

A multivariate analysis with direct additive and hidden inbreeding depression load effects

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Introduction (I)

- Inbreeding is caused by the mating of related individuals
- Inbreeding depression is a reduction in the phenotypic yield of fitness-related traits
- Homozygosity caused by inbreeding exposes the presence of recessive alleles or losses the advantage of over-dominance
- Inbreeding depression can vary depending on the genotype of the individuals whose alleles produce identity by descent (IBD)

Introduction (II)

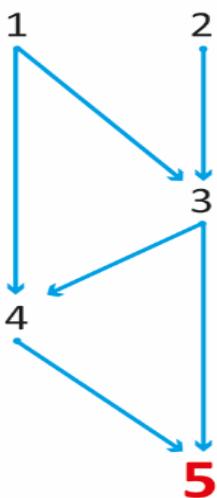
- Inbreeding depression load can be considered an hereditary trait whose phenotype is only expressed when inbreeding occurs in its offspring
- Purging is process of selection against recessive alleles
- “Artificial” purging can be achieved by removing individuals with bad inbreeding loads
- A prediction of the individual inbreeding load for “young” individuals is required

Inbreeding decomposition

Founder decomposition

0.2500 from founder 1
0.1250 from founder 2

Lacy et al., 1996



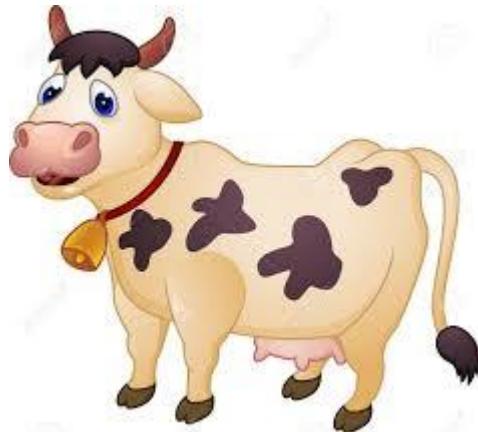
$$F_5 = 0.375$$

Mendelian decomposition

0.1875 from founder 1
0.0625 from founder 2
0.1250 from the mendelian sampling of 3

Caballero and Toro, 2000
García-Cortés et al., 2010

The Model (I)



- Systematic effects (sex, age of dam, herd, year, season, etc)
- Additive genetic effects
- Residual effects
- If inbred:
 - Inbreeding depression generated by:
 - Founders
 - Mendelian Sampling of non-founders

The Model (II)

- Casellas (2018)

$$\mathbf{y} = \mu + \mathbf{Z}\mathbf{a} + \mathbf{T}\boldsymbol{\varepsilon}_i + \mathbf{e}$$

$$\mathbf{a} \sim N(0, A\sigma_a^2)$$

$$\boldsymbol{\varepsilon}_i \sim N(0, I\sigma_i^2)$$

$$\mathbf{e} \sim N(0, I\sigma_e^2)$$

$$\boldsymbol{\varepsilon}_i \sim N(0, Q\sigma_i^2)$$

$$Q = \begin{pmatrix} 1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \frac{1}{2} \left(\frac{F_S + F_D}{2} \right) \end{pmatrix}$$

Inbreeding loads for individuals without inbred descendants can not be predicted

The Model (III)

$$\boldsymbol{i} = \boldsymbol{Pi} + \boldsymbol{\varepsilon}_i$$

$$\boldsymbol{\varepsilon}_i = (\boldsymbol{I} - \boldsymbol{P})\boldsymbol{i}$$

$$\boldsymbol{y} = \mu + \boldsymbol{Zu} + \boldsymbol{Ki} + \boldsymbol{e}$$

$$\boldsymbol{K} = \boldsymbol{T}(\boldsymbol{I}-\boldsymbol{P})$$

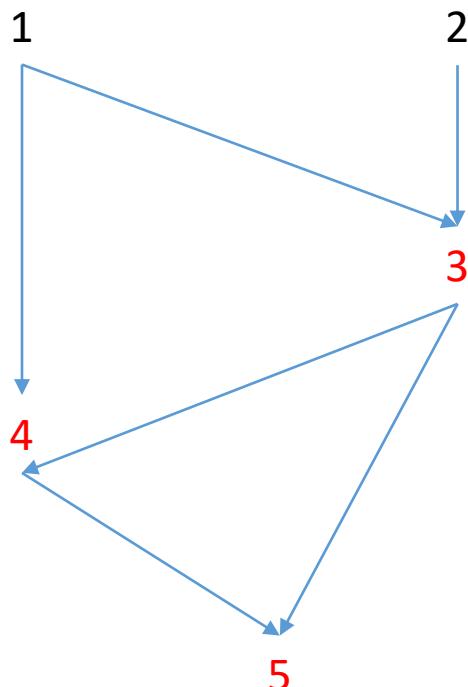
$$\boldsymbol{i} \sim N\left(0,\boldsymbol{A}\sigma_i^2\right)$$

