



## **Pedigree and genomic evaluation of pigs using a terminal cross model**

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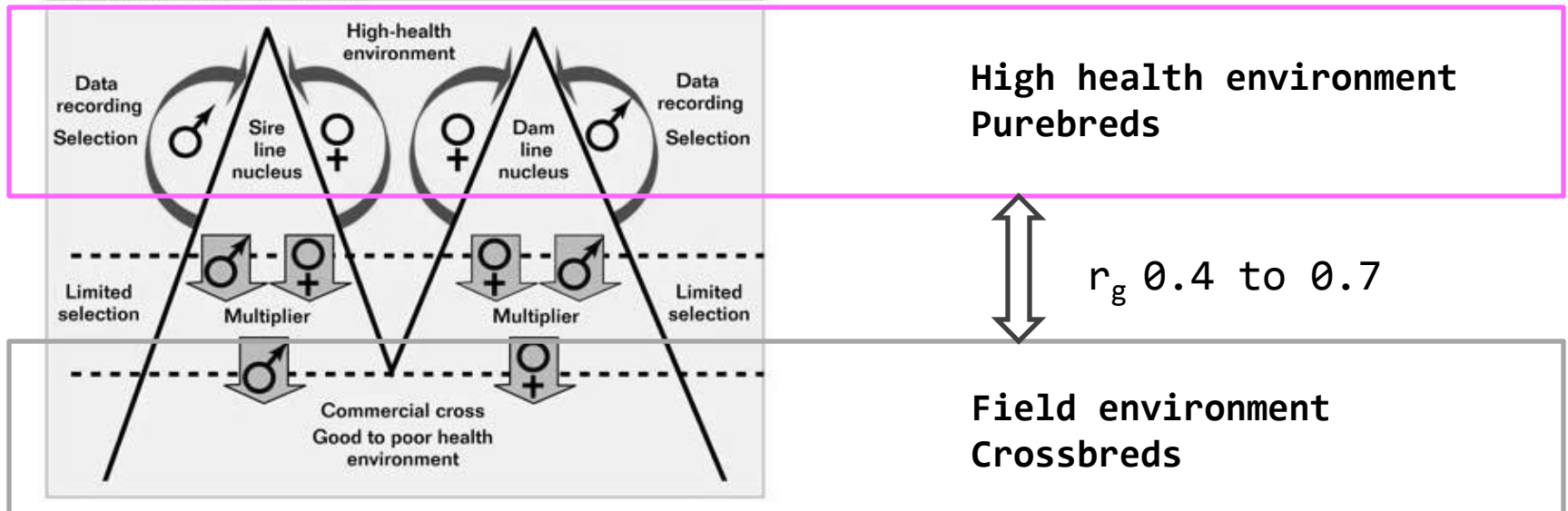
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SelDir SelGen Metaprogramme



# Introduction

Selection in pig breeding programs is entirely performed in the purebred nucleus, aiming to improve crossbred performance

