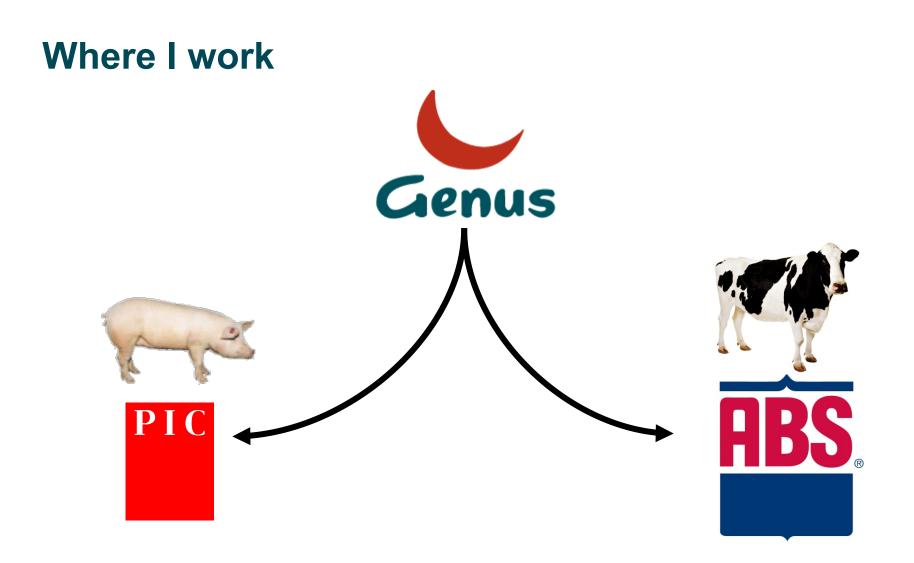


## Implementation of Genomic Selection in Commercial Pig Breeding

Selma Forni June 1<sup>st</sup>, 2012



## **Genomic Selection in the beginning**

- Bayesian Regressions to identify markers associated with specific traits too expensive HD genotyping all selection candidates.
- Estimate marker effects for each trait in each line.
- Estimate BV combining marker and pedigree information of selection candidates.
- Update marker effects when new genotypes/phenotypes are available.

		Accuracy		
Line	Trait	Pre-Genomics	Post-Genomics	% Increase
Sire Line	Scrotal Hernia	0.239	0.332	38.9%
Sire Line	Mortality	0.215	0.340	58.1%
Dam Line (LR)	Total Born	0.560	0.787	40.5%

## But we want to implement Genomic Selection for all traits in all lines ...

- Bayesian Regressions to identify markers associated with specific traits too expensive HD genotyping all selection candidates.
- Estimate marker effects for each trait in each line.

Training" requires a large number of individuals with genotypes, and phenotypes or progeny recorded. This is problematic in swine populations that are usually much smaller than other species such as dairy cattle.

• Estimate BV combining marker and pedigree information of selection candidates.

