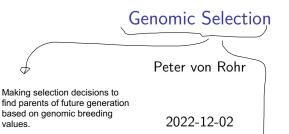
So far:

\* Using predicted breeding values as selection criteria to find parents of future generations using all available <u>phenotypic</u> information together with <u>pedigree</u> relationships.

\* Used linear mixed effect models to get to predicted breeding values

Traditional approach



use marker information on a large scale to predict breeding values

Shift in paradigm, mainly in cattle breeding

#### Introduction

\* Meuwissen et al. (2001): How to use total genotypic values for prediction of breeding values.

\* Genotypic values (V\_{ij}) for a single locus model: with values

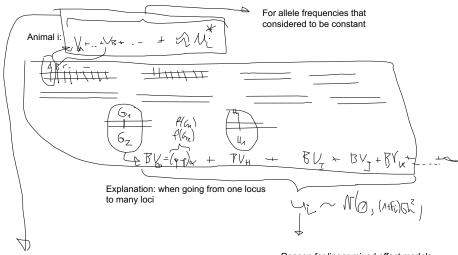
G162 + 01

- ► Proposed in 2001
- ▶ Widely adopted in 2007/2008
- Costs of breeding program reduced due to shorter generation intervals
- In cattle: young sire selection versus selection based on sire proofs
- ▶ In pigs: early selection among full sibbs
- ► Inbreeding must be considered

accurate predictions at very young ages

By consequently basing selection decisions on genomics|breeding values, costs of a cattle breeding program could be reduced by about 90%

Cattle: As soon as calf is born, a hair sample taken and is sent to the lab and after 2-4 weeks, genomic breeding values are available. Reliabilities range between 30-50%



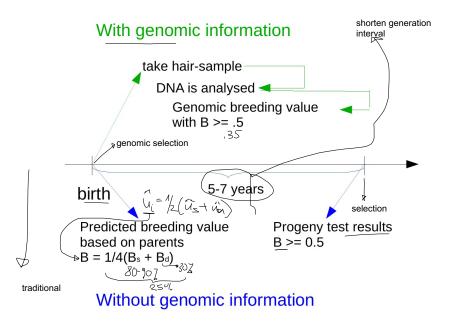
Reason for linear mixed effect models

The idea of Meuwissen allows to use fixed linear effect models

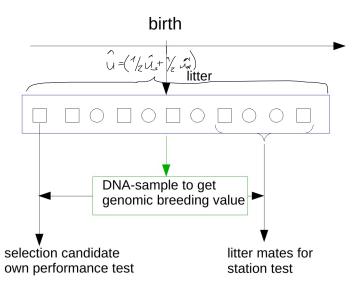
## **Terminology**

- ► **Genomic Selection**: use of genomic Information for selection decisions
- Genomic Information is used to predict genomic breeding values

#### Benefits in Cattle

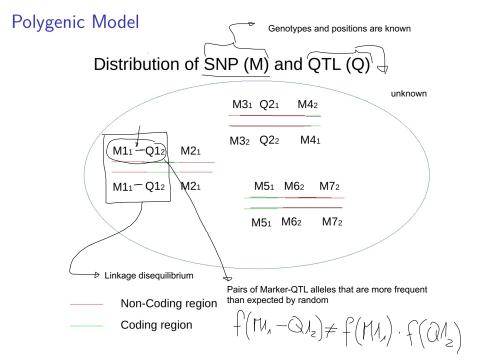


# Benefits in Pigs



#### Genetic Model

- Recall: BLUP animal model is based on infinitesimal model
- Prediction of genomic breeding values is based on polygenic model
- ► In polygenic model: Single Nucleotide Polymorphisms (SNP) are used as markers
- Marker genotypes are expected to be associated with genotypes of Quantitative Trait Loci (QTL)



### Statistical Models



Two types of models are used

- 1. marker-effect models (MEM)
- 2. genomic-breeding-value based models (BVM)