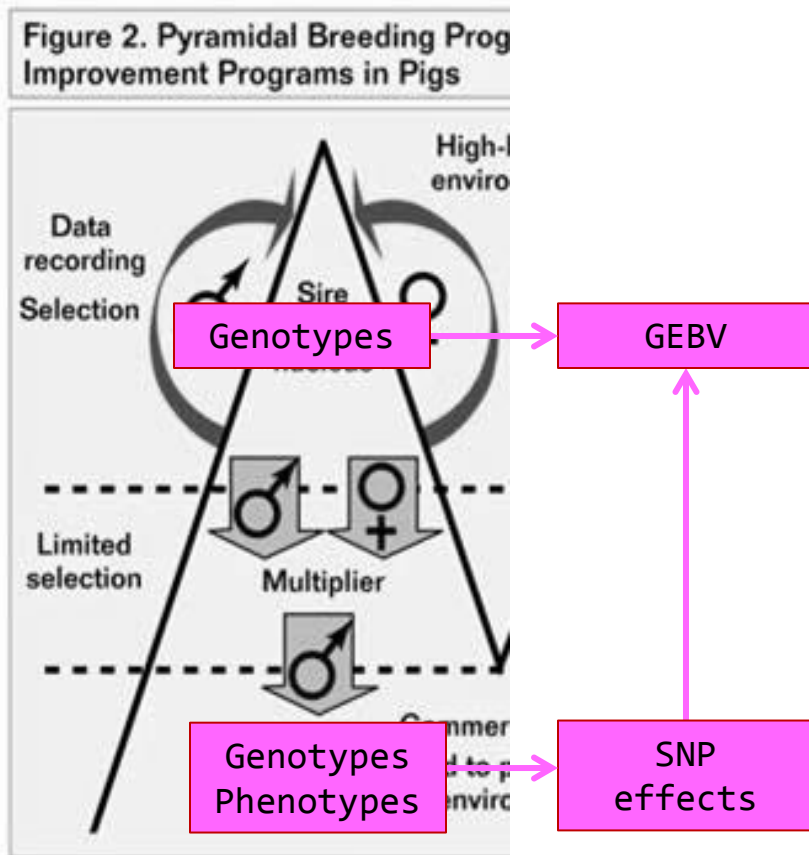
Figure 2. Pyramidal Breeding Program Typical for Genetic Improvement Programs in Pigs



# Introduction

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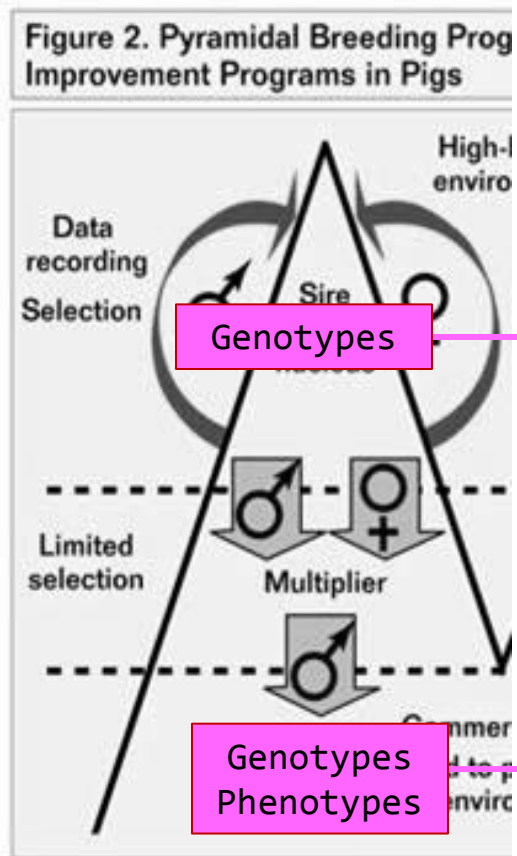
Can we expect a change with the use of genomic information?



