

Progress in GWAS for large datasets with GBLUP and single-step GBLUP

Ignacy Misztal, Daniela Lourenco and Matias Bermann



Specificity of plant and animal breeding

- Plants

- Find genes in wild species
- Introgress into inbred lines
- Genetic evaluation of inbred crosses across environments
 - All crosses genotyped

- Animals

- Selection usually within breeds and lines
- Commercial animals purebreds or crossbreds
- Many animals ungenotyped
- Single-step GBLUP dominant methodology

Single-step GBLUP –pedigree and genomic relationships combined

Matrix H (Legarra ,2009)



$$\mathbf{H} = \mathbf{A} + \begin{bmatrix} \mathbf{A}_{12}\mathbf{A}_{22}^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{I} \\ \mathbf{I} \end{bmatrix} [\mathbf{G} - \mathbf{A}_{22}] [\mathbf{I} \quad \mathbf{I}] \begin{bmatrix} \mathbf{A}_{22}^{-1}\mathbf{A}_{21} & \mathbf{0} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}$$

Inverse of H (Aguilar et al., 2010)

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

G –genomic relationship matrix

1 –ungenotyped animals

2-genotyped animals

Christensen and Lund, 2010

Boemcke et al., 2011

ssGBLUP for Genome Wide Association Studies

- Large research interest in GWAS
- Limitations for current methods
 - Simple models
 - Single trait
 - Complicated if not all animals genotyped



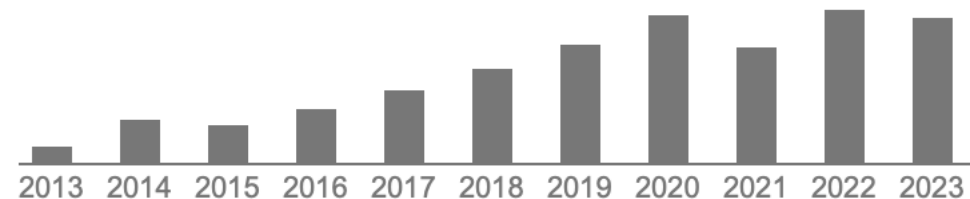
Can ssGBLUP be used for GWAS?

Genet. Res., Camb. (2012), **94**, pp. 73–83. © Cambridge University Press 2012
doi:10.1017/S0016672312000274

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Genome-wide association mapping including phenotypes
from relatives without genotypes

Cited by 537



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GWAS with ssGBLUP (Wang et al., 2012)