every day – automated system and accessed in 36 countries

Update marker effects when new genotypes/phenotypes are available.

```
every week : ~60 traits ~8 lines
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## Much simpler if we use Single-Step Genomic Evaluation

✓ Easily integrated into systems for routine BLUP that we have been using for years.

✓ Estimate BV for genotyped and non-genotyped all at once.

✓ Automatically links newest phenotypes and genotypes with pedigree information.

 $\checkmark$  It can be implemented in any model (multiple traits, maternal effects).

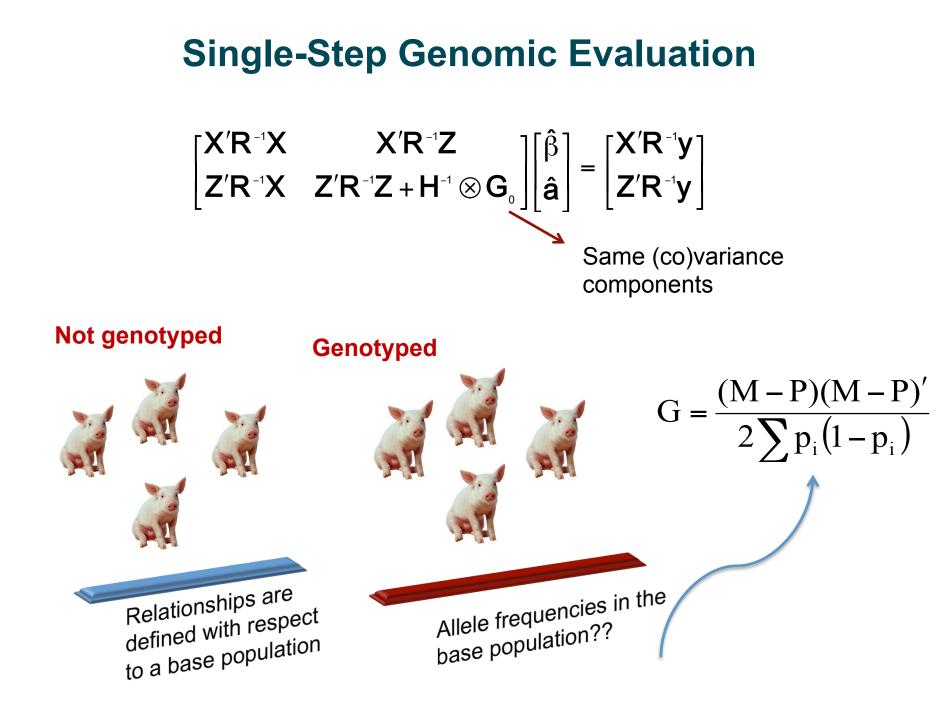
 $\checkmark$  The number of parameters do not increase with the number of markers.

**Necessary change:** 

A priori distribution for marker effects: Normal Very small impact for most traits Tue class

We can revisit that in the future





	Average	Average off-	Additive variance	Accuracy GEBV
	diagonal	diagonal	(se)	(PEV)
А	1.000	0.032	2.27 (±0.52)	0.22
G05	1.253	0.595	3.43 (±0.56)	0.37
GMF	1.697	1.022	3.43 (±0.56)	0.49
GOF	0.936	0.000	2.41 (±0.39)	0.30
GOF*	0.505	0.000	4.46 (±0.73)	0.43
GN	1.002	0.000	2.25 (±0.36)	0.28

- A = Pedigree-based Relationship
- G05 = Genomic Relationship with allele frequency equal to 0.5
- **GMF** = Genomic Relationship with allele frequency equal to average MAF
- **GOF** = Genomic Relationship with observed allele frequency
- **GOF\*** = Genomic Relationship with allele frequency following a Beta distribution
- **GN** = Normalized Relationship Matrix

$$GN = \frac{(M-P)(M-P)^{'}}{\left\{ trace \left[ (M-P)(M-P)^{'} \right] \right\}_{n}}$$

Forni et al. (2011)

### The algorithm evolved!!

Thur class

Vitezica et al. (2011)

$$\mathbf{G}^* = \left(1 - \frac{1}{2}\alpha\right)\mathbf{G} + \mathbf{11'}\alpha$$

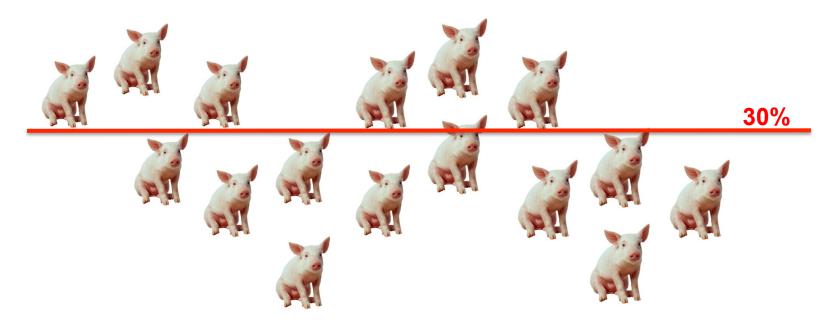
Christensen et al. (2012)

 $G_a = \beta G + \alpha$ ,

where  $\beta$  and  $\alpha$  solved the system of equations

Avg(diag(G)) $\beta + \alpha = Avg(diag(A_{11})),$ Avg(G) $\beta + \alpha = Avg(A_{11}).$ 

### **Does all that really matter ... \$\$\$**?



GN is the "best job" that we can do: 597 animals selected / year

How many animals would not had been selected?				
А	G05	GMF	GOF*	GOF
141	30	29	43	10

#### What we have learned

• Pedigree and genomic relationships need to be calculated with respect to the same base population.

