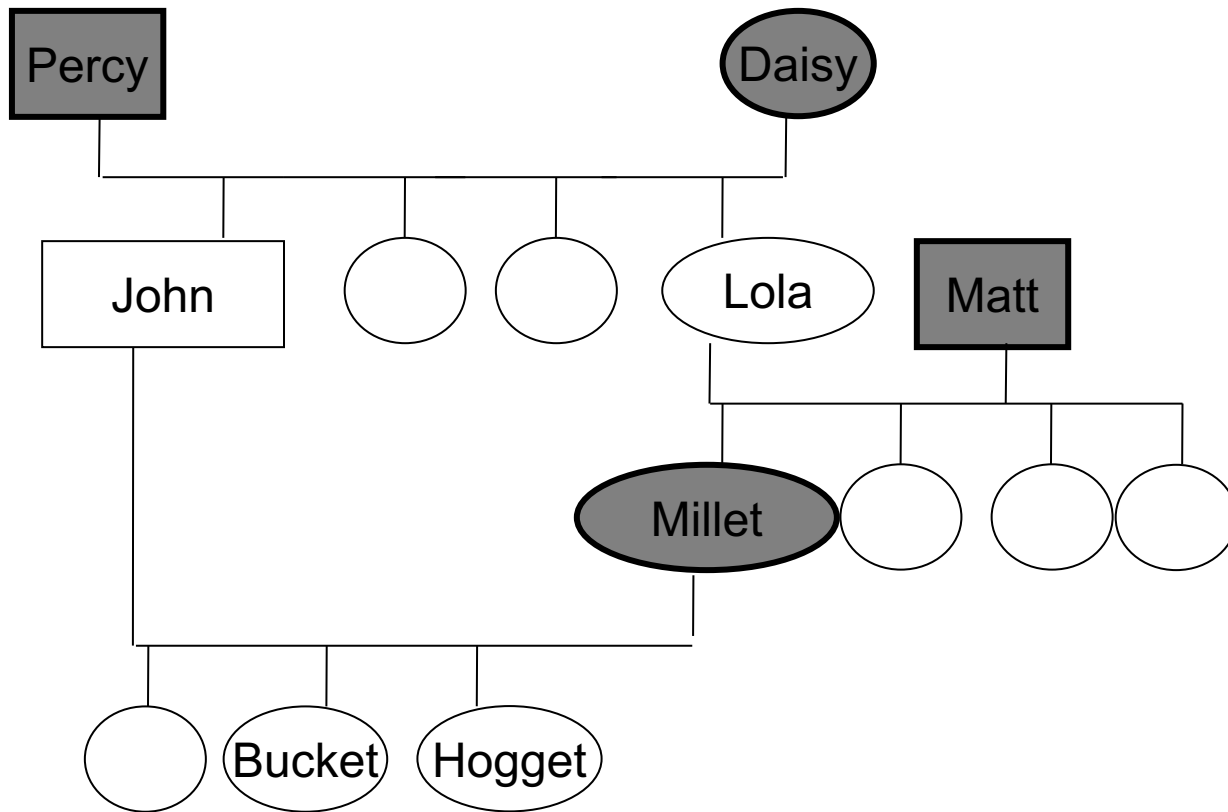
Cousins is  $0.17 - 0.07$



We have extended genomic relationships to all the pedigree

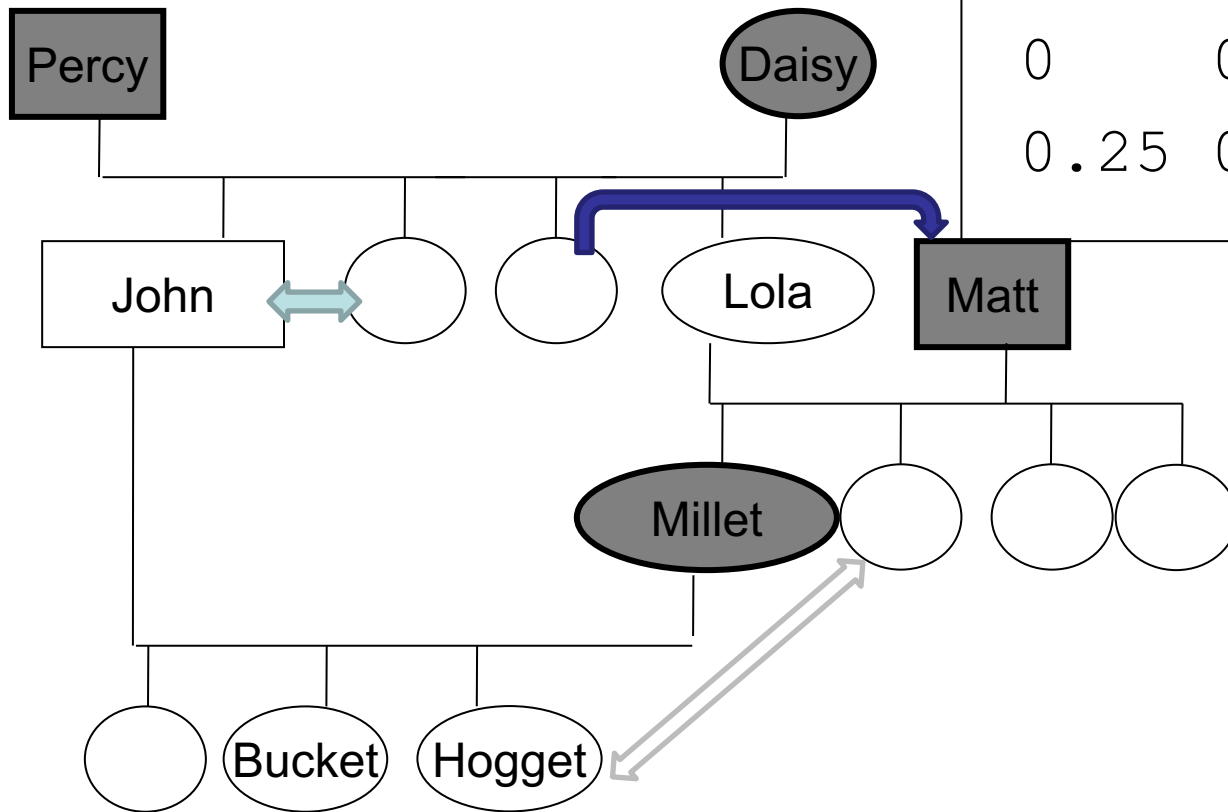
# More complex example

- Pedigree; grey is genotyped



# More complex example

- Before genotyping

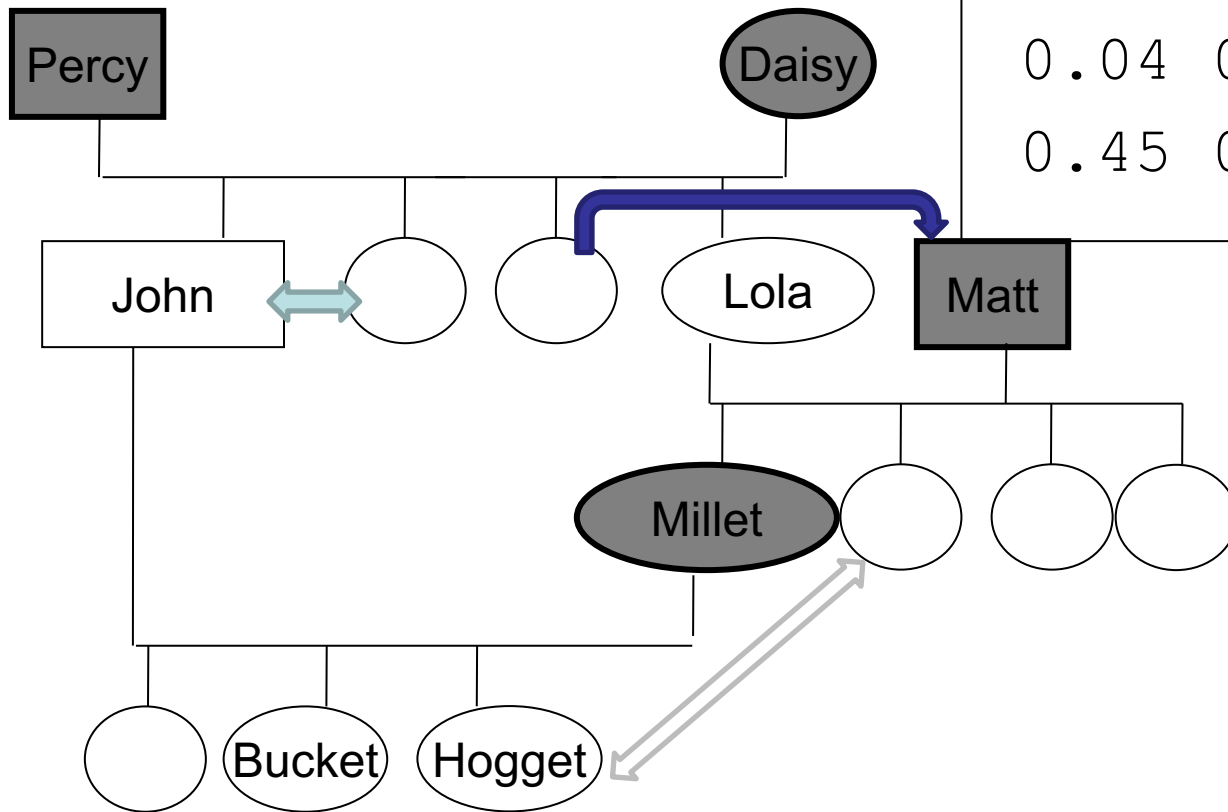


$A_{22} =$

1.00	0	0	0.25
0	1	0	0.25
0	0	1	0.50
0.25	0.25	0.50	1.00

# More complex example

- After genotyping



**G=**

1.13	0.08	0.04	0.45
0.08	0.91	0.14	0.32
0.04	0.14	1.12	0.62