# Introduction

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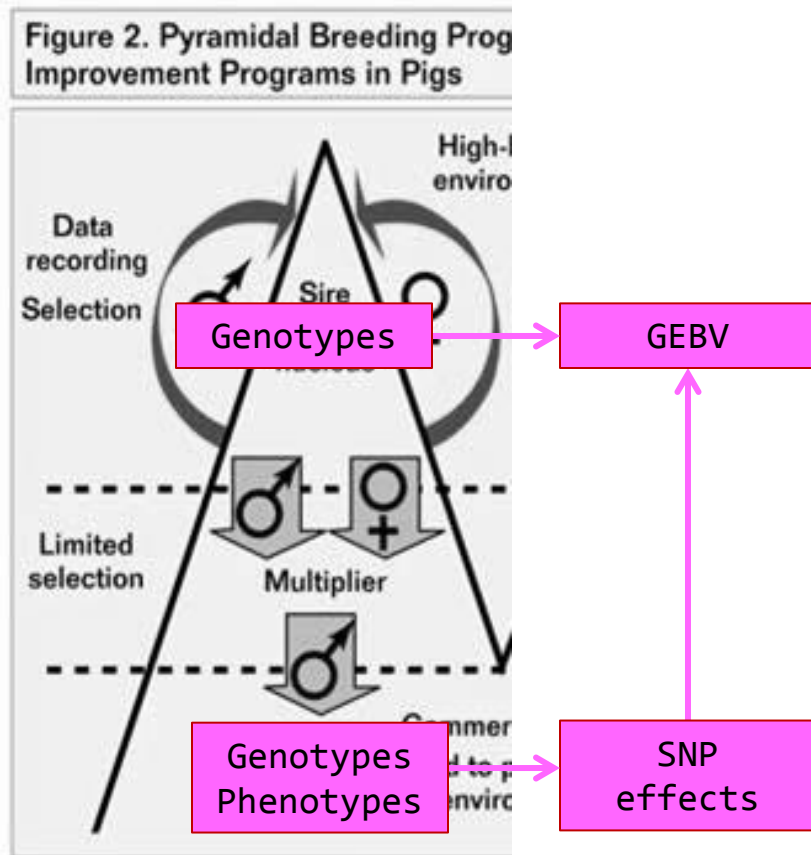
## Genomic selection approaches:

Estimate marker effects on crossbred performance in field to obtain EBV of purebreds

Combine both genomic and pedigree information to get the EBV

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Can we expect a change with the use of genomic information?



## Genomic selection approaches:

Estimate marker effects on crossbred performance in field to obtain EBV of purebreds

Combine both genomic and pedigree information to get the EBV

- ✓ Increased EBV accuracy
- ✓ Greater response to selection
- ✓ Lower rate of inbreeding
- ✓ No pedigree connecting PB with CB needed (not always)
- ✓ SNP effect estimates can be used for several generations

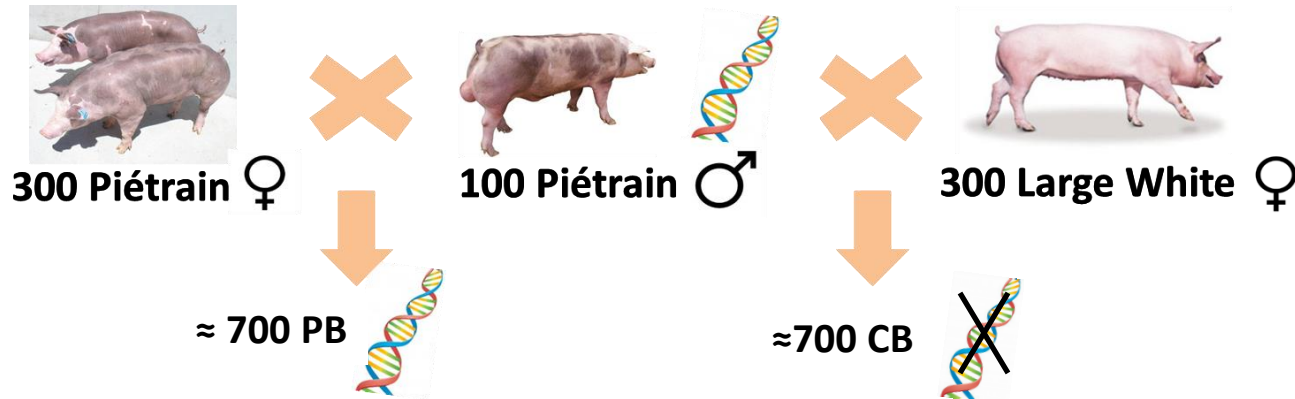
# OBJECTIVE

To present a **single-step terminal-cross model** for the estimation of genetic parameters of several production traits in a terminal cross population of pigs.