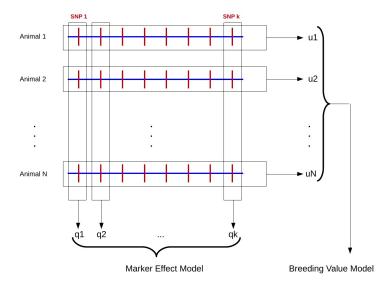
MEM fixed effect
$$y_{i} = M + \beta_{1} \cdot a_{1} + \beta_{2} \cdot a_{2} + \dots + \beta_{k} \cdot a_{k} + \varepsilon_{i}$$

- marker effects (a-values) are fitted using
  - ightharpoonup a simple linear model ightharpoonup marker effects are fixed
  - lacktriangle a linear mixed effects model ightarrow marker effects are random
- Problem of finding which markers are associated to QTL
- ► With high number of SNP compared to number of genotyped animals: very large systems of equations to solve

### **BVM**

- genomic breeding values as random effects
- similar to animal model
- genomic relationship matrix (G) instead of numerator relationship matrix (A)

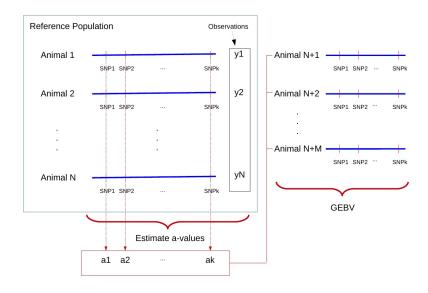
#### MEM versus BVM



### Logistic Procedures

- ► Two Step:
  - use reference population to get marker effects using MEM
  - use marker effects to get to genomic breeding values
- ► Single Step
  - MEM or BVM in a single evaluation
  - difficulty how to combine animals with and without genotypes

## Two Step Procedure



# Single Step GBLUP

- Use a mixed linear effect model
- ightharpoonup Genomic breeding values g are random effects

$$y = Xb + Zg + e$$

with

- ► E(e) = 0,  $var(e) = I * \sigma_e^2$
- ► E(g) = 0,  $var(g) = G * \sigma_g^2$
- Genomic relationship matrix G

## Solution Via Mixed Model Equations

► All animals have genotypes and observations

$$\begin{bmatrix} X^T X & X^T Z \\ Z^T X & Z^T Z + \lambda * G^{-1} \end{bmatrix} \begin{bmatrix} \hat{b} \\ \hat{g} \end{bmatrix} = \begin{bmatrix} X^T y \\ Z^T y \end{bmatrix}$$

with  $\lambda = \sigma_e^2/\sigma_g^2$ .

#### Animals Without Observations

- Young animals do not have observations
- Partition  $\hat{g}$  into
  - $ightharpoonup \hat{g}_1$  animals with observations and
  - $ightharpoonup \hat{g}_2$  animals without observations
- lacktriangle Resulting Mixed Model Equations are (assume  $\lambda=1$ )

$$\begin{bmatrix} X^T X & X^T Z & 0 \\ Z^T X & Z^T Z + G^{(11)} & G^{(12)} \\ 0 & G^{(21)} & G^{(22)} \end{bmatrix} \begin{bmatrix} \hat{b} \\ \hat{g}_1 \\ \hat{g}_2 \end{bmatrix} = \begin{bmatrix} X^T y \\ Z^T y \\ 0 \end{bmatrix}$$

Predicted Genomic Breeding Values

Last line of Mixed model equations

$$G^{(21)}\cdot \hat{g}_1+G^{(22)}\cdot \hat{g}_2=0$$

### Solutions

► Solving for  $\hat{g}_2$ 

$$\hat{g}_2 = -(G^{(22)})^{-1} \cdot G^{(21)} \cdot \hat{g}_1$$

## Genomic Relationship Matrix

- Breeding value model uses genomic breeding values g as random effects
- ▶ Variance-covariance matrix of g are proposed to be proportional to matrix G

$$var(g) = G * \sigma_g^2$$

where G is called **genomic relationship matrix** (GRM)

