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### Practical integration of genomic selection in dairy cattle breeding schemes

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#### Introduction



Genomic selection : a revolution for animal breeders

- Big data : information at 1000s of markers for 1000s of animals
- Bigger and bigger data:
  - Huge increase in the number of genotyped animals
  - Denser SNP chips or even sequence data
- Change in the breeding program structures:
  - Reduction in generation intervals
  - More frequent (on-demand) genomic evaluations

In this context, how to make effective selection decisions? In practice, which strategies were implemented?





### Outline

- 1. The novel idea underlying genomic selection
- 2. Integrating big genomic data in genetic evaluations
- 3. Impact on the structure of breeding schemes and expected benefits
- 4. Practical breeding strategies for implementing genomic selection across countries





# Limits of conventional selection methods

Related animals resemble more than unrelated ones because they share common genetic material (genes, QTL)

Var(G) = Additive relationship matrix \* genetic variance

Traditionally, additive relationships estimated from pedigrees

- ⇒ Full sibs without performance have the same estimated breeding values (EBV)
- $\Rightarrow$  Progeny-testing (PT) of bulls necessary before selection to :
  - $\Rightarrow$  Get high EBV accurary
  - $\Rightarrow$  Be able to differenciate between sibs
  - ⇒ But long (5 yrs) and expensive (40 000€ / bull)







# Innovative idea underlying genomic selection

Genetic markers (SNPs) used as proxies to detect the QTL mix inherited by an animal from its parents

SNP technology : profiling many animals for thousands of markers in a single analysis

Dense marker maps covering the whole genome:

- Follow the transmission of chromosomic regions across generations
- Strong linkage disequilibrium (LD) between SNPs and QTL
  - $\Rightarrow$  within breed, 1 marker allele strongly associated with 1 QTL allele

Genomic EBV = £ (effects estimated at marker loci)



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#### Challenges to be faced

Thousands of markers

→ (n<p)</p>

Thousands of animals

Challenges:

- To handle & manipulate the data (storage, quality checks)
- To compute GEBVs (construction & inversion of genomic matrices, genotype imputations...)
- To integrate this flow of information in breeding schemes





### Basic principles of genomic evaluation (Meuwissen et al., 2001)

Reference Population with genotypes AND phenotypes used to build prediction equations of genetic merit

 $\Rightarrow$  Usually bulls with daughters





Different methods to estimate GEBV, mainly:

- Genomic-BLUP approach
- Bayesian models

>>> In practice, increase in computing time compared to conventional BLUP





#### Focus on the G-BLUP approach

<u>2-step approach (Van Raden, 2008):</u>

- Construct the additive relationship matrix based on genotypes the so-called G-matrix (Van Raden, 2008; Forni et al., 2011)
- ⇒ Estimate a genomic value at markers for genotyped animals (DGV)
- $\Rightarrow$  Combine it with pedigree-based EBV to get GEBV

<u>1-step approach (Misztal et al., 2009; Christensen & Lund, 2010):</u>

directly include genotyped and ungenotyped individual in a single relationship matrix H

$$H^{-1} = A^{-1} + \begin{bmatrix} 0 & 0 \\ 0 & G^{-1} - A_{genotyped} \end{bmatrix}^{-1}$$



#### G-BLUP approach - Computing issues -

Genomic relationship matrix = dense matrix without known structure

Multi-trait analysis of type traits in the USA, time needed for computing GEBV was doubled when including ~7000 genotyped animals (Tsuruta et al., 2011)

New strategies to reduce computations:

- $\Rightarrow$  Directly build an approximate inverse of the G-matrix (Faux et al., 2012)
- ⇒ Strategies to directly update the inverse of the G matrix with only new genotypes (Meyer et al., 2013)





#### **Computing issues**

Other efficient approaches were developed to boost computations based on:

- Dimensionality reduction through principal component analysis (Solberg et al., 2009; Macciotta et al., 2009; Long et al., 2011)
- SNP selection (Legarra et al., 2011; Croiseau et al., 2011; Colombani et al., 2011)

Whatever the genomic evaluation approach, high interest in developing high-throughput computing (Wu et al., 2011, 2012; Cole et al., 2012)

- Parallel programming
- Use new hardware: graphical processing units (GPU)





### **Benefits of genomic selection**

Increase in EBV reliability for young candidates without performance (CD ~ 0.25 ' 0.65 for milk production traits in Holsteins)

⇒ GBLUP and Bayesian approaches render similar GEBV reliabilities for real data

Possibility to differenciate young candidates from both sexes on GEBV:

- without own performance or offspring
- both within- and between-families







### Impact of implementing genomic selection in dairy cattle

Compared to the PT scheme, selection on a trait with  $h^2=0.3$ 

Scheme	Generation interval	Annual genetic gain	Inbreeding rates		
	L	• G <sub>a</sub> *	<ul> <li>F/ generation</li> </ul>	• F / year	
PS	~constant	+ 9 –16%	Reduced	Reduced	
TURBO	halved	+29 –100%	Constant to reduced	Increased (if nb of AI bulls not enlarged)	

