

Introduction to Mixed Linear Models

Vincent Ducrocq

GABI, Jouy-en-Josas
France



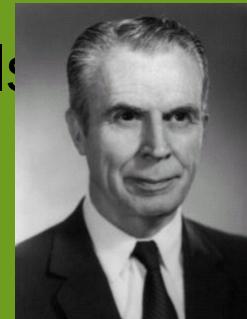
Historical aspects

- A long time ago...
 - Selection / genetic improvement of livestock = visual appreciation
 - creation of dairy cattle breeds in Europe : 19th century
- Early 20th century: milk recording starts in Europe (Denmark)
 - « selection criterion »: best production (milk or fat) in one day for cows
- Then, daughter-dam comparison for bulls... ($\text{âbull} = \text{daughter} - \text{dam}$)
- Then, herdmate comparison
 - compare the average production of daughters of a bull with the average production of their herdmates
 - significant genetic gain



Quickly, unfair comparison because herdmates of daughters of young bulls are often daughters of selected (better) bulls

- Modified herdmate comparison 1989 in the USA...



Meanwhile: 1949-1952: **C.R. Henderson's thesis**

The basis of « mixed models » and variance component estimation

1959: a theoretical statistical treatment of mixed models

1963: a first presentation of BLUP

1973: « Sire evaluation and genetic trends »

1976: « A method to compute the inverse of the numerator relationship matrix »

C.R. Henderson's framework

We want to estimate/predict the additive genetic effect of one (ai) or several (**a**) animals, from the available data (y)

Case 1: we know **all genetic parameters** (*genetic variances and covariances* (or equivalently: *genetic correlations*) and *heritabilities*)
+ · we know how to correct for environmental conditions

(e.g., very large groups of animals with similar characteristics are raised in exactly the same conditions – as in poultry breeding)

Take \hat{a} = Best Linear Prediction of **a** (BLP)

In fact = Selection index theory (Smith, 1936; Hazel, 1943)

C.R. Henderson's framework

Case 2: we know **all genetic parameters** (*genetic variances and covariances* (or equivalently: *genetic correlation*) and *heritabilities*)

+ · we know how to correct for environmental conditions

(e.g., in cattle breeding : every month, there are new cows calving, at a different age, and different lactation number, in small herds with different feeding systems)

we need to correct the data for environmental effects β

C.R. Henderson's framework

Case 3: we know **all genetic parameters** (*genetic variances and covariances* (or equivalently: *genetic correlation*) and *heritabilities*)
(e.g., because we are studying a new breed, a new trait, a new environment)

- we know how to correct for environmental conditions

- we need to estimate genetic parameters (« variance components »)
- Then take \hat{a} = Best Linear Unbiased Prediction of a (BLUP)
assuming that the estimated genetic parameters are the correct ones

This is a very strong assumption, **especially when we don't have much data** to estimate genetic parameters (but, in that case, a Bayesian approach can be used to do both at the same time (estimation of genetic parameters + genetic evaluations))

- With large data sets, it is not so important as long as genetic parameters are estimated by **Restricted Maximum Likelihood** (REML)

BLUP: objective

$$E[\hat{\omega}_i] = E[\omega_i]$$

BLUP: relationship with BLP

Mixed Model Equations

$$\begin{array}{ccccc} \text{?} & \text{X}'\mathbf{R}^{-1}\text{X} & & \text{X}'\mathbf{R}^{-1}\text{Z} & \text{?} \\ \text{?} & \text{Z}'\mathbf{R}^{-1}\text{X} & & \text{Z}'\mathbf{R}^{-1}\text{Z} + \mathbf{G}^{-1} & \text{?} \\ & & & \text{?} & \text{?} \\ & & & \text{B} & \text{?} \\ & & & \text{a} & \text{?} \\ & & & \text{?} & \text{?} \\ & & & \text{?} & \text{?} \\ & & & \text{?} & \text{?} \end{array}$$

here:

- **R** is the matrix of (co)variances between residuals (with relationships accounted for)
- **G-1** = inverse of **G**, the matrix of **genetic (co)variances**

Advantages compared to BLP:

- no intermediate computation of **bi**
- **R-1** and **G-1** have a (known) simple structure (much simpler than **B-1**)
- Size of the system = size of **β** + size of **a** (and not size of **y**)

Mixed Model Equations: example

$$\begin{matrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{X}'\mathbf{R}^{-1}\mathbf{Z} \\ \mathbf{Z}'\mathbf{R}^{-1}\mathbf{X} & \mathbf{Z}'\mathbf{R}^{-1}\mathbf{Z} + \mathbf{G}^{-1} \end{matrix} \begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} = \begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} \begin{matrix} \mathbf{X}'\mathbf{R}^{-1}\mathbf{y} \\ \mathbf{Z}'\mathbf{R}^{-1}\mathbf{y} \end{matrix} \begin{matrix} \text{?} \\ \text{?} \end{matrix}$$