• To achieve that one needs to use the best guess of allele frequencies in the base population and adjust G (tunning).

#### • Otherwise:

- Bias in GEBV
- Underestimation of PEV
- Bias in variance components
- Less than optimal selection decisions

#### ACC improvement even for sires and dams that already have progeny data

TRAIT	# Daughters	ACC EBV	ACC GEBV	increase
Total Number born	high	0.57	0.66	16%
Stillborn	high	0.57	0.66	16%
Litter weaning weight	high	0.45	0.52	15%
Interval weaning - mate	high	0.45	0.53	18%
Survival birth - weaning	high	0.33	0.36	9%
Survival birth - weaning	high	0.33	0.36	9%

#### • 4,200 animals genotyped 60k

#### • Greater ACC improvement for young sires and dams

TRAIT	# Daughters	ACC EBV	ACC GEBV	increase
Total Number born	low or zero	0.44	0.56	27%
Stillborn	low or zero	0.44	0.56	27%
Litter weaning weight	low or zero	0.38	0.46	21%
Interval weaning - mate	low or zero	0.31	0.42	35%
Survival birth - weaning	low or zero	0.26	0.30	15%

#### • 1,000 animals genotyped 60k

#### ACC improvement for progeny of genotyped sires and dams – these animals were not genotyped

TRAIT	Progeny of all sires and dams genotyped		Progeny of <mark>young</mark> sires and dams genotyped			
	ACC EBV	ACC GEBV	increase	ACC EBV	ACC GEBV	increase
Total Number born	0.39	0.42	7%	0.36	0.41	14%
Stillborn	0.39	0.41	5%	0.36	0.40	11%
Litter weaning weight	0.41	0.43	5%	0.31	0.34	10%
Interval weaning - mate	0.37	0.39	5%	0.25	0.29	16%
Survival birth - weaning	0.29	0.30	3%	0.41	0.43	5%

#### But we still have the same BV for full siblings

#### ACC improvement for the entire population

#### Table 2 Daily gain

	All		Genotyp		Non-genotyped		
	Cor (GBV, y <sub>c</sub> )	Reg	Cor (GBV, y <sub>c</sub> )	Reg	Cor(GBV, y <sub>c</sub> )	Reg	
Univariate							
Ped	0.193 <sup>a</sup>	0.91	0.179 <sup>a</sup>	0.72	0.193 <sup>a</sup>	0.90	
1-step	0.226 <sup>b</sup>	0.92	0.345 <sup>b</sup>	0.94	0.217 <sup>b</sup>	0.90	
1-step-a	0.229 <sup>c</sup>	0.93	0.353°	0.97	0.219 <sup>c</sup>	0.91	
GBLUP			0.351 <sup>b,c</sup>	0.80			
Bivariate							
Ped	0.193 <sup>a</sup>	0.90	0.177ª	0.72	0.193 <sup>a</sup>	0.90	
1-step	0.225 <sup>d</sup>	0.92	0.344 <sup>b</sup>	0.94	0.216 <sup>d</sup>	0.90	
1-step-a	0.228 <sup>e</sup>	0.93	0.352°	0.97	0.218 <sup>e</sup>	0.91	
GBLUP			0.352 <sup>b,c</sup>	0.806			

Christensen et al. (2012)

#### Imputation

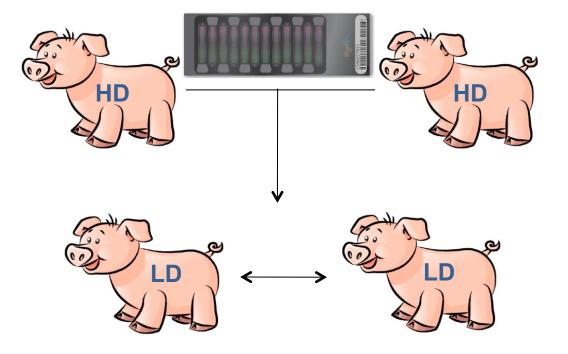