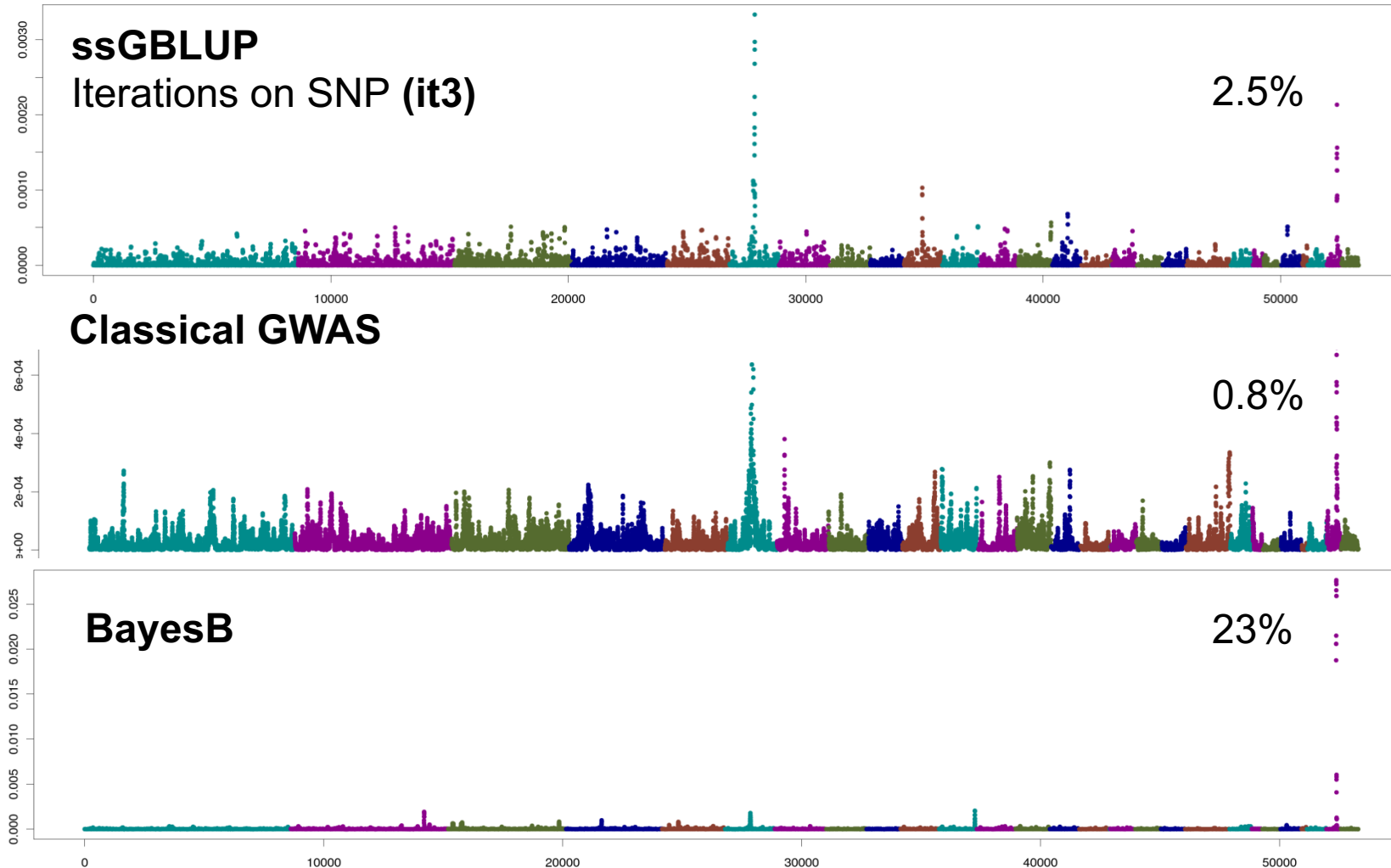
- Convert GEBV to SNP effects
- Estimate individual SNP variances
- Incorporate variances in G
- Possibly recompute GEBV and iterate

1. $D=I$
2. $G=ZDZ'/q$
3. Compute a
4. $u=DZ'/q G^{-1} a$
5. $d_i=2p_i(1-p_i)u_i^2$
6. $D=n D/\text{tr}(D)$
7. Loop to 2

Output as % of variance explained in a window

Discrepancies in GWAS methods

Chicken weight



P-values for GWAS in (ss)GBLUP

$$pval_i = 2 \left(1 - \Phi \left(\left| \frac{s\hat{n}p_i}{sd(s\hat{n}p_i)} \right| \right) \right) \quad (\text{Chen et al., 2017})$$

If $sd(s\hat{n}p_i)$ approximately constant, Manhattan plots based on $|s\hat{n}p_i|$ and $pval_i$ similar

Large data – APY algorithm

- Due to LD, genomic information compresses well: about 15k for cattle and about 5k for pigs and chicken
- APY algorithm: $u_{\text{noncore}} = P u_{\text{core}} + \varepsilon$
- Number of core animals ~ equal to dimensionality



J. Dairy Sci. 97:3943–3952

<http://dx.doi.org/10.3168/jds.2013-7752>

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Using recursion to compute the inverse of the genomic relationship matrix