$$\begin{pmatrix} \mathbf{u} \\ \mathbf{i} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \boldsymbol{G} \otimes \boldsymbol{A}\right)$$

Example

$$y = \mu + Zu + Ki + e$$

$$K = T(I - P)$$



$$T = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0.25 & 0 & 0 & 0 & 0 \\ 0.1875 & 0.0625 & 0.125 & 0 & 0 \end{bmatrix}$$

$$I - P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ -0.5 & -0.5 & 1 & 0 & 0 \\ -0.5 & 0 & -0.5 & 1 & 0 \\ 0 & 0 & -0.5 & -0.5 & 1 \end{bmatrix}$$

$$K = T(I - P) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0.25 & 0 & 0 & 0 & 0 \\ 0.125 & 0 & 0.125 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} \mathbf{1}'\mathbf{1} & \mathbf{1}'\mathbf{Z} & \mathbf{1}'\mathbf{K} \\ \mathbf{Z}'\mathbf{1} & \mathbf{Z}'\mathbf{Z} + \mathbf{A}^{-1}\mathbf{g}^{11}\sigma_e^2 & \mathbf{Z}'\mathbf{K} + \mathbf{A}^{-1}\mathbf{g}^{12}\sigma_e^2 \\ \mathbf{K}'\mathbf{1} & \mathbf{K}'\mathbf{Z} + \mathbf{A}^{-1}\mathbf{g}^{21}\sigma_e^2 & \mathbf{K}'\mathbf{K} + \mathbf{A}^{-1}\mathbf{g}^{22}\sigma_e^2 \end{bmatrix} \begin{bmatrix} \hat{\boldsymbol{\mu}} \\ \hat{\boldsymbol{a}} \\ \hat{\boldsymbol{i}} \end{bmatrix} = \begin{bmatrix} \mathbf{1}'\mathbf{y} \\ \mathbf{Z}'\mathbf{y} \\ \mathbf{K}'\mathbf{y} \end{bmatrix}$$

Beef cattle data: weaning weight

	Pirenaica	Rubia Gallega
Pedigree	308,836	384,434
Number of Data	35,126	75,194
Mean	258.37 kg (\pm 57.97 kg)	281.36 kg (\pm 46.70 kg)
Average Inbreeding	0.030 (\pm 0.056)	0.020 (\pm 0.048)

Partial inbreeding coefficients

Partial Inbreeding	Pirenaica	Rubia Gallega
$<10^{-4}$	10,996,924 (68.30 %)	1,564,740 (30.80 %)
$10^{-4} - 10^{-3}$	3,967,842 (24.65 %)	2,559,733 (50.38 %)
$10^{-3} - 10^{-2}$	1,028,578 (6.39 %)	823,410 (16.21 %)
$10^{-1} - 10^{-2}$	126,238 (0.78 %)	124,155 (2.44 %)
$>10^{-1}$	9,792 (0.06 %)	8.419 (0.17 %)

PIRENAICA
8,721 ancestors

RUBIA GALLEGА
3,601 ancestors

Statistical Model

$$\mathbf{y} = \mathbf{t}\mathbf{c} + \mathbf{X}\mathbf{b} + \mathbf{W}\mathbf{p} + \mathbf{Z}\mathbf{a} + \mathbf{K}\mathbf{i} + \mathbf{e}$$

- y** Phenotypes
- c** Covariate with age of recording (170-250 days of life)
- b** sex (2 levels) and age of dam (15 levels)
- p** Herd-year-season effects (6,305 and 5,251 levels)
- a** direct additive genetic effects
- i** inbreeding load effects
- e** residuals

Gibbs Sampler: 2 chains of 550,000 iterations after discarding the first 50,000.

