

# Present and future of genomic selection at the commercial level

Ignacy Misztal

University of Georgia

# Genomic selection

- Many studies— simulation and field data
- Different results by methods and species
- Contradictions
  
- Studies at UGA with many data sets
  - Dairy (up to 75k genotypes), Chicken (up to 14k genotypes), Pigs (up to 5k genotypes), Sheep (up to 5k genotypes)
  - 
  - Single-step, GBLUP and Bayesian Regression (BayesA, B, etc.; Bayesian Lasso);
  - weighted single-step/GBLUP: “poor man BayesB”: assign more weight to SNPs of large effect
  
- Is consistent picture emerging?
- If so, what next?

# Experiences in dairy

- High accuracy if many genotypes
- Little improvement from adding female genotypes
- Little improvement with high density chip
- Little predictivity across breeds
  - Predictivity if mixed reference populations
- Smaller accuracy for animals with few ancestors genotyped
- Foreign genotypes may help or not
  
- Nonlinear/Bayesian Regression/weightedGBLUP help if major genes (Fat & Protein). Otherwise prone to errors

# Experiences – other species

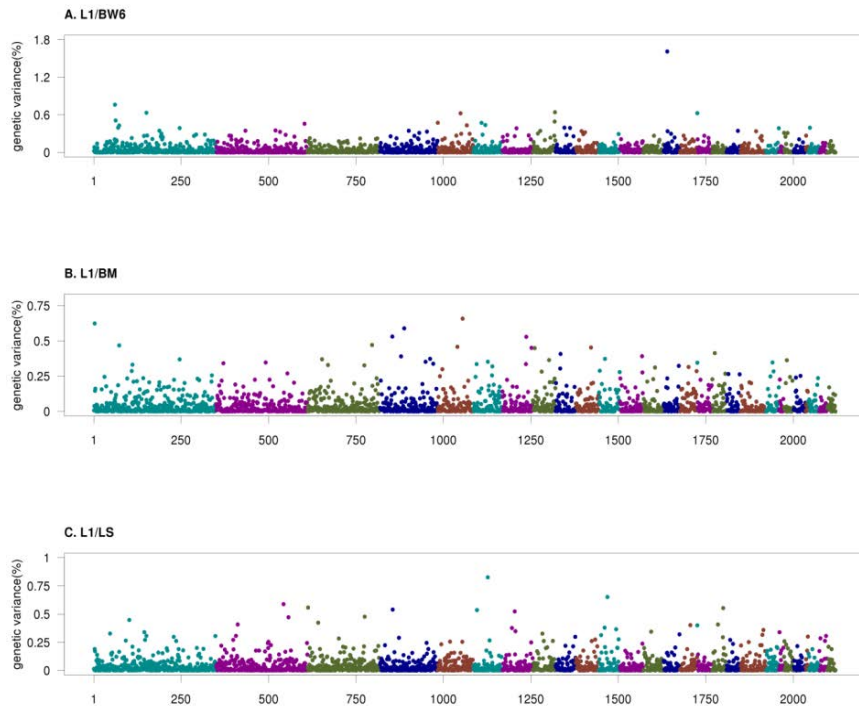
- Pigs
  - Moderate increases in accuracy with many genotypes
  - Outliers
- Chicken
  - Moderate increases with many genotypes
  - Males and females contribute
- Sheep
  - Moderate increases in dairy sheep
  - Small or no increases in meat with many genotypes

# GBLUP or BayesX/nonlinear/... ?

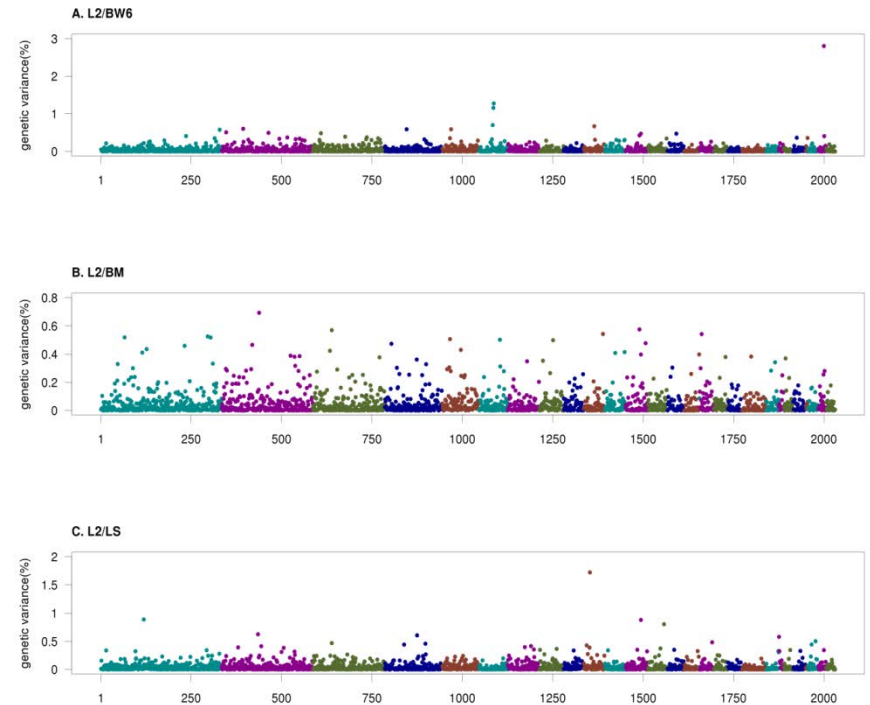
- Are major genes important?
  - If so → predictivity across lines/breeds