>> Advantage of genomic selection schemes larger for low heritability traits



(<sup>\*</sup> Review from Buch et al., 2012; Colleau et al., 2009; Lillehammer et al., 2011; Pryce et al., 2010)



### Reasons of the success for TURBO schemes

Increase in • G on the sire-to-offspring genetic pathway :

- reduction in the generation interval
- although reduction in selection accuracy of AI sires
- Increase in G on the dam-to-offspring pathway :
  - Reduction in the generation interval
  - Higher selection accuracy, especially for low heritability trait
  - Less bias in GEBV than EBV: lesser impact of preferential treatments
- Large gains in G when genotyping even small proportion of females (Sørensen and Sørensen, 2009)
  - Strategies needed to optimally allocate genotypes to males / females





# Increasing the reference population size

The bigger the reference population, the higher the accuracy of GEBV

- ⇒ Creation of across-country consortia to exchange genotypes
  - 3 main for Holsteins : Eurogenomics (Lund et al., 2010), Consortium USA-Canada-UK-Italy, Consortium Australia-Ireland- NZ(LIC)
  - 1 worldwide consortium for the Brown Swiss (Santus, EAAP 2013)
- $\Rightarrow$  Integration of cows in reference populations
  - $\Rightarrow$  Simulation of the Irish Holstein population (McHugh et al., 2011):

	TURBO	TURBO	TURBO
Ref. Population size	+500 B / yr	+ 500 B / yr + 500 @/ yr	+ 500 B / yr +3 500 @/ yr
Annual • G	0.34 Ã <sub>g</sub> (-)	0.37 Ã <sub>g</sub> (+9%)	0.49 Ã <sub>g</sub> (+44%)
Annual • F	+0.7%	+0.4%	+0.4%



# Importance of the reference population design

Optimal design of the reference population when :

- Low relationship among reference sires
- High relationship between reference population and candidates (Pszczola et al., 2012)

Constitution of multi-breed reference populations:

- No increase in reliability with 54K if distant breeds and low heritability (Karoui et al., 2012)
- Would require denser maps to get strong LD between SNP and QTL across breeds (Schrooten et al., EAAP 2013)





### Managing the risk of TURBO schemes

At the herd level, use teams of bulls to mitigate the risk of using bulls with poor merit (Schefers and Weigel, 2012)

#### To curb annual inbreeding rates

- Enlarge the number of young genomic bulls and ensure balanced use of them
- ⇒ Avoid further use of genomic bulls once they have milking daughters, except if strict rules for managing genetic diversity (Colleau et al., 2009)
- Promising results when integrating genomic data in methods for preserving genetic diversity
  - $\Rightarrow$  Selection based on optimal contributions (Sonesson et al., 2010, 2012)
  - $\Rightarrow$  Mate allocation with constraints on progeny inbreeding (Pryce et al., 2012)





#### **Current-state implementation of genomic selection : Holstein breed**

	USA	UK	FRA	GER	NLD	AUS	IRL	NZL (LIC)
Ref. Pop. (# of bulls)	~23 000	~23 000	~26 000	~26 000	~26 000	~4 800	~4 800	~4 800
Including cows in the Ref. Pop	Yes, 53 396 @	No	No	No	No	Yes, 8716 @	No	Yes
Genomic evaluation method	2-step BayesA	2-step G-BLUP	BLUP- QTL	2-step GBLUP	2-step Bayesian SSVS <sup>a</sup>	2-step GBLUP	2-step GBLUP	1-step GBLUP

>> Large increase in reference population sizes since Apr. 2011 (Pryce & Daetwyler, 2012)



<sup>a</sup> Calus et al., 2008



#### **Current-state implementation of genomic selection : Holstein breed**

	USA	UK	FRA	GER	NLD	AUS	IRL	NZL
Nb of genotyped calves / yr	25 000B 135 000@	2500	50 000 3-4000B	12 000 B 6000 @	2500 B 5000 @	580 B 2000 @	NA	NA
Young sires selected /yr	1 000	NA	~ 400	~ 500	20	NA	40	10-15
Organized PT of bulls	Yes	NA	No	No	Yes, 120	Yes	No	Yes
Market-share of genomic bulls	48%	NA	57%	55%	35%	NA	54%	30%

Compared to a 2011 survey (Pryce & Daetwyler, 2012):

>> Large increase in the number of genotyped calved in all countries

>> Ceasing of organized PT in several countries

>> Increase in the market-share of genomic bulls





#### Conclusion

Breeding schemes are being changed to integrate genomic selection:

- <u>Key drivers</u>: Improvement of the technical & economical efficiency
- New opportunities :
  - improve genetic gain on new traits / traits difficult to select
  - better control of inbreeding rates

Increasing amounts of genotypic information collected through time Need to adapt on several aspects:

- Computing infrastructure (data storage, hardware architecture)
- Computing strategies & programming to gain in efficiency