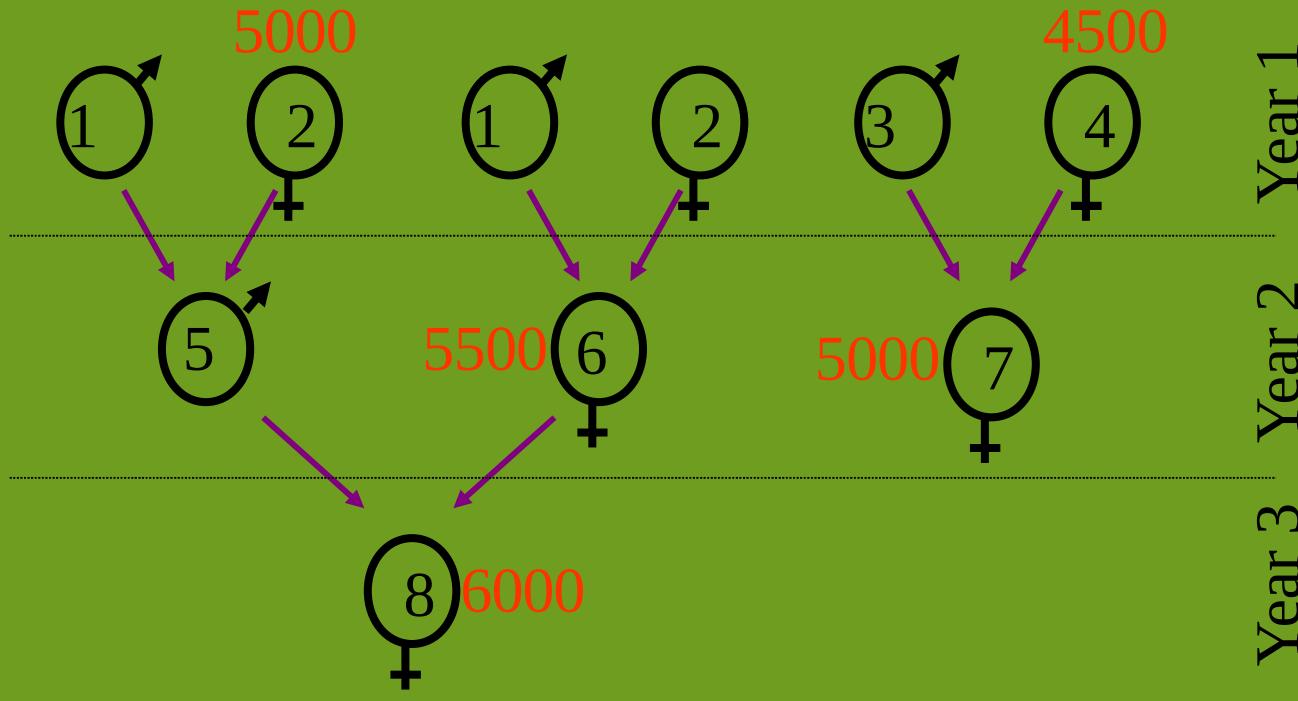
- For a univariate evaluation, with an additive genetic effect
 - Assume iid (independent and identically distributed) residuals
 - $\square \mathbf{R} = \mathbf{I} \ \sigma_e^2$
 - $\text{Var}(\text{additive genetic effect}) = \mathbf{G} = \mathbf{A}$ ($\mathbf{A} = \text{relationship matrix}$)
 - Multiplying both sides by σ_e^2 :

$$\begin{matrix} \mathbf{X}'\mathbf{X} & \mathbf{X}'\mathbf{Z} \\ \mathbf{Z}'\mathbf{X} & \mathbf{Z}'\mathbf{Z} + \alpha \mathbf{A}^{-1} \end{matrix} \begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} = \begin{matrix} \text{?} & \text{?} \\ \text{?} & \text{?} \end{matrix} \begin{matrix} \mathbf{X}'\mathbf{y} \\ \mathbf{Z}'\mathbf{y} \end{matrix} \begin{matrix} \text{?} \\ \text{?} \end{matrix}$$

$$\text{where } \alpha = \frac{\sigma_e^2}{\sigma_a^2} = \frac{1-h^2}{h^2}$$

- Note: all this can also be obtained with a Bayesian approach

Example



$$y_i = \beta_j + a_i + e_i$$

Mixed Model Equations: Construction

for the small example:

$$\begin{array}{l} \mathbf{X}'\mathbf{X} = \begin{pmatrix} ? & 0 & 0 & ? \\ ? & 2 & 0 & ? \\ ? & 0 & 1 & ? \end{pmatrix} \quad \mathbf{X}'\mathbf{Z} = \begin{pmatrix} ? & 1 & 0 & 0 & 0 & 0 & ? \\ ? & 0 & 0 & 0 & 1 & 1 & 0 \\ ? & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad \mathbf{X}'\mathbf{y} = \begin{pmatrix} ? & 0000 + 4500 \\ ? & 500 + 5000 \\ ? & 6000 \end{pmatrix} \\ \mathbf{Z}'\mathbf{X} = \begin{pmatrix} ? & 0 & 0 & ? \\ ? & 0 & 0 & ? \\ ? & 0 & 0 & ? \\ ? & 0 & 0 & ? \\ ? & 1 & 0 & ? \end{pmatrix} \quad \mathbf{Z}'\mathbf{Z} = \begin{pmatrix} ? & 0 & 0 & 0 & 0 & 0 & ? \\ ? & 1 & 0 & 0 & 0 & 0 & 0 \\ ? & 0 & 0 & 0 & 0 & 0 & 0 \\ ? & 0 & 0 & 1 & 0 & 0 & 0 \\ ? & 0 & 0 & 0 & 0 & 1 & 0 \\ ? & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad \mathbf{Z}'\mathbf{y} = \begin{pmatrix} ? & 0 \\ ? & 0000 \\ ? & 0 \\ ? & 4500 \\ ? & 0 \\ ? & 500 \\ ? & 0000 \\ ? & 0000 \end{pmatrix} \end{array}$$

Annotations: Red circles highlight the diagonal elements of $\mathbf{X}'\mathbf{Z}$ and $\mathbf{Z}'\mathbf{Z}$. A blue circle highlights the sum of the first two elements in the $\mathbf{X}'\mathbf{y}$ vector. A blue bracket groups the last three elements of $\mathbf{Z}'\mathbf{y}$.

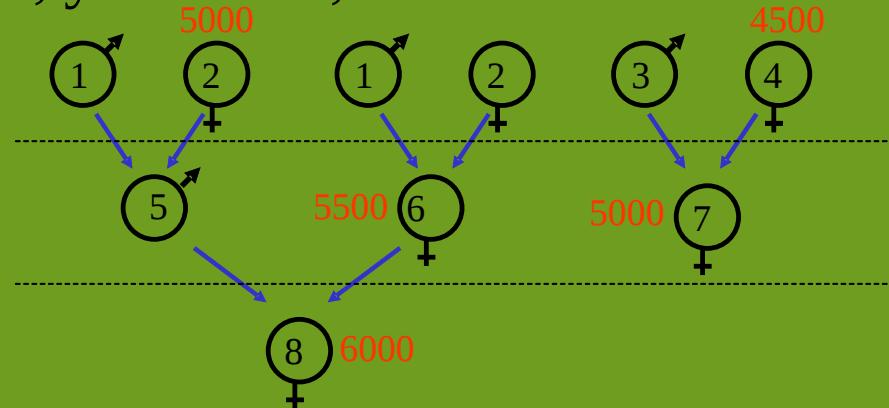
m_{ij} = number of records influenced by both level i and level j