## Imputation\*: using well-spaced LD genotypes on selection candidates to 'fill-in' missing HD genotypes

GN parents, grandparents, ...

All HD genotyped

**GN** progeny

HD genotype imputed from LD panel and pedigree HD



## **Alphalmpute Results**

## Imputation accuracy for two lowdensity panels

	384	3k
<b>Both Parents</b>	0.96	0.99
Sire and MGS	0.89	0.98
<b>Dam and PGS</b>	0.94	0.99
Sire	0.87	0.98
Dam	0.87	0.97
Other	0.81	0.95

## Accuracy will be improved by imputing 60k genotypes on selection candidates

TRAIT	Have their own record	ACC EBV	ACC GEBV	Increase
Total Number born	NO	0.36	0.62	71%
Total Number born xbred	NO	0.22	0.39	75%

Phenotype measured in commercial farms
Expensive to measure
How we can generate \$\$ for our costumers
Genetic improvement depends on multitrait analysis

## Pedigree is not always "fair"

Thur class

	Animals in the	Parents without	Animals	Time to
	pedigree	records or	related to	converge
		genotypes	genotyped	
PED_full	605,046	154,075	6,987	38h 56min
PED_18	473,825	22,854	6,987	30h 20min
PED_10	473,789	22,818	6,951	33h 20min
PED_3	471,234	20,236	5,366	4h 20min
PED_2	468,057	17,086	5,058	2h 40min
PED_1	463,609	12,638	4,691	2h 20min

## Pedigree is not always "fair"

Thur class

	Diagonals	Off-diagonals	All
PED_full	0.31	0.72	0.78
PED_18	0.31	0.72	0.78
PED_10	0.31	0.72	0.78
PED_3	0.37	0.70	0.74
PED_2	0.39	0.72	0.70
PED_1	0.39	0.75	0.69

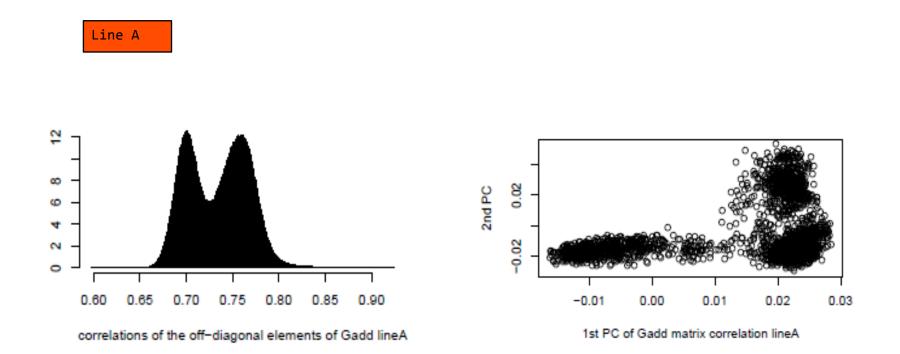
## Large fluctuations in GEBV when young genotyped animals were added

#### **Correlations between GEBVs from consecutive months**

TRAIT	G_MATRIX_DEC	G_MATRIX_JAN
TOTAL BORN	0.99	0.95
STILLBORN**	0.99	0.08
TOTAL BORN XBRED	0.98	0.98
STILLBORN XBRED**	0.35	0.06
SURVIVAL**	0.93	0.75
LITTER WEANING WEIGHT	0.99	0.99
DAYS FROM FARROWING TO NEXT MATING	0.99	0.99

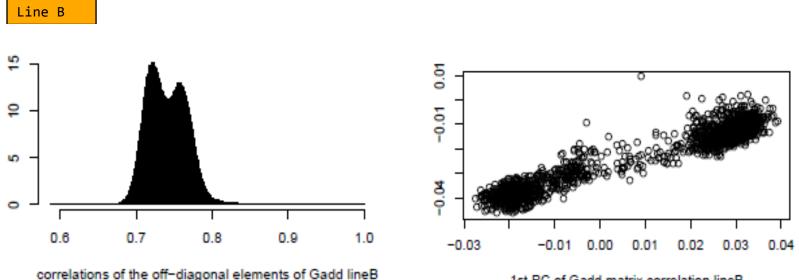
\*\* Traits with low h<sup>2</sup> (< 0.10) and recorded in few herds

## **Principal Components of G: population stratification**



Groups of animals more related between themselves than to the rest of the population.

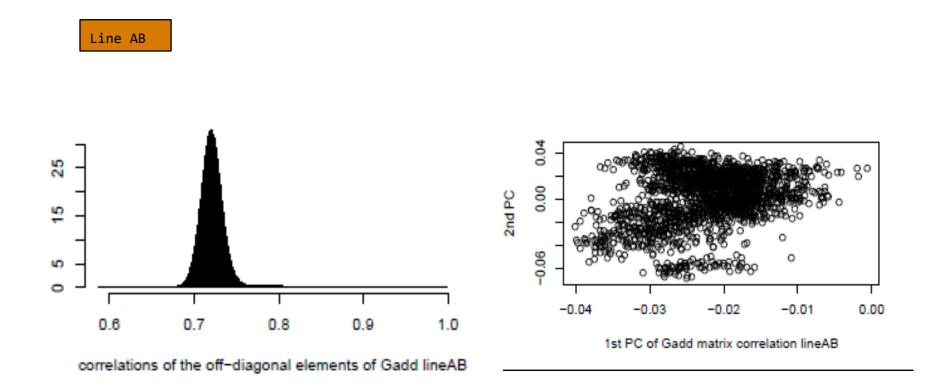
### **Principal Components of G: population stratification**



1st PC of Gadd matrix correlation lineB

Groups of animals more related between themselves than to the rest of the population.

### **Principal Components of G: population stratification**







## **Questions?**

# **THANK YOU**