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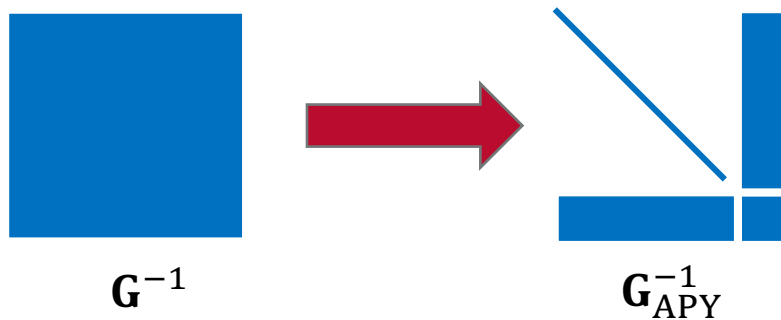
[‡]Instituto Nacional de Investigación Agropecuaria, Las Brujas 90200, Uruguay

Inexpensive Computation of the Inverse of the Genomic Relationship Matrix in Populations with Small Effective Population Size

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$$A^{-1} + \begin{pmatrix} 0 & 0 \\ 0 & G^{-1} - A_{22}^{-1} \end{pmatrix} \longrightarrow A^{-1} + \begin{pmatrix} 0 & 0 \\ 0 & G_{APY}^{-1} - A_{22}^{-1} \end{pmatrix}$$

APY Single-step GWAS

- **Model**

$$y = W\alpha + Zu + \eta$$

- **Procedure**

1. Calculate $Var(\mathbf{u})^{-1} = \mathbf{H}_{APY}^{-1}$
2. Estimate variance components
3. Calculate $\hat{\mathbf{u}}_{2c}$ and approximate $Var(\hat{\mathbf{u}}_{2c}) = \mathbf{G}_{cc} - \mathbf{C}^{u_{2c}u_{2c}}$
4. For each marker:
 1. Calculate $\hat{b}_i = \mathbf{x}'_{ci} \mathbf{G}_{cc}^{-1} \hat{\mathbf{u}}_2$
 2. Calculate $sd(\hat{b}_i) = \sqrt{\mathbf{x}'_{ci} \mathbf{G}_{cc}^{-1} (\mathbf{G}_{cc} - \mathbf{C}^{u_{2c}u_{2c}}) \mathbf{G}_{cc}^{-1} \mathbf{x}_{ci}}$
 3. Calculate p-value as $pvalue_i = 1 - \Phi\left(\frac{\hat{b}_i}{sd(\hat{b}_i)}\right)$

On the equivalence between marker effect models and breeding value models and direct genomic values with the Algorithm for Proven and Young

Matias Bermann^{1*}, Daniela Lourenco¹, Natalia S. Forneris^{2,3}, Andres Legarra⁴ and Ignacy Misztal¹

Efficient approximation of reliabilities for single-step genomic best linear unbiased predictor models with the Algorithm for Proven and Young