h_i = sum of records influenced by level i

Mixed Model Equations: Construction

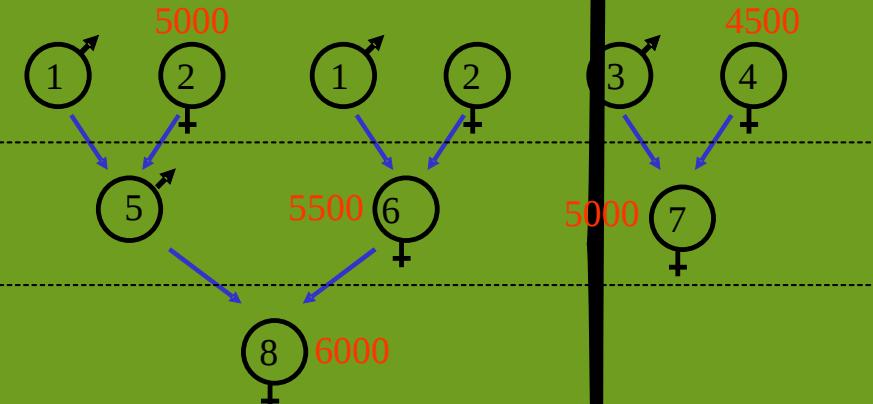
- Read a **data file**: animal n°, year effect, record

2	1	5000
4	1	4500
6	2	5500
7	2	5000
8	3	6000



A : the Numerator Relationship Matrix

2 simple rules:



$$g_{ii} = (1 + F_i) = 1 + \frac{1}{2} g_{sd}$$

$$g_{ij} = \frac{1}{2} (g_{is} + g_{id})$$

	1	2	3	4	1x2	1x2	3x4	5x6
1	1	0	0	0	0.5	0.5	0	0.5
2	0	1	0	0	0.5	0.5	0	0.5
3	0	0	1	0	0	0	0.5	0
4	0	0	0	1	0	0	0.5	0
5	0.5	0.5	0	0	1	0.5	0	0.75
6	0.5	0.5	0	0	0.5	1	0	0.75
7	0	0.5	0.5	0.5	0	0	1	0
8	0.5	0.5	0	0	0.75	0.75	0	1 + 0.25

Henderson's rules to construct A-1 (1976)



Henderson's rules to construct A-1 (1976)

Henderson's rules : application

- Read the **pedigree file**: animal n°, sire n°, dam n°

$$\mathbf{A}^{-1} = \begin{matrix} & \begin{matrix} ? & 1 & 1 & 1 & 1 & 0 & 0 & -1 & -1 & 0 & 0 & ? \\ ? & + & + & - & - & 0 & 0 & -1 & -1 & 0 & 0 & ? \\ ? & 2 & 2 & 2 & 2 & 0 & 0 & -1 & -1 & 0 & 0 & ? \\ ? & 1 & 1 & 1 & 1 & 0 & 0 & -1 & -1 & 0 & 0 & ? \\ ? & - & + & - & + & 0 & 0 & -1 & -1 & 0 & 0 & ? \\ ? & 2 & 2 & 2 & 2 & 0 & 0 & -1 & -1 & 0 & 0 & ? \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & ? \\ 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & ? \\ 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & ? \\ 4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & ? \\ 5 & 1 & 2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & ? \\ 6 & 1 & 2 & -1 & -1 & 0 & 0 & 2 & 1 & 0 & -1 & ? \\ 7 & 3 & 4 & -1 & -1 & 0 & 0 & 1 & 1 & 0 & -1 & ? \\ 8 & 5 & 6 & 0 & 0 & -1 & -1 & 2 & 2 & 2 & 0 & ? \\ & 0 & 0 & 0 & 0 & 0 & -1 & -1 & -1 & 0 & 2 & ? \end{matrix} \end{matrix}$$

Mixed Model Equations: construction

$$\begin{matrix} \mathbf{X}'\mathbf{X} & \mathbf{X}'\mathbf{Z} & \mathbf{Z}'\mathbf{X} \\ \mathbf{Z}'\mathbf{X} & \mathbf{Z}'\mathbf{Z} + \alpha\mathbf{A}^{-1} & \mathbf{Z}'\mathbf{y} \end{matrix} = \begin{matrix} \mathbf{X}'\mathbf{y} \\ \mathbf{Z}'\mathbf{y} \end{matrix}$$

$$\left(\begin{array}{ccc|cccccc}
 2 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\
 0 & 2 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \\
 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
 \hline
 0 & 0 & 0 & 0+2\alpha & 0+\alpha & 0 & 0-\alpha & 0-\alpha & 0 \\
 1 & 0 & 0 & 0+\alpha & 1+2\alpha & 0 & 0-\alpha & 0-\alpha & 0 \\
 0 & 0 & 0 & 0 & 0 & 0+1.5\alpha & 0+0.5\alpha & 0 & 0 \\
 1 & 0 & 0 & 0 & 0 & 0+0.5\alpha & 1+1.5\alpha & 0 & 0 \\
 0 & 0 & 0 & 0-\alpha & 0-\alpha & 0 & 0+2.5\alpha & 0+0.5\alpha & 0 \\
 0 & 1 & 0 & 0-\alpha & 0-\alpha & 0 & 0+0.5\alpha & 1+2.5\alpha & 0 \\
 0 & 1 & 0 & 0 & 0 & 0-\alpha & 0 & 1+2\alpha & 0 \\
 0 & 0 & 1 & 0 & 0 & 0 & 0-\alpha & 0 & 1+2\alpha
 \end{array} \right) \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \\ a_6 \\ a_7 \\ a_8 \end{pmatrix} = \begin{pmatrix} 5000+4500 \\ 5500+5000 \\ 6000 \\ 0 \\ 5000 \\ 0 \\ 4500 \\ 0 \\ 5500 \\ 5000 \\ 6000 \end{pmatrix}$$