Compare the obtained **genetic parameter estimates** and **breeding value accuracies** with:

- a pedigree-based terminal-cross model
- 2 univariate single-step models for PB and CB performance.

# Experimental design



## PEDIGREE AND GENOMIC INFORMATION

- 2 pedigrees: 3,084 Piétrain and 2,686 Large White animals
- Illumina 60K SNP-bead chip genotypes 39,650 SNPs kept for the analyses

## ANALYZED TRAIT

- Growth rate between 35Kg and slaughter (110kg)
- ...

# SINGLE-STEP TERMINAL-CROSS MODEL (GEN)

We have adapted the terminal-cross model proposed by Wei and Van der Werf (1994) to combine both genomic and pedigree information

$$\begin{bmatrix} \mathbf{y}_A \\ \mathbf{y}_C \end{bmatrix} = \begin{bmatrix} \mathbf{X}_A & 0 \\ 0 & \mathbf{X}_C \end{bmatrix} \begin{bmatrix} \mathbf{b}_A \\ \mathbf{b}_C \end{bmatrix} + \begin{bmatrix} \mathbf{W}_A & 0 \\ 0 & \mathbf{W}_C \end{bmatrix} \begin{bmatrix} \mathbf{p}_A \\ \mathbf{p}_C \end{bmatrix} + \begin{bmatrix} \mathbf{Z}_A & 0 & 0 \\ 0 & \mathbf{Z}_{AC} & \mathbf{Z}_{BC} \end{bmatrix} \begin{bmatrix} \mathbf{u}_{AA} \\ \mathbf{u}_{AC} \\ \mathbf{u}_{BC} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_A \\ \mathbf{e}_C \end{bmatrix}$$

Systematic effects      Pen nested within batch effects      Additive genetic effects

- The purebred model includes an animal additive genetic effect:  $\mathbf{u}_{AA}$ .
- The additive genetic effect in the crossbred model is decomposed into Piétrain sire and Large White dam additive genetic allelic effects for crossbred performance:

$$\mathbf{u}_{CC} = \mathbf{u}_{AC} + \mathbf{u}_{BC} + \boldsymbol{\phi}_A + \boldsymbol{\phi}_B$$

$$\mathbf{e}_C = \boldsymbol{\phi}_A + \boldsymbol{\phi}_B + \mathbf{e}_C^*$$



# SINGLE-STEP TERMINAL-CROSS MODEL (**GEN**)

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## Genetic (co)variance matrix

$$\text{var} \begin{bmatrix} \mathbf{u}_{AA} \\ \mathbf{u}_{AC} \\ \mathbf{u}_{BC} \end{bmatrix} = \begin{bmatrix} \mathbf{H}\sigma_A^2 & \mathbf{H}\sigma_{A(AC)} & 0 \\ \mathbf{H}\sigma_{(AC)A} & \mathbf{H}\sigma_{AC}^2 & 0 \\ 0 & 0 & \mathbf{A}_{(B)}\sigma_{BC}^2 \end{bmatrix}$$

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

Legarra et al. 2009

- A **genetic covariance** between Piétrain genetic effect ( $\mathbf{u}_{AA}$ ) and sire Piétrain additive genetic effect for CB performance

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Legarra et al. 2009

- A **genetic covariance** between Piétrain genetic effect ( $\mathbf{u}_{AA}$ ) and sire Piétrain additive genetic effect for CB performance
- The **dam genetic effect** ( $\mathbf{u}_{BC}$ ) is included as another random effect not correlated with the other two genetic effects.