Matias Bermann^{1*}, Daniela Lourenco, and Ignacy Misztal



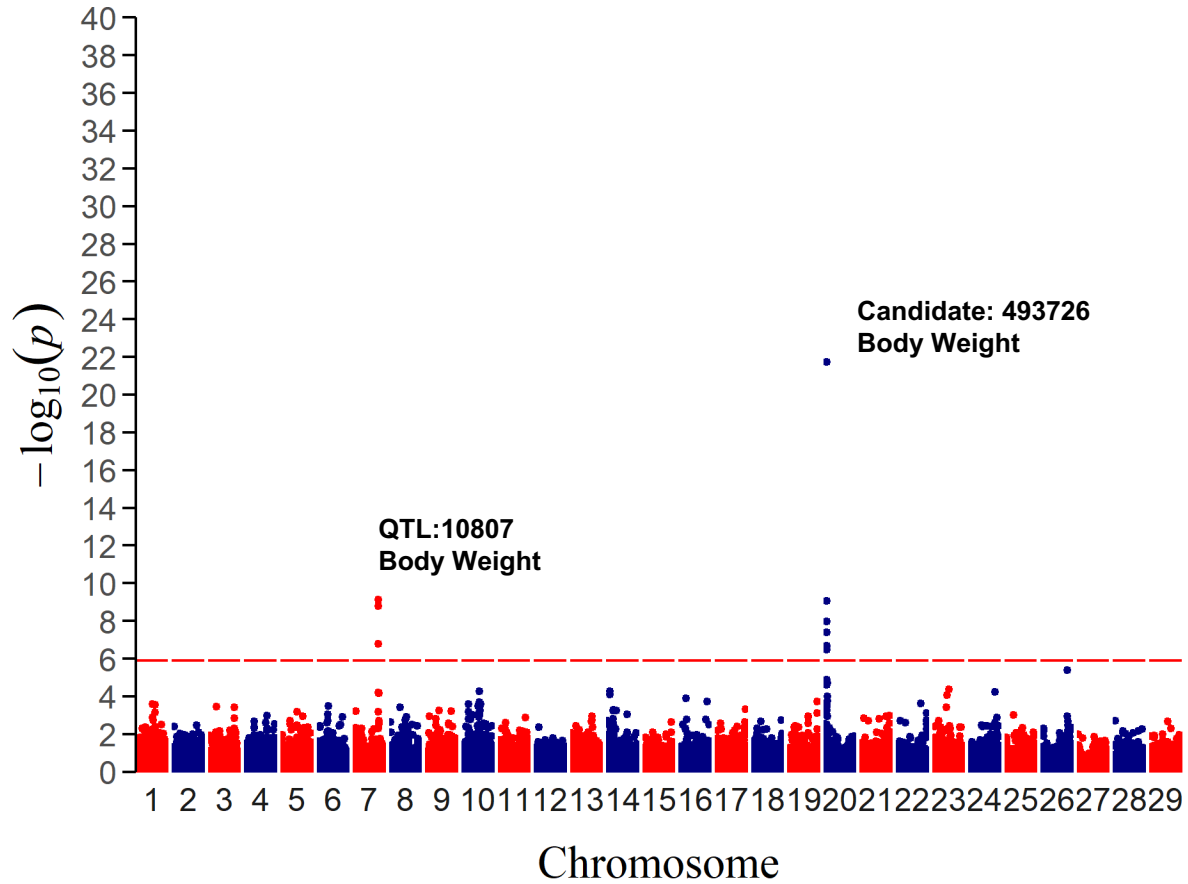
Application example

- Post-weaning gain in American Angus
- 845,000 phenotypes
- 450,000 genotypes
- 1,570,000 animals in the pedigree
- ssGWAS (50k genotyped animals) vs. APY-ssGWAS (450k genotyped animals)
- We expect:
 - Higher power
 - Less noise
 - Less false-positives