Mixed Model Equations: solutions

$$\begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \\ \hat{a}_1 \\ \hat{a}_2 \\ \hat{a}_3 \\ \hat{a}_4 \\ \hat{a}_5 \\ \hat{a}_6 \\ \hat{a}_7 \\ \hat{a}_8 \end{pmatrix} = \begin{pmatrix} 4750 \\ 5250 \\ 5930 \\ 28 \\ 83 \\ -28 \\ -83 \\ 56 \\ 83 \\ -83 \\ 70 \end{pmatrix}$$

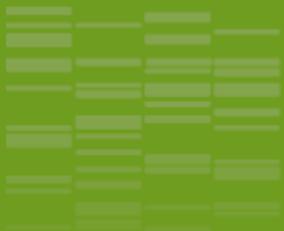
Sum for
« base animals »
=0

Mean = 18.6

Mean = 70

genetic trend
/ generation

$$y_8 = 6000 = 5930 + 70 \quad \text{connection through pedigree}$$



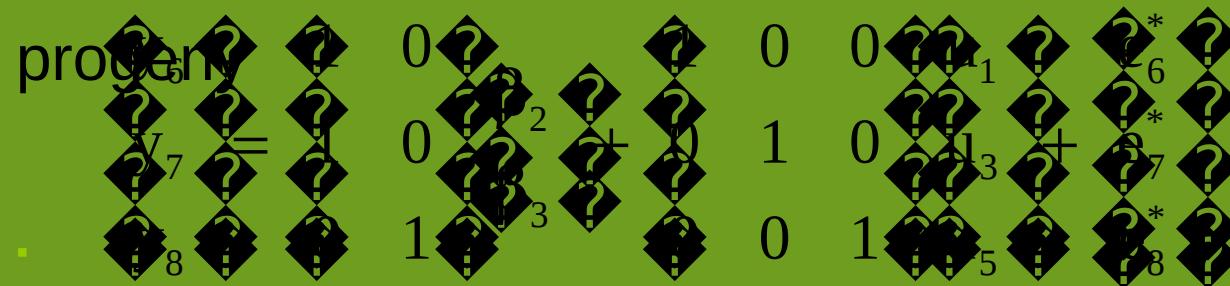
When the **base population** (= population with unknown parents) is not related, not inbred and not selected and when **all** the data used for selection and planned matings are **included** in the BLUP evaluation, the use in the mixed model equations of the complete relationship matrix **A** and the additive genetic variance σ_a^2 of the base population accounts for changes in expected value and variance of additive genetic values related to selection, genetic drift, inbreeding and planned matings (Sorensen et Kennedy, 1982).



- animal model
 - fixed and random effects are estimated together
 - all pedigree information is used
 - all data on which selection was based are used
 - (including on correlated traits) multi-trait evaluation
 - needs σ_a^2 in the base (not selected, not related, not inbred) population
- **Multi-trait BLUP animal model** (t traits \times (na animals + nf fixed effects))
- **All other models are simplified versions, with extra hypotheses**



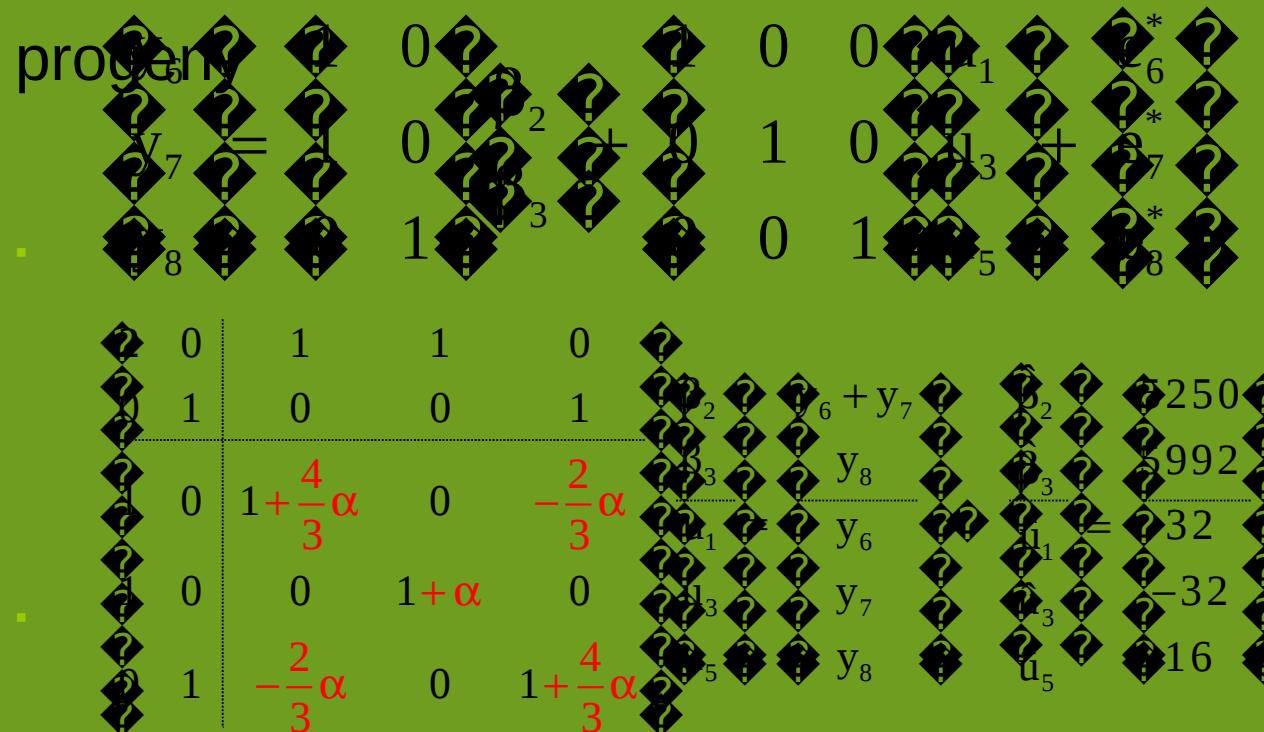
- $y_i = \beta_j + a_i + e_i$ \diamond $y_i = \beta_j + u_s + e_i^*$
- records from dams 2 and 4 can't be used (unknown sire)
- assume each dam unselected, unrelated with at most one progeny



$$\mathbf{G} = \text{var}(u) = \frac{1}{4} \sigma_a^2 \mathbf{A} \quad \text{with } \mathbf{A}^{-1} = \begin{pmatrix} 1 & 0 & -2 \\ 0 & 3 & ? \\ -3 & ? & 3 \end{pmatrix}$$