# BENCHMARK MODELS

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## PEDIGREE-BASED TERMINAL-CROSS MODEL (PED)

$$\begin{bmatrix} \mathbf{y}_A \\ \mathbf{y}_C \end{bmatrix} = \begin{bmatrix} \mathbf{X}_A & 0 \\ 0 & \mathbf{X}_C \end{bmatrix} \begin{bmatrix} \mathbf{b}_A \\ \mathbf{b}_C \end{bmatrix} + \begin{bmatrix} \mathbf{W}_A & 0 \\ 0 & \mathbf{W}_C \end{bmatrix} \begin{bmatrix} \mathbf{p}_A \\ \mathbf{p}_C \end{bmatrix} + \begin{bmatrix} \mathbf{Z}_A & 0 & 0 \\ 0 & \mathbf{Z}_{AC} & \mathbf{Z}_{BC} \end{bmatrix} \begin{bmatrix} \mathbf{u}_{AA} \\ \mathbf{u}_{AC} \\ \mathbf{u}_{BC} \end{bmatrix} + \begin{bmatrix} \mathbf{e}_A \\ \mathbf{e}_C \end{bmatrix}$$

$$\text{var} \begin{bmatrix} \mathbf{u}_{AA} \\ \mathbf{u}_{AC} \\ \mathbf{u}_{BC} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{(A)}\sigma_A^2 & \mathbf{A}_{(A)}\sigma_{A(AC)} & 0 \\ \mathbf{A}_{(A)}\sigma_{(AC)A} & \mathbf{A}_{(A)}\sigma_{AC}^2 & 0 \\ 0 & 0 & \mathbf{A}_{(B)}\sigma_{BC}^2 \end{bmatrix}$$

## TWO UNIVARIATE SINGLE-STEP MODELS (GEN\_UNIC)

$$\mathbf{y}_A = \mathbf{X}_A \mathbf{b}_A + \mathbf{W}_A \mathbf{p}_A + \mathbf{Z}_A \mathbf{u}_{AA} + \mathbf{e}_A$$

$$\mathbf{y}_C = \mathbf{X}_C \mathbf{b}_C + \mathbf{W}_C \mathbf{p}_C + \mathbf{Z}_{AC} \mathbf{u}_{AC} + \mathbf{Z}_{BC} \mathbf{u}_{BC} + \mathbf{e}_C$$

# COMPARISON - Breeding value accuracies

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$$R_{i,j} = \sqrt{1 - \frac{PEV_{i,j}}{(1 + F_i)\sigma_{k,j}^2}}$$

$i$  = 1,...,individuals

$k$  = A, AC

$j$  = pedigree model, single-step model

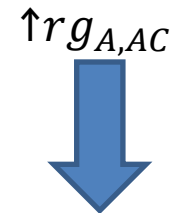
$PEV$  = prediction error variance

$F$  = inbreeding coefficient

# RESULTS - Genetic parameter estimates

## POSTERIOR MEAN [HPD at 95%]

Model	$r_{g_{A,AC}}$	$h_A^2$	$u_{AC}^2$	$u_{BC}^2$
PED	<b>0.79</b> [0.37,1.00]	<b>0.33</b> [0.08,0.57]	<b>0.24</b> [0.11,0.40]	<b>0.29</b> [0.12,0.44]
GEN	<b>0.84</b> [0.45,1.00]	<b>0.22</b> [0.05,0.37]	<b>0.25</b> [0.03,0.45]	<b>0.28</b> [0.12,0.44]



In the same environment, PB selection is already successful to indirectly improve CB performance

# RESULTS - Genetic parameter estimates

## POSTERIOR MEAN [HPD at 95%]

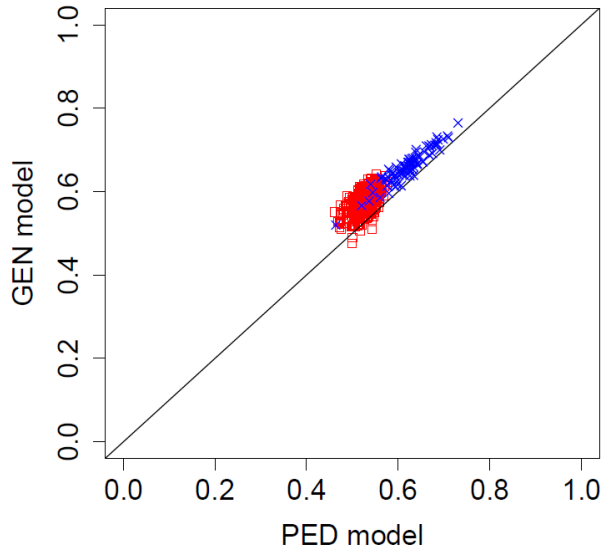
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HPD95% are narrower in the GEN model, possibly because of the higher amount of information used.