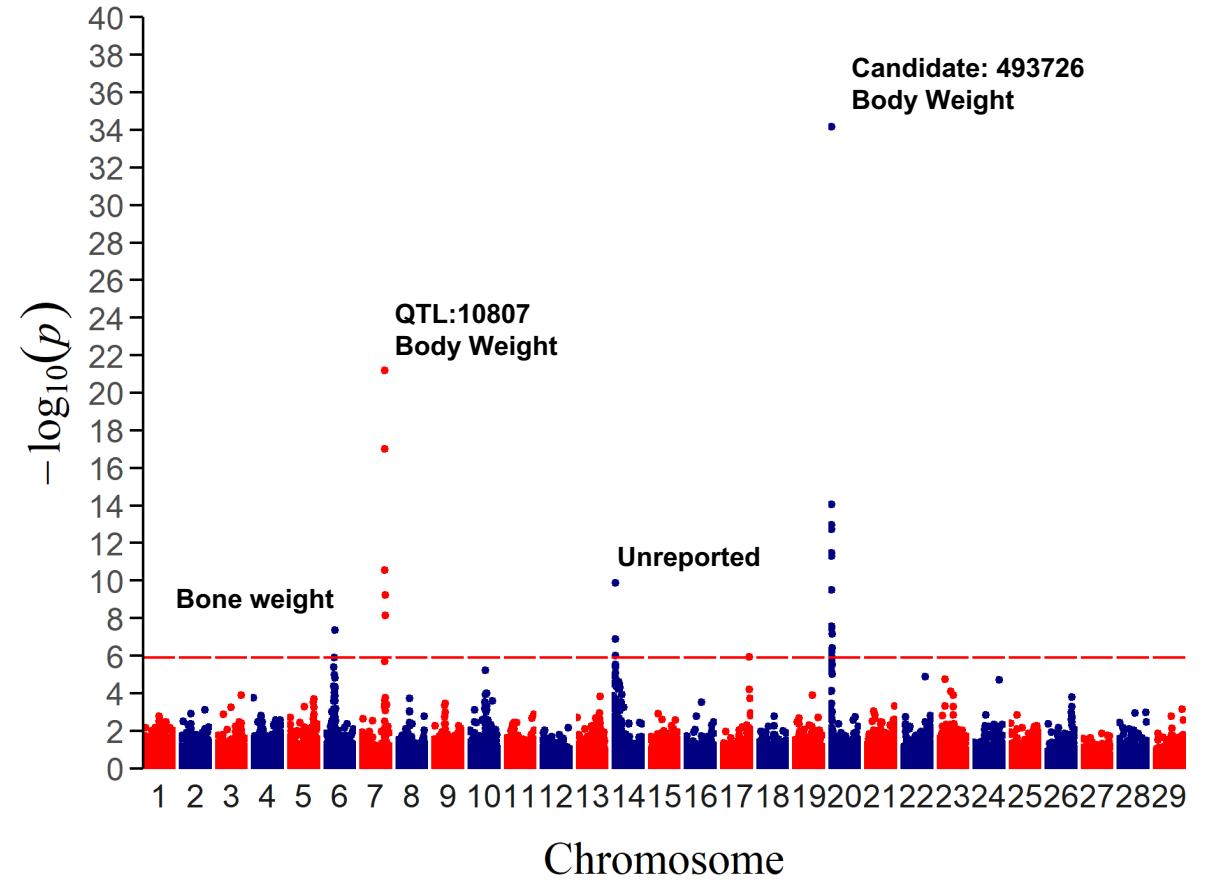


Leite et al.
(in progress)

50k genotyped animals



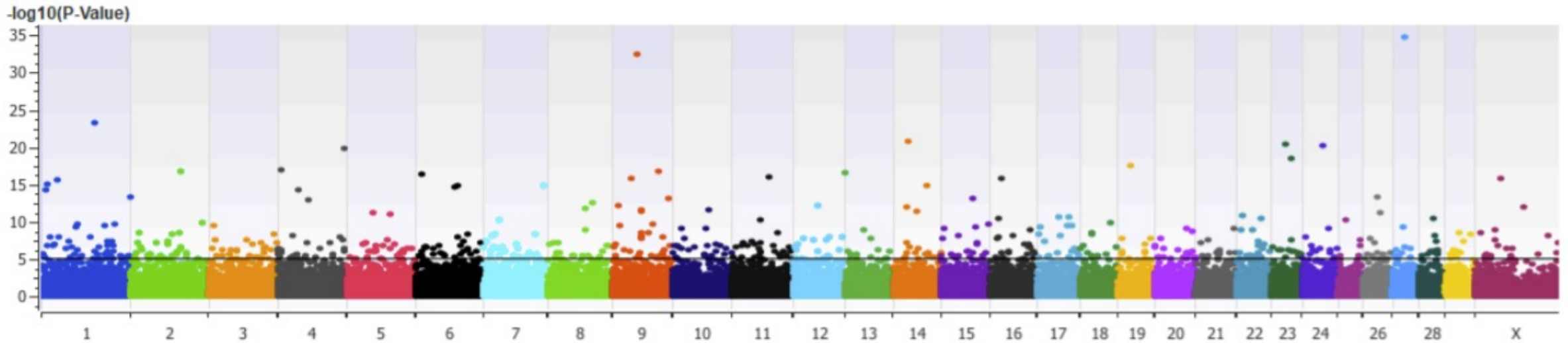
500k genotyped animals



Questions with GWAS and predictions

- GWAS by
 - % of variance explained usually per 1Mb
 - p-values
- Few regions explain $> 1\%$ additive variance
- Lots of QTLs detected with small data sets
- Fewer QTLs detected with large data