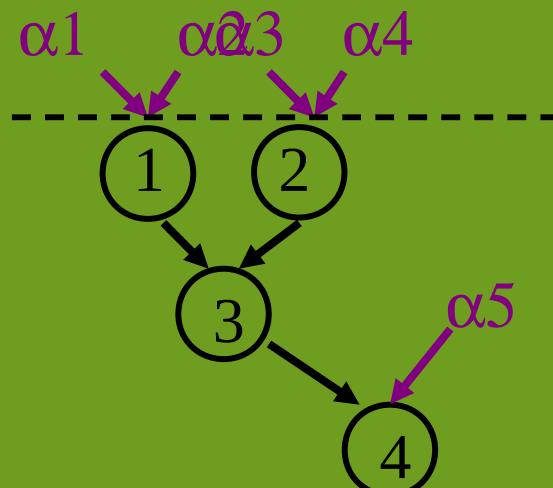
and $\alpha = \frac{\sigma_e^2}{\sigma_u^2} = \frac{\sigma_e^2 + \frac{3}{4}\sigma_a^2}{\frac{1}{4}\sigma_a^2}$

- $y_i = \beta_j + a_i + e_i$ \diamond $y_i = \beta_j + u_s + e_i^*$
- records from dams 2 and 4 can't be used (unknown sire)
- assume each dam unselected, unrelated with at most one



BLUP : Groups of unknown parents

› Example:



Definition of unknown parent groups

by sex of progeny and year of birth:

- α_1, α_2 = parents of males of generation 1
- α_3, α_4 = parents of females of generation 1
- α_5 = parent of females of generation >1

$$Qg = \begin{matrix} & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0.5 & 0.5 & 0 \\ 0.25 & 0.25 & 0.5 \end{matrix} \\ \begin{matrix} ?_1 \\ ?_0 \\ ?_{0.5} \\ ?_{0.25} \end{matrix} & \begin{matrix} ?_1 & ?_0 & ?_{0.5} & ?_{0.25} \\ ?_0 & ?_1 & ?_0 & ?_{0.5} \\ ?_{0.5} & ?_0 & ?_1 & ?_{0.25} \\ ?_{0.25} & ?_{0.5} & ?_{0.25} & ?_1 \end{matrix} \end{matrix}$$

Groups of unknown parents

- $y = X\beta + Z \mathbf{a} + e$
 $= X\beta + Z (\mathbf{Qg} + \mathbf{a}^*) + e$ with $\mathbf{a}^* = \mathbf{a} - \mathbf{Qg}$
 $= [X \quad ZQ] \begin{matrix} \text{?} \\ \text{?} \\ \text{?} \\ \text{?} \\ \text{?} \end{matrix} + Za^* + e$ \mathbf{g} is a particular fixed effect

► Mixed Model Equations (after some transformations):

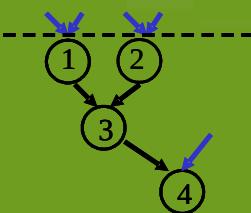
Interest: MME more sparse, easier to construct. \mathbf{A} obtained directly

Quaas' rules to construct

$$\begin{matrix} Q'A^{-1}Q & -\alpha Q'A^{-1} \\ \alpha A^{-1}Q & A^{-1} \end{matrix}$$

- read the pedigree file: i , s , d
(animal, sire or group of unknown sire, dam or group of unknown dam)
- Determine d_i^{-1} function of number of known parents
 - add d_i^{-1} to $A(i,i)$
 - add $-0.5 d_i^{-1}$ to $A(i,s), A(s,i), A(i,d), A(d,i)$
 - add $0.25 d_i^{-1}$ to $A(s,s), A(s,d), A(d,s), A(d,d)$

Example



$$Qg = \begin{matrix} \begin{array}{ccccccccc} ? & 1 & 0 & 0 & g_1 & g_1 \\ ? & 0 & 1 & 0 & g_2 & g_2 \\ ? & 0.5 & 0.5 & 0 & g_2 & g_3 \\ ? & 0.25 & 0.25 & 0.5 & 4 & 3 \\ ? & 0.25 & 0.25 & 0.5 & 4 & 3 \end{array} \end{matrix}$$

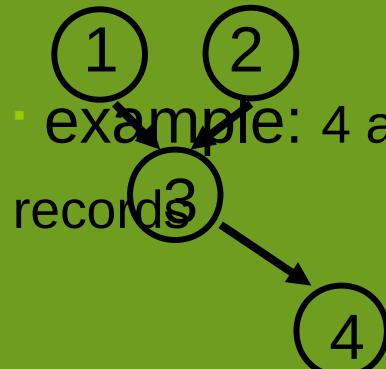
$d_i^{-1} = 1$
2
 $4/3$

$$\begin{matrix} \begin{array}{ccccccccc} ? & +\frac{1}{4}+\frac{1}{4}+\frac{1}{4} & 0 & 0 & -\frac{1}{2}-\frac{1}{2} & 0 & 0 & 0 & -(g_1) \\ ? & 0 & \frac{1}{4}+\frac{1}{4}+\frac{1}{4}+\frac{1}{4} & 0 & 0 & -\frac{1}{2}-\frac{1}{2} & 0 & 0 & -(g_2) \\ ? & 0 & 0 & \frac{1}{3} & 0 & 0 & 0 & -\frac{2}{3} & -(g_3) \\ ? & 0 & -\frac{1}{2}-\frac{1}{2} & 0 & 1+\frac{1}{2} & \frac{1}{2} & -1 & 0 & -(1) \\ ? & 0 & -\frac{1}{2}-\frac{1}{2} & 0 & \frac{1}{2} & 1+\frac{1}{2} & -1 & 0 & -(2) \\ ? & 0 & 0 & -1 & -1 & -1 & 2+\frac{1}{3} & -\frac{2}{3} & -(3) \\ ? & 0 & 0 & -\frac{2}{3} & 0 & 0 & -\frac{2}{3} & \frac{4}{3} & -(4) \end{array} \end{matrix}$$