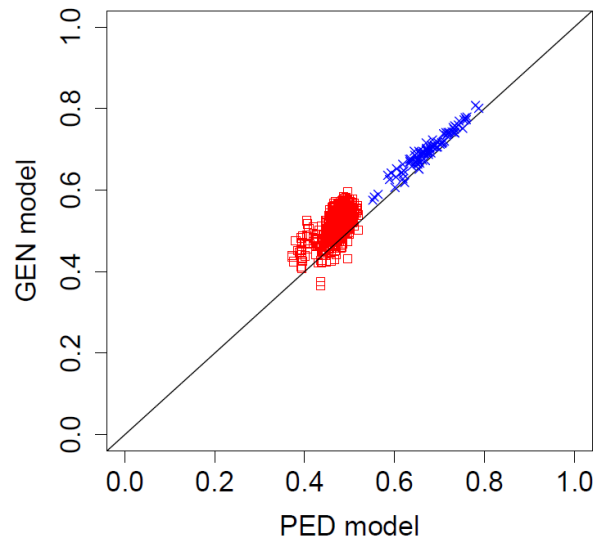
Posterior mean estimate of the  $h^2$  is higher with the PED than with the GEN model but posterior modes are similar.

# RESULTS - Breeding value accuracies

Accuracy PB performance, Growth rate



Accuracy CB performance, Growth rate



## PED model vs GEN model

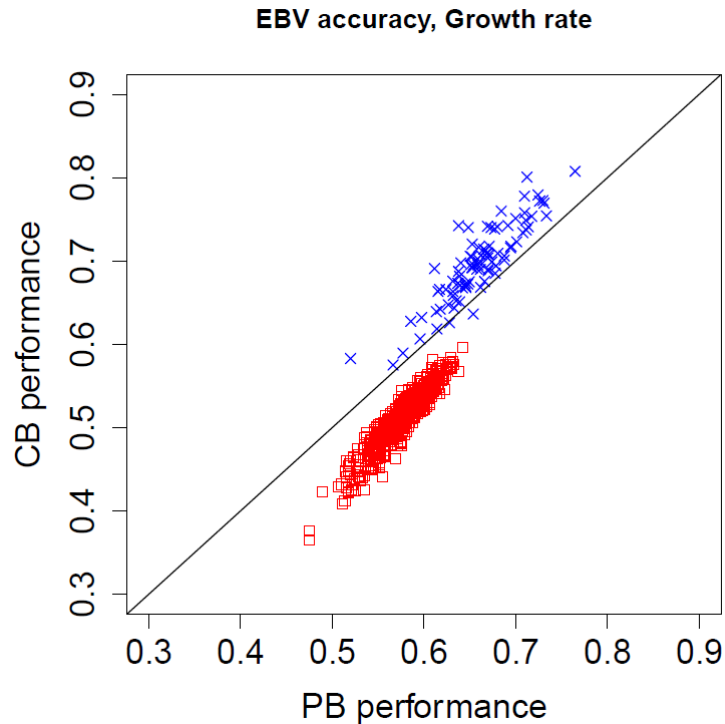
Genotyped animals obtained higher EBV accuracies with the single-step than with the pedigree-based model.

- PB offspring
- × Sires

# RESULTS - Breeding value accuracies

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## PB vs CB performance – GEN model



× Sires

Sire accuracy was higher than PB offspring accuracy  
The EBV accuracies were higher when sires were evaluated for CB than for PB performance.