Results: Variance Component Estimation

	Population	
	Pirenaica	Rubia Gallega
σ_a^2	695.016 (25.688)	439.803 (18.121)
σ_i^2	29966.800 (5868.275)	28222.360 (5454.273)
r(a,i)	-0.429 (0.102)	-0.043 (0.087)
σ_p^2	1035.209 (27.714)	320.023 (11.273)
σ_e^2	483.060 (15.010)	1018.207 (12.612)

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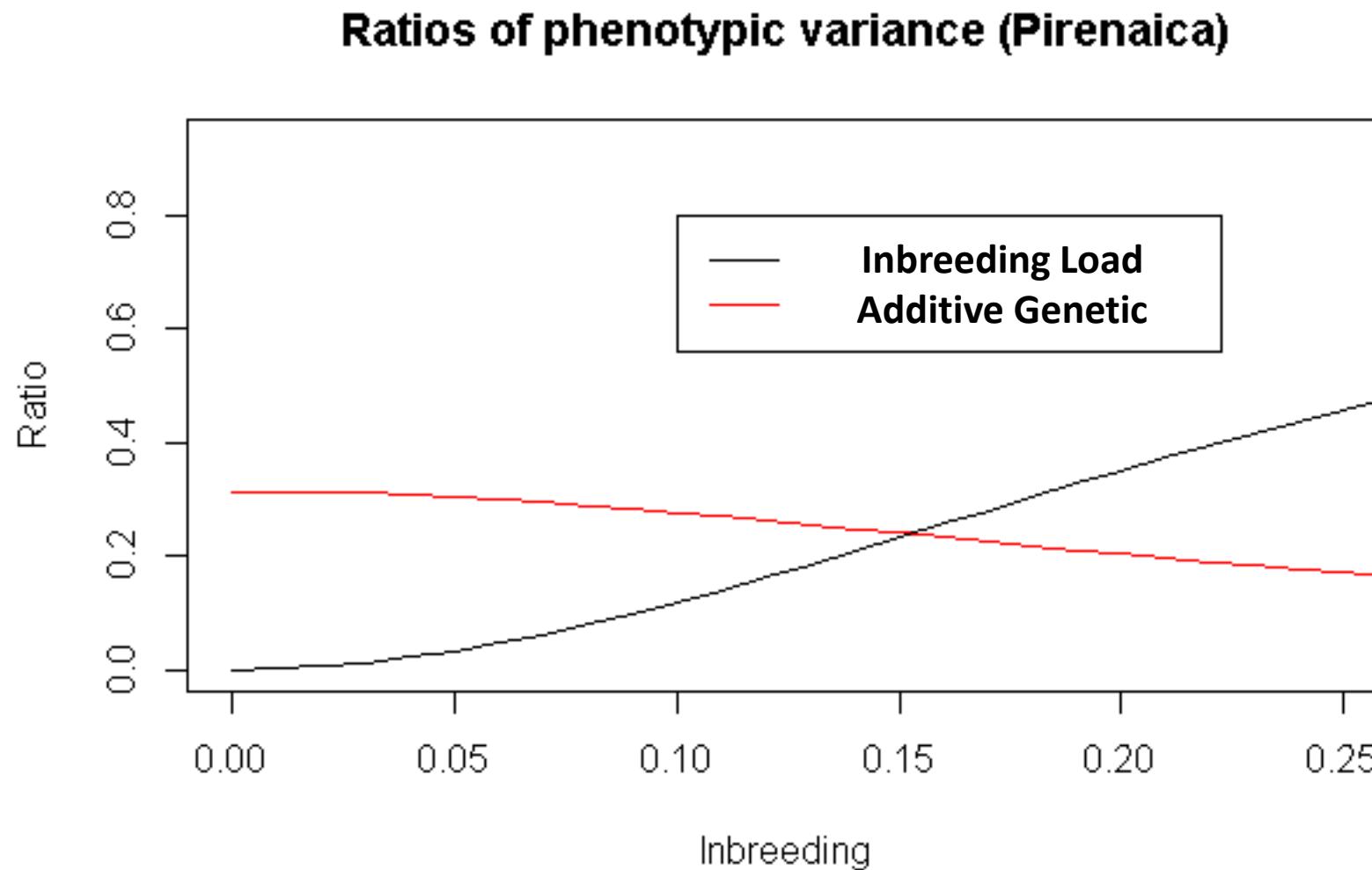
F=1.00