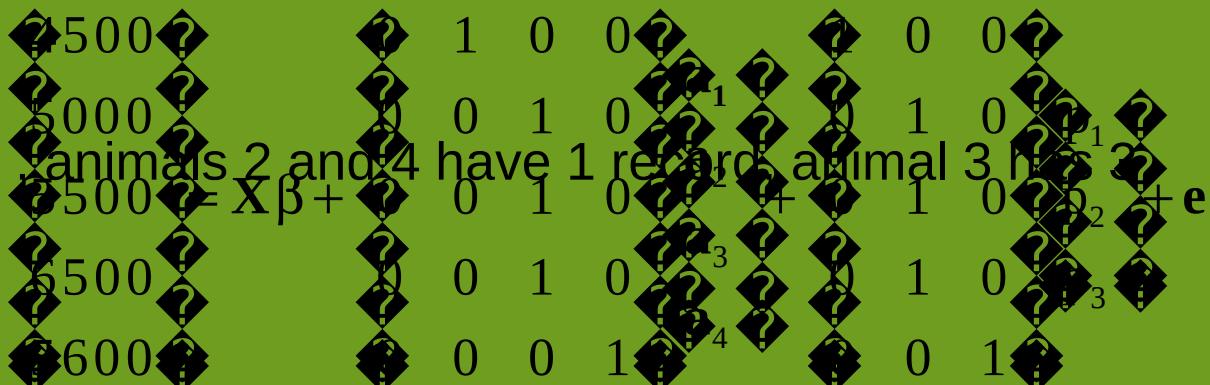
pedigree file

- When we have repeated records on a same animal, all these records share a same « permanent environment »
= same non (additive) genetic characteristics of the animal, which are affecting each record in the same way (e.g., consequences of a poor growth rate, or a disease, a lost quarter, etc...)

- $y = Xb + Za + Wp + e$



example: 4 animals, animals 2 and 4 have 1 record, animal 3 has 2 records





- Var $\begin{pmatrix} ? & ? \\ ? & ? \\ ? & ? \\ ? & ? \end{pmatrix} = \begin{pmatrix} ? & \alpha\sigma_a^2 \\ ? & ? \\ ? & ? \\ ? & ? \end{pmatrix}$ $\begin{pmatrix} 0 & 0 & ? \\ I\sigma_w^2 & 0 & ? \\ 0 & I\sigma_e^2 & ? \end{pmatrix}$

Mixed Model Equations:

$$\begin{pmatrix} ? & X'X \\ ? & Z'X \\ ? & W'X \end{pmatrix}$$

$$X'Z$$

$$Z'Z + \alpha_1 A^{-1}$$

$$\begin{pmatrix} X'W \\ Z'W \\ W'W + \alpha_2 I \end{pmatrix}$$

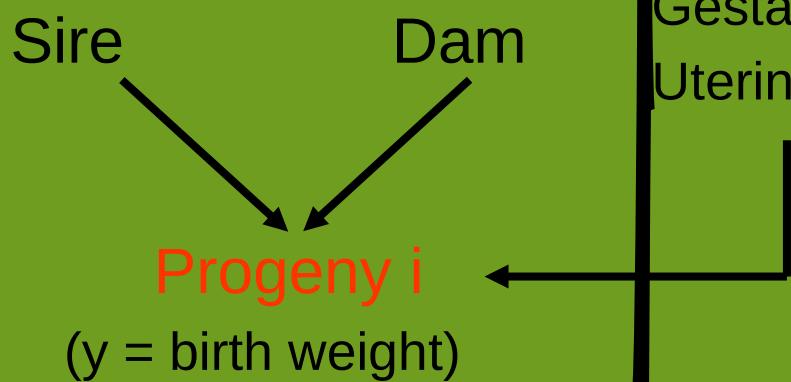
$$W'Z$$

$$\begin{pmatrix} ? & ? \\ ? & ? \\ ? & ? \\ ? & ? \end{pmatrix} = \begin{pmatrix} ? & X'y & ? \\ ? & Z'y & ? \\ ? & W'y & ? \end{pmatrix}$$

$$\text{with } \alpha_1 = \frac{\sigma_e^2}{\sigma_a^2} = \frac{1-r}{h^2}$$

$$\text{and } \alpha_2 = \frac{\sigma_e^2}{\sigma_w^2} = \frac{1-r}{r-h^2}$$

- Maternal effect = all (genetic or not genetic) characteristics of the dam which influence the observation of a progeny
 - Example: birth weight:



Format = characteristics of the dam
Gestation length with immediate effect on
Uterine capacity birth weight
→Act as an environmental
effect on progeny

- direct effect animal model (y = record of the progeny)
 - maternal effect repeatability model (y = record of the dam)



- $y =$ fixed effect affecting the progeny or the dam
 - + direct effect (additive genetic value of the progeny)
 - + maternal effect (additive genetic value + perm. environ. effect of the dam)
- $\mathbf{y} = \mathbf{X}\beta + \mathbf{U}\mathbf{a} + \mathbf{Z}\mathbf{m} + \mathbf{W}\mathbf{p} + \mathbf{e}$
- Adding columns of 0 to **U** and **Z**, **a** and **m** can be made of same length = they represent the same (all) animals. Then for any pair of related animals i, j with relationship coefficient g_{ij} :

$$\text{cov}(a_i, a_j) = g_{ij} \sigma_a^2$$

$$\text{cov}(m_i, m_j) = g_{ij} \sigma_m^2$$

$$\text{cov}(a_i, m_j) = g_{ij} \sigma_{am}$$

Var

$$\begin{matrix} \text{?} & \text{?} & \text{?} & \sigma_a^2 \mathbf{A} & \sigma_{am} \mathbf{A} & 0 & \text{?} \\ \text{?} & \text{?} & \text{?} & \mathbf{A} & \sigma_m^2 \mathbf{A} & 0 & \text{?} \\ \text{?} & \text{?} & \text{?} & \text{?} & 0 & 0 & \text{?} \\ \text{?} & \text{?} & \text{?} & \text{?} & \text{?} & \sigma_p^2 \mathbf{I} & \text{?} \end{matrix}$$