First conception rate on 2k Holstein heifers



Estimated heritability 36% (normally 1%)

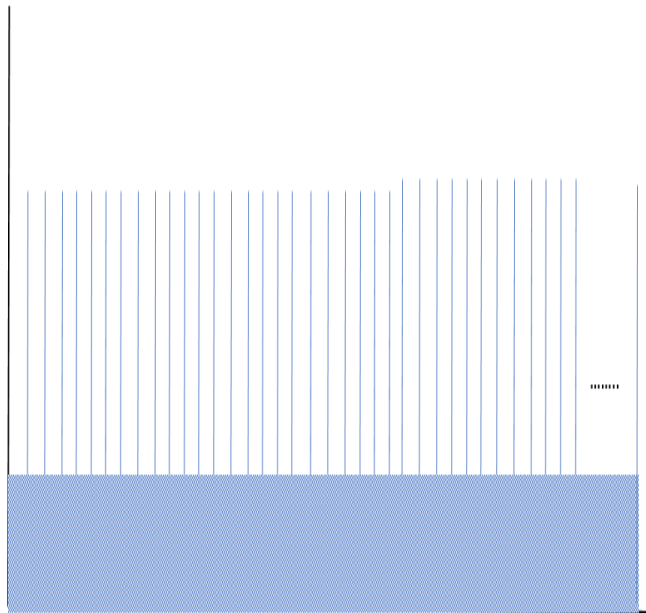
Identified 146 unique loci at $p < 5 \times 10^{-8}$ level

Galliou et al., 2020, <https://doi.org/10.3390/genes11070767>

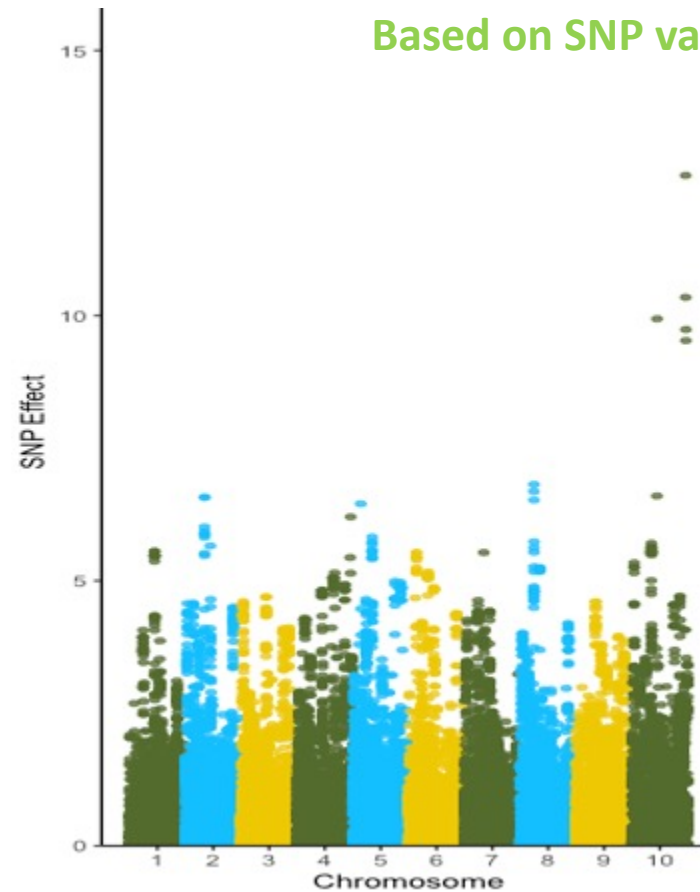
Manhattan plots for simulated population with 100 identical equidistant QTNs