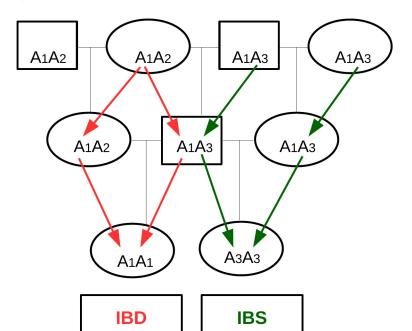
### Properties of *G*

- genomic breeding values g are linear combinations of q
- ightharpoonup g as deviations, that means E(g)=0
- ightharpoonup var(g) as product between G and  $\sigma_g^2$  where G is the genomic relationship matrix
- G should be similar to A

## Change of Identity Concept

- ► A is based on identity by descent
- ► *G* is based on identity by state (including ibd), assuming that the same allele has the same effect
- IBS can only be observed with SNP-genotype data

## Identity



#### Linear Combination

- ► SNP marker effects (a values) from marker effect model are in vector q
- Genomic breeding values from breeding value model are determined by

$$g = U \cdot q$$

Matrix U is determined by desired properties of g

#### Deviation

 Genomic breeding values are defined as deviation from a certain basis

$$\rightarrow E(g) = 0$$

▶ How to determine matrix U such that E(g) = 0

## Equivalence Between Models

Decomposition of phenotypic observation  $y_i$  with

► Marker effect model

$$y_i = w_i^T \cdot q + e_i$$

Breeding value model

$$y_i = g_i + e_i$$

▶  $g_i$  and  $w_i^T \cdot q$  represent the same genetic effects and should be equivalent in terms of variability

## **Expected Values**

- ightharpoonup Required:  $E(g_i) = 0$
- ightharpoonup Take q as constant SNP effects
- Assume  $w_i$  to be the random variable with:

$$w_i = \left\{egin{array}{ll} 1 & ext{with probability} & p^2 \ 0 & ext{with probability} & 2p(1-p) \ -1 & ext{with probability} & (1-p)^2 \end{array}
ight.$$

 $\rightarrow E(w_i)$ : For a single locus

$$E(w_i) = 1 * p^2 + 0 * 2p(1-p) + (-1)(1-p)^2 = p^2 - 1 + 2p - p^2 = 2p - 1 \neq 0$$

# Specification of g

Set

$$g_i = (w_i^T - s_i^T) \cdot q$$

with  $s_i = E(w_i) = 2p - 1$ 

Resulting in

$$g = U \cdot q = (W - S) \cdot q$$

with matrix S having columns j with all elements equal to  $2p_j-1$  where  $p_j$  is the allele frequency of the SNP allele associated with the positive effect.

#### Genetic Variance

- Requirement:  $var(g) = G * \sigma_g^2$
- ▶ Result from Gianola et al. (2009):

$$\sigma_g^2 = \sigma_q^2 * \sum_{i=1}^k (1 - 2p_i(1 - p_i))$$

From earlier:  $g = U \cdot q$ 

$$var(g) = var(U \cdot q) = U \cdot var(q) \cdot U^{T} = UU^{T}\sigma_{q}^{2}$$

Combining

$$var(g) = UU^{T}\sigma_{q}^{2} = G * \sigma_{q}^{2} * \sum_{i=1}^{k} (1 - 2p_{i}(1 - p_{i}))$$

# Genomic Relationship Matrix

$$G = rac{UU^T}{\sum_{j=1}^k (1 - 2p_j(1 - p_j))}$$

# How To Compute G

- Read matrix W
- For each column j of W compute frequency  $p_j$
- ► Compute matrix S and  $\sum_{j=1}^{k} (1 2p_j(1 p_j))$  from  $p_j$
- Compute U from W and S
- Compute G