› Start with $y = X\beta + Ua + Zm + Wp + e$

i.e. $y_i = \mathbf{x}_i'\beta + a_i + m_{\text{dam}} + p_{\text{dam}} + e_i$

› Using $a_i = \frac{1}{2}a_{\text{sire}} + \frac{1}{2}a_{\text{dam}} + \varphi_i$

$$y_i = \mathbf{x}_i'\beta + \frac{1}{2}a_{\text{sire}} + \frac{1}{2}a_{\text{dam}} + m_{\text{dam}} + p_{\text{dam}} + (\varphi_i + e_i)$$

$$y_i = \mathbf{x}_i'\beta + \frac{1}{2}a_{\text{sire}} + \frac{1}{4}a_{\text{mgs}} + \frac{1}{4}a_{\text{mgd}} + \frac{1}{2}\varphi_{\text{dam}} + (\varphi_i + e_i)$$

$$\begin{aligned} &+ \frac{1}{4}a_{\text{mgs}} \\ &+ \frac{1}{2}m_{\text{mgs}} \\ &+ \frac{1}{2}m_{\text{mgd}} + \varphi_{\text{dam}}^m \\ &+ p_{\text{dam}} \end{aligned}$$

→

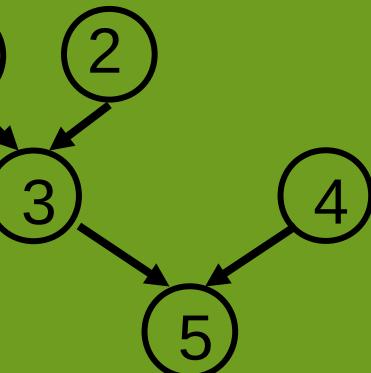
$$y_i = \mathbf{x}_i'\beta + u_{\text{sire}} + v_{\text{mgs}} + t_{\text{dam}} + e_i^*$$

(should have 1 daughter per maternal grand dam)



- Animal sex contemporary group Backfat thickness ADG

1	1	1	22 mm	6500
2	2	1	15	570
3	1	2	19	590
4	2	2	24	700
5	2	2	21	620



- model for animal i, trait j :

$$y_{ij} = \mathbf{x}'_{ij}\beta + \mathbf{z}'_{ij}\mathbf{a} + e_{ij}$$

$$\begin{matrix} \text{?}_1 & \text{?}_1 & \text{X}_1 & \text{?}_1 \\ \text{?}_2 & \text{?}_2 & \text{X}_2 & \text{?}_2 \\ \text{?}_3 & \text{?}_3 & \text{X}_3 & \text{?}_3 \\ \text{?}_4 & \text{?}_4 & \text{X}_4 & \text{?}_4 \\ \text{?}_5 & \text{?}_5 & \text{X}_5 & \text{?}_5 \end{matrix} = \begin{matrix} \text{?}_1 & \text{?}_1 & \text{?}_1 & \text{?}_1 \\ \text{?}_2 & \text{?}_2 & \text{?}_2 & \text{?}_2 \\ \text{?}_3 & \text{?}_3 & \text{?}_3 & \text{?}_3 \\ \text{?}_4 & \text{?}_4 & \text{?}_4 & \text{?}_4 \\ \text{?}_5 & \text{?}_5 & \text{?}_5 & \text{?}_5 \end{matrix} \beta + \begin{matrix} \text{?}_1 & \text{?}_1 & \text{?}_1 & \text{?}_1 \\ \text{?}_2 & \text{?}_2 & \text{?}_2 & \text{?}_2 \\ \text{?}_3 & \text{?}_3 & \text{?}_3 & \text{?}_3 \\ \text{?}_4 & \text{?}_4 & \text{?}_4 & \text{?}_4 \\ \text{?}_5 & \text{?}_5 & \text{?}_5 & \text{?}_5 \end{matrix} a \quad \text{with } X_i = \begin{matrix} \text{?}_{i1} \\ \text{?}_0 \end{matrix}, \quad x_{i2}, \quad \text{and } Z_i = \begin{matrix} \text{?}_{i1} \\ \text{?}_0 \end{matrix}, \quad z_{i2},$$



- The hypotheses required to get the « ideal » properties of Animal model BLUP are better fulfilled
 - Correction of bias related to selection on correlated traits
- Better accuracy □ stronger genetic gain
 - (except when genetic and residual correlations between two traits are the same)
- Better data structure (less disconnection)
- Optimal weights for a multiple trait selection objective =
economic weights (no need to worry about combining univariate (but correlated) predicted breeding values)



- Estimation of genetic parameters (covariances): difficult, **costly** and needs a lot of data to be accurate
- parameters can be wrong ☐ sometimes worse than univariate (**but** in univariate analyses, we assume covariances = 0)
- Computing work for t traits : **t2 or t3** x computing work for 1 trait



- Discrete data: several types
 - Binary (0/1, dead/alive, sick/healthy)
 - Generalized linear models (Threshold models, logistic)
 - Ordered categorical (1/2/3; no help/easy calving/difficult calving)
 - Generalized linear models (Threshold models)
 - ... many others

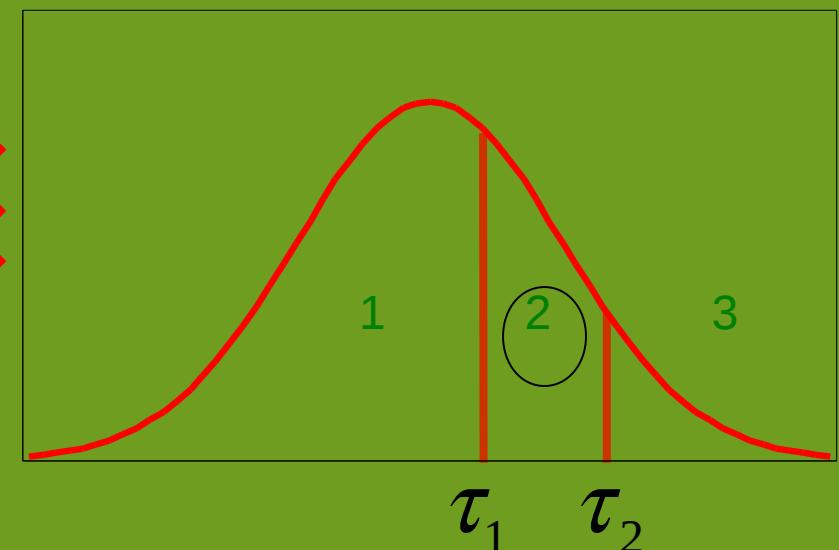


- Calving ease: no help = 1 / easy = 2 / difficult = 3
Assume a non observable underlying variable for animal i