# Manhattan plots for 2 lines in chicken

## Line 1



## Line 2



No overlap across lines!

# GBLUP/BayesB/.. – Questions?

- Can major genes remain in selected populations?
- Are major genes important in index selection?
- Advantage of Bayesian Regression greater if multigenerational genotypes – retained haplotypes?
- If SNP of large effect, can use W(eighted) GBLUP (fastBayesA; Sun et al. 2012) and W(eighted)ssGBLUP (Wang et al., 2012) – not based on sampling

# Genomic accuracy in daughter equivalents

No contributions from other lines (except by LD)

Low contribution from low accuracy animals

$$DE_i \sim \sum_{j, j \neq i} \left[ (g_{ij} - a_{22,ij})^2 acc_j^2 \right]$$

*SD* ≈ 0.04

summation over genotyped animals

DE – daughter equivalents

$g_{ij}$  – genomic relationships

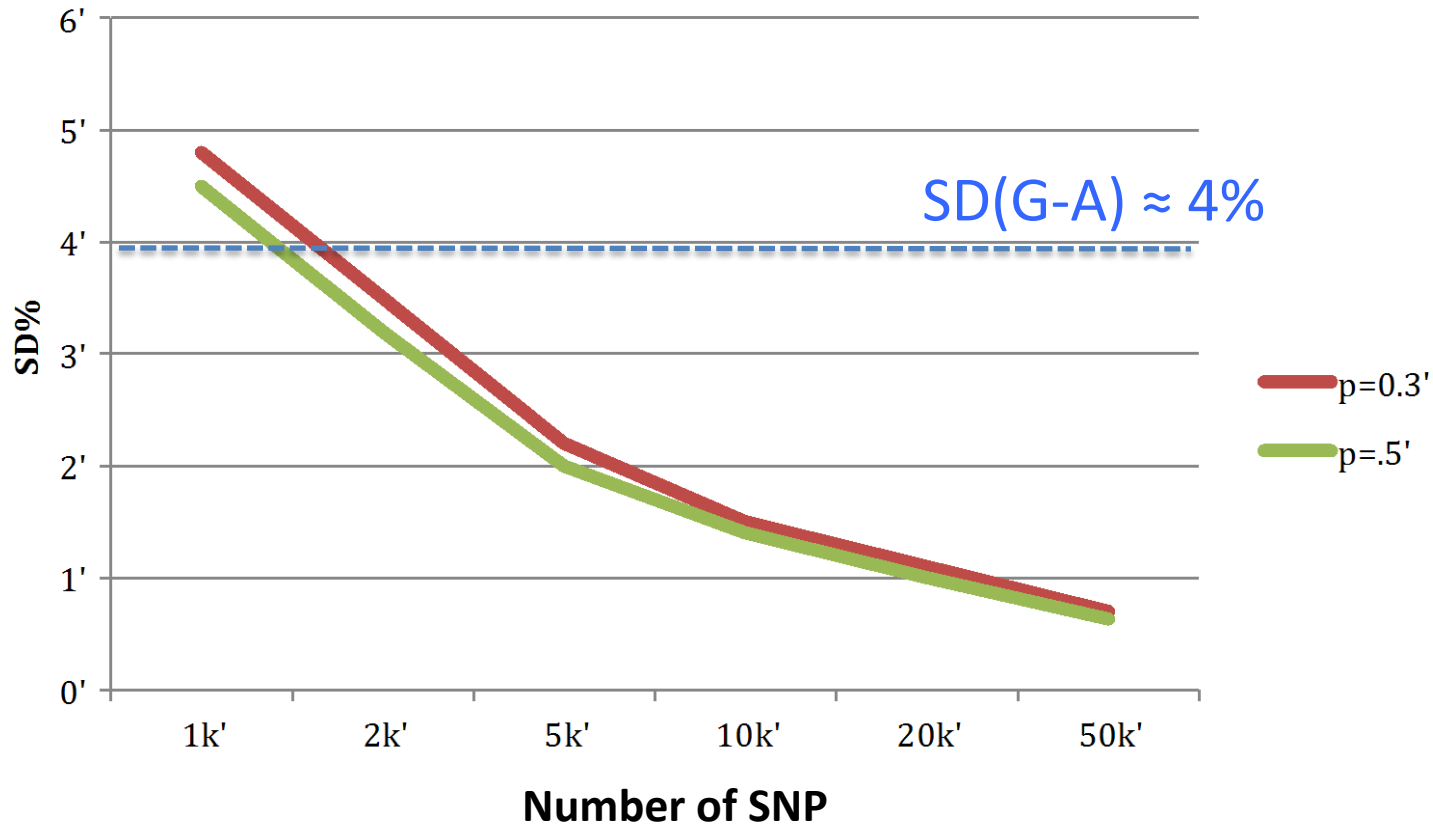
$a_{22,ij}$  – pedigree relationship

acc – accuracy

Misztal et al., 2012



# Approximate SD of G with limited number of SNP



Small improvement beyond 20k

# Specifics of species

- Dairy – large progeny groups
  - Holsteins –almost single population worldwide but some composites
- Pigs – Smaller progeny groups, open populations
- Chicken – small progeny groups, closed populations
- Sheep - single breed multibreed, heterogeneous data structure

# Case studies at UGA

- Single-Step vs. multistep (deregressed proofs + Bayesian Regression)
  - Similar accuracies in dairy with many genotypes and high acc bulls
    - Pseudo-observations  $\approx$  EBV, index with PA unimportant
  - SS better otherwise
    - No approximations due to pseudo-obs or index
  - SS worse if model deficiency
- Recent cases at UGA
  - Best acc for BLUP  $\rightarrow$  wrong validation
  - Large biases for one trait  $\rightarrow$  add one fixed effect
  - Low PA/GEN acc for specific traits  $\rightarrow$  cut old data
  - Nearly zero GEN accuracies  $\rightarrow$  bad imputation

All modeling or quality control issues

# Future

- Genotyping costs decrease / possibly millions genotyped
- High computing cost at little marginal benefit? Or loss...
- Need tools for multi-trait genomic selection that unify all information:
  - Simple
  - Fool proof
  - Allow for model refinement and account for changes over time
- Single step a la Aguilar et. al. (2010), Meuwissen et. al. (2011),...,?

Computationally realistic?

Example: move from CC (Contemporary Comparison) to BLUP

## Problem

Inversion of A expensive

Creation of MME expensive

Programming for complex models hard, poor convergence

Slow computing if many effects and traits:  $LHS \mathbf{q} = (\mathbf{W}'\mathbf{W})\mathbf{q}$

Computing with GS expensive,  
 $cost \sim \#genotypes^{2-3}$

## Solution

Algorithm to create  $A^{-1}$  directly  
(Henderson, 1975)

Iteration on data (Schaeffer and Kennedy, 1986; Misztal et al., 1997)

PCG algorithm (Berger et al., 1987; Lidauer et al, 1999; Tsuruta et al., 2001)

Sequential multiplication:  
 $LHS=(\mathbf{W}(\mathbf{W}'\mathbf{q}))$  (Stranden, 1999)

**Simple algorithm to account for all genomic info (?????, 2014?)**

# Conclusions

- Better understanding of genomic selection
- Genomic selection for commercial use closer to maturity
  - Attention to detail of utmost importance !
- Breakthrough(s) welcome

# Acknowledgements

- Discussions with countless individuals including Andres Legarra, Shogo Tsuruta, Ignacio Aguilar, Bill Muir, Zulma Vitezica, Selma Forni, Romdhane Rekaya,...
- Grants from Holsteins Assoc., Angus Assoc., Cobb Vantress
- AFRI grants 2009-65205-05665 and 2010-65205-20366 from the USDA NIFA
- BARD Project IS-4394-11 R

# EBV for young animals

$$u_i = \frac{u_s + u_d + \sum_{j, j \neq i} (-\tau g^{ij} + \omega a_{22}^{ij}) u_j}{2 + \tau g^{ii} - \omega a_{22}^{ii}} =$$

$$w_1 \text{PA} + w_2 \text{GEBV} - w_3 \text{GPI}$$

PA = Parent Average

GEBV = Genomic EBV

GPI = Parental Index for genotyped animals



# Large genomic information

In dairy for popular bulls:  $g^{ii} \approx 2$ ,  $g^{ii} \approx a_{22}^{ii}$

$$u_i \approx \frac{\sum_{j, j \neq i} (-\tau g^{ij}) u_j}{\tau g^{ii}} = \frac{\sum_{j, j \neq i} (-g^{ij}) u_j}{g^{ii}} = \text{GEBV}$$

Scaling factors cancel out

# Prior influence: BayesX

19

- BayesB
- Prior:
- Chain 1
- Chain 2
- Chain 3
- Chain 4
- Average