0.45	0.32	0.62	1.10

# Classical A (pedigree)

1.00	0.00	0.00	0.50	0.50	0.50	0.5	0.25	0.25	0.25	0.25	0.38	0.38	0.38
0.00	1.00	0.00	0.50	0.50	0.50	0.5	0.25	0.25	0.25	0.25	0.38	0.38	0.38
0.00	0.00	1.00	0.00	0.00	0.00	0.0	0.50	0.50	0.50	0.50	0.25	0.25	0.25
0.50	0.50	0.00	1.00	0.50	0.50	0.5	0.25	0.25	0.25	0.25	0.62	0.62	0.62
0.50	0.50	0.00	0.50	1.00	0.50	0.5	0.25	0.25	0.25	0.25	0.38	0.38	0.38
0.50	0.50	0.00	0.50	0.50	1.00	0.5	0.25	0.25	0.25	0.25	0.38	0.38	0.38
0.50	0.50	0.00	0.50	0.50	0.50	1.0	0.50	0.50	0.50	0.50	0.50	0.50	0.50
0.25	0.25	0.50	0.25	0.25	0.25	0.5	1.00	0.50	0.50	0.50	0.62	0.62	0.62
0.25	0.25	0.50	0.25	0.25	0.25	0.5	0.50	1.00	0.50	0.50	0.38	0.38	0.38
0.25	0.25	0.50	0.25	0.25	0.25	0.5	0.50	0.50	1.00	0.50	0.38	0.38	0.38
0.25	0.25	0.50	0.25	0.25	0.25	0.5	0.50	0.50	0.50	1.00	0.38	0.38	0.38
0.38	0.38	0.25	0.62	0.38	0.38	0.5	0.62	0.38	0.38	0.38	1.12	0.62	0.62
0.38	0.38	0.25	0.62	0.38	0.38	0.5	0.62	0.38	0.38	0.38	0.62	1.12	0.62
0.38	0.38	0.25	0.62	0.38	0.38	0.5	0.62	0.38	0.38	0.38	0.62	0.62	1.12