Results: Variance Component Estimation

	Population	
	Pirenaica	Rubia Gallega
σ_a^2	695.016 (25.688)	439.803 (18.121)
σ_i^2	299.66 (58.68)	282.224 (54.54)
r(a,i)	-0.429 (0.102)	-0.043 (0.087)
σ_p^2	1035.209 (27.714)	320.023 (11.273)
σ_e^2	483.060 (15.010)	1018.207 (12.612)

F=0.10

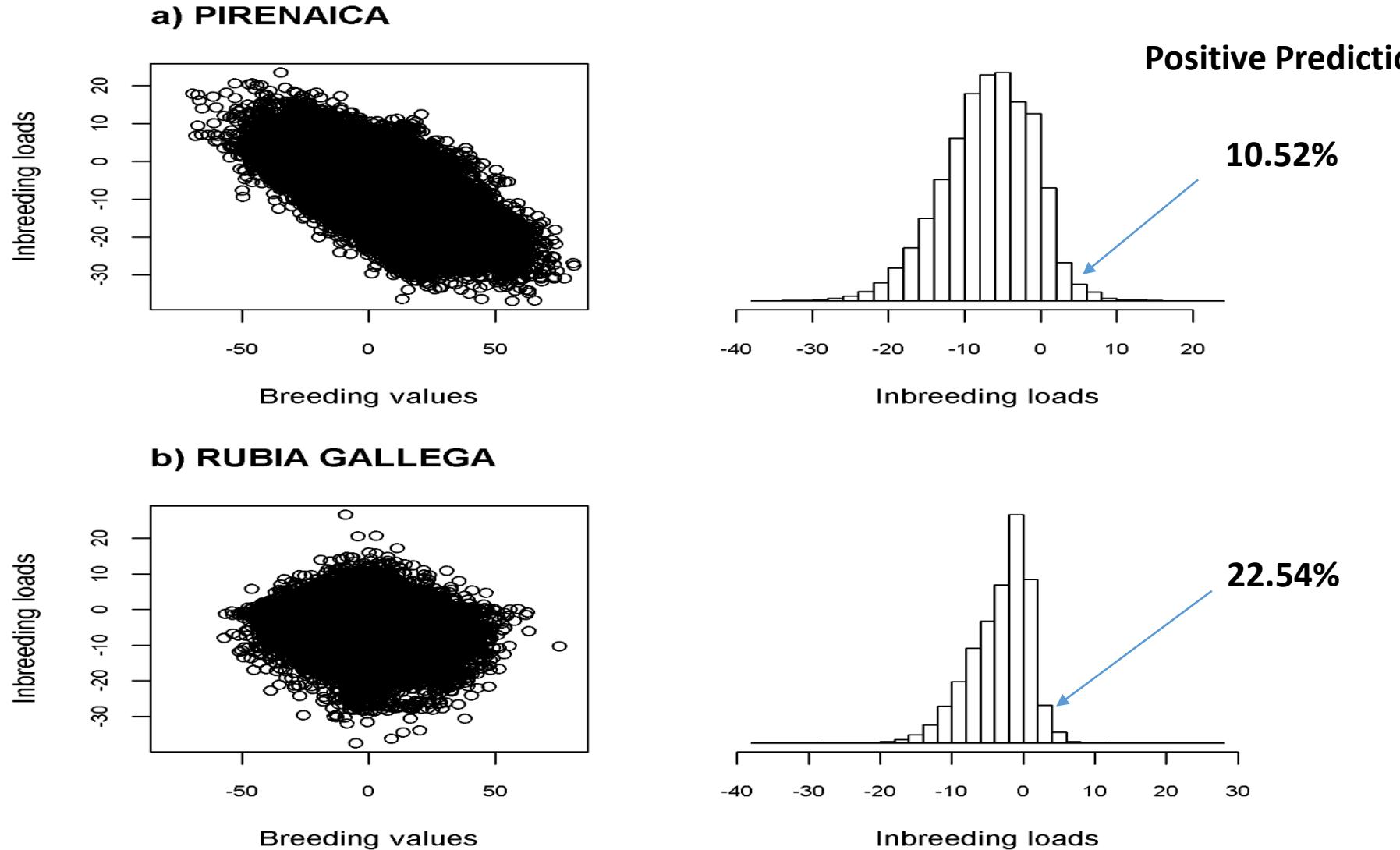
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Results: Breeding values and Inbreeding Loads



Conclusions

- Predictive ability of inbreeding load of “young” individuals
- Useful for “artificial” purging
- Inbreeding load explains a relevant percentage of variance
- Negative correlation between direct additive effects and inbreeding loads

Thank you!!!