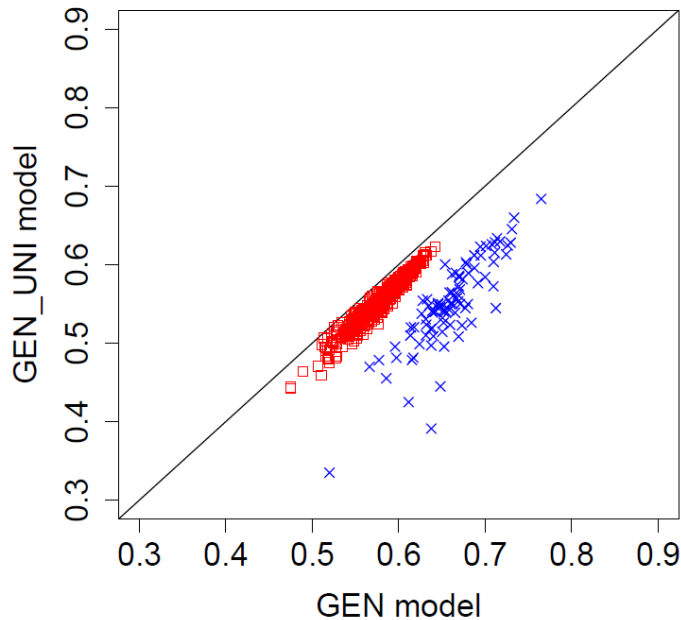
□ PB offspring

The EBV accuracies were higher when PB offspring were evaluated for PB than for CB performance.



# RESULTS - Breeding value accuracies

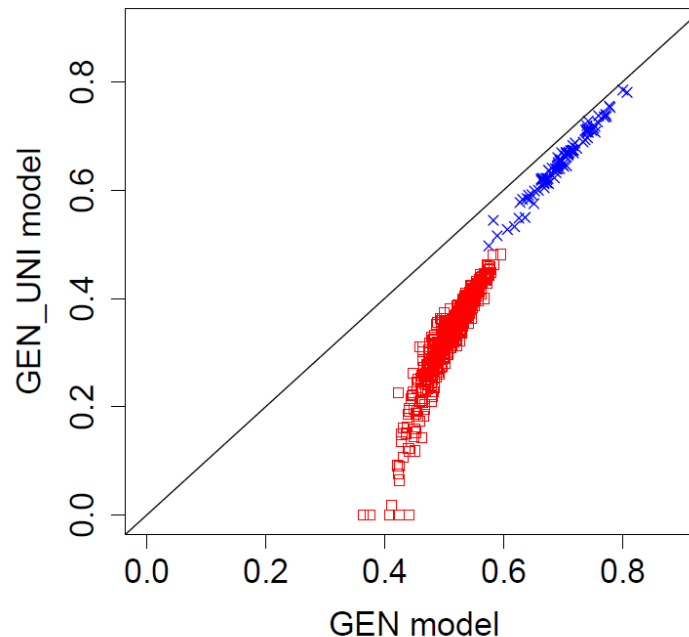
EBV accuracy for PB performance, Growth rate



## GEN model vs GEN\_UNIC models

The EBV accuracies were always higher using a 2 trait model (GEN) than using an univariate model (GEN\_UNIC) for both PB and CB performances.

EBV accuracy for CB performance, Growth rate



# Conclusions

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We have developed and empirically used a single-step terminal-cross model that uses the sire genotype to model crossbred performance.

Need to be compared with a more complex single-step method for genomic evaluation making full use of PB and CB genotypes.

Given the high genetic correlations, within line selection in purebreds is already successful to indirectly improve crossbred performance (in the same environment).

This improvement can be higher when accounting for crossbred performance together with genomic information because precision of the genetic parameter estimates and the accuracy of the EBV increase.



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**Thank you**