$$\Pi_{ij} = \text{Prob}(\tau_{j-1} < y_i < \tau_j)$$

$$\Pi_{ij} = \Phi\left(\frac{\eta_i - \tau_j}{\sigma_i}\right) - \Phi\left(\frac{\eta_i - \tau_{j-1}}{\sigma_i}\right)$$

$$\eta_i = \mathbf{x}_i' \boldsymbol{\beta} + \mathbf{z}_i' \mathbf{a}$$



- « link function » = F = probit = integral of the normal density



› Example: growth, test day milk production...

› Random regression models + BLUP

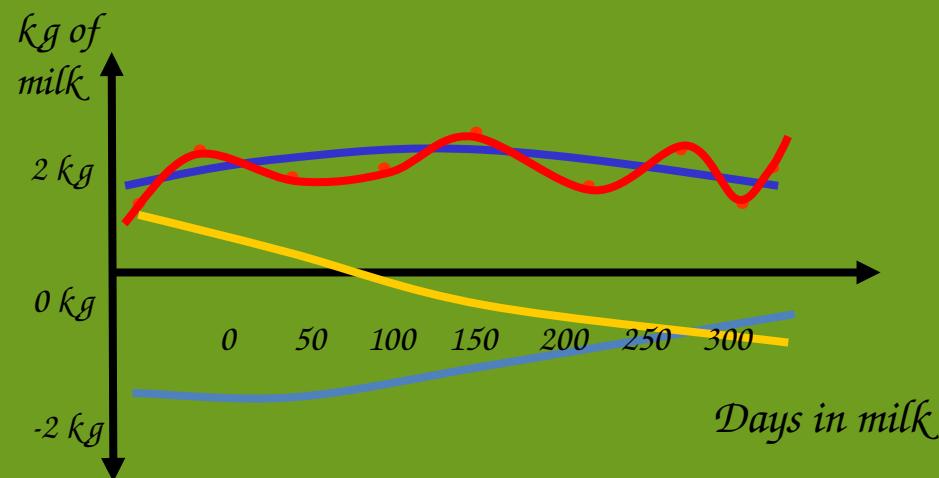
Consider one genetic value « per day » and describe it as a function of time t

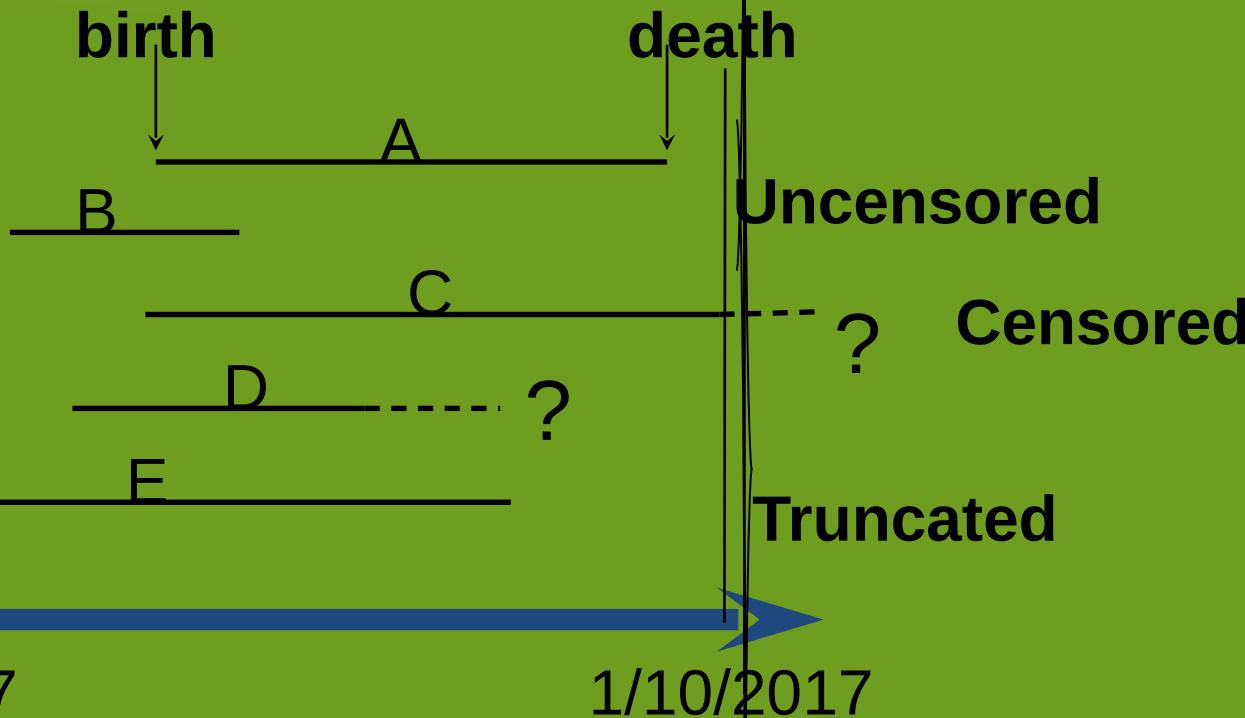
$$a(t) = \lambda_0 + \lambda_1 t + \lambda_2 t^2 + \lambda_3 t^3 + \lambda_4 t^4$$



$$a(t) = \alpha_1(t) \textcircled{a}_1 + \alpha_2(t) \textcircled{a}_2$$

Mean production Persistency





- › Bayesian approach prior \times likelihood
- › In the likelihood construction, special treatment of censored records