Full-sibs is 0.50

Uncle-nephew is 0.38



Unrelated is 0

# H (pedigree + markers)

1.13	0.08	0.04	0.60	0.60	0.60	0.65	0.45	0.34	0.34	0.34	0.52	0.52	0.52
0.08	0.91	0.14	0.50	0.50	0.50	0.50	0.32	0.32	0.32	0.32	0.41	0.41	0.41
0.04	0.14	1.12	0.09	0.09	0.09	0.09	0.62	0.61	0.61	0.61	0.35	0.35	0.35
0.60	0.50	0.09	1.05	0.55	0.55	0.58	0.38	0.33	0.33	0.33	0.72	0.72	0.72
0.60	0.50	0.09	0.55	1.05	0.55	0.58	0.38	0.33	0.33	0.33	0.47	0.47	0.47
0.60	0.50	0.09	0.55	0.55	1.05	0.58	0.38	0.33	0.33	0.33	0.47	0.47	0.47
0.65	0.50	0.09	0.58	0.58	0.58	1.09	0.62	0.59	0.59	0.59	0.60	0.60	0.60
0.45	0.32	0.62	0.38	0.38	0.38	0.62	1.10	0.62	0.62	0.62	0.74	0.74	0.74
0.34	0.32	0.61	0.33	0.33	0.33	0.59	0.62	1.10	0.60	0.60	0.48	0.48	0.48
0.34	0.32	0.61	0.33	0.33	0.33	0.59	0.62	0.60	1.10	0.60	0.48	0.48	0.48
0.34	0.32	0.61	0.33	0.33	0.33	0.59	0.62	0.60	0.60	1.10	0.48	0.48	0.48
0.52	0.41	0.35	0.72	0.47	0.47	0.60	0.74	0.48	0.48	0.48	1.23	0.73	0.73
0.52	0.41	0.35	0.72	0.47	0.47	0.60	0.74	0.48	0.48	0.48	0.73	1.23	0.73
0.52	0.41	0.35	0.72	0.47	0.47	0.60	0.74	0.48	0.48	0.48	0.73	0.73	1.23



Full-sibs is 0.55

Uncle-nephew is 0.48



“Unrelated” is 0.14 ➡ Because pedigree founders are related in **G**



# Some properties of $\mathbf{H}$

- Semi-positive definite always
- Positive definite & invertible iff  $\mathbf{G}$  is invertible
- In practice, if  $\mathbf{G}$  is too different (wrong pedigree or genotyping) from  $\mathbf{A}_{22}$ , this gives lots of numerical problems
- If everyone is genotyped, Single Step is GBLUP
- If no one is genotyped, Single Step is BLUP

# H matrix

- H is then a relationship matrix constructed with markers and pedigree
- But Henderson taught us how to use relationship matrices of any kind

# Single step GBLUP

Single Step = Your regular BLUP with small modifications

**W**: incidence matrix of animals on data

$$\begin{bmatrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{X}'\mathbf{R}^{-1}\mathbf{W} \\ \mathbf{W}\mathbf{R}^{-1}\mathbf{X} & \mathbf{W}\mathbf{R}^{-1}\mathbf{W} + \mathbf{H}^{-1}\sigma_u^{-2} \end{bmatrix} \begin{bmatrix} \hat{\mathbf{b}} \\ \hat{\mathbf{u}} \end{bmatrix} = \begin{bmatrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{y} \\ \mathbf{W}\mathbf{R}^{-1}\mathbf{y} \end{bmatrix}$$

$$\mathbf{H}^{-1} = \mathbf{A}^{-1} + \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^{-1} - \mathbf{A}_{22}^{-1} \end{bmatrix}$$

**A**: pedigree relationship matrix

**A**<sub>22</sub>: pedigree matrix among genotyped individuals

**G**

This **G** could be *any* matrix describing « genomic » covariances of breeding values;  
it does not restrict to VanRaden's (2008) GBLUP

# Single step GBLUP

- So the Single Step GBLUP is like regular BLUP changing one small submatrix !!!
- It is almost too simple to be true...

# Single Step GBLUP

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

$$\hat{\mathbf{a}} = \frac{\mathbf{Z}' \mathbf{G}^{-1} \hat{\mathbf{u}}_2}{2 \sum pq}$$

- Avoids selection bias due to genomic preselection  
(Patry & Ducrocq, 2011)

# Single Step GBLUP

- What models have we fit so far in SSGBLUP?
  - Multiple traits ( up to 18 so far)
  - Multiple trait + correlated genetic maternal effects (beef cattle)
  - Random regressions (lactation curves)
  - Threshold (probit) models
  - Horse rankings (Thurstonian model)
- *Anything* that was fit in BLUP can be fit in SSGBLUP, changing **A** to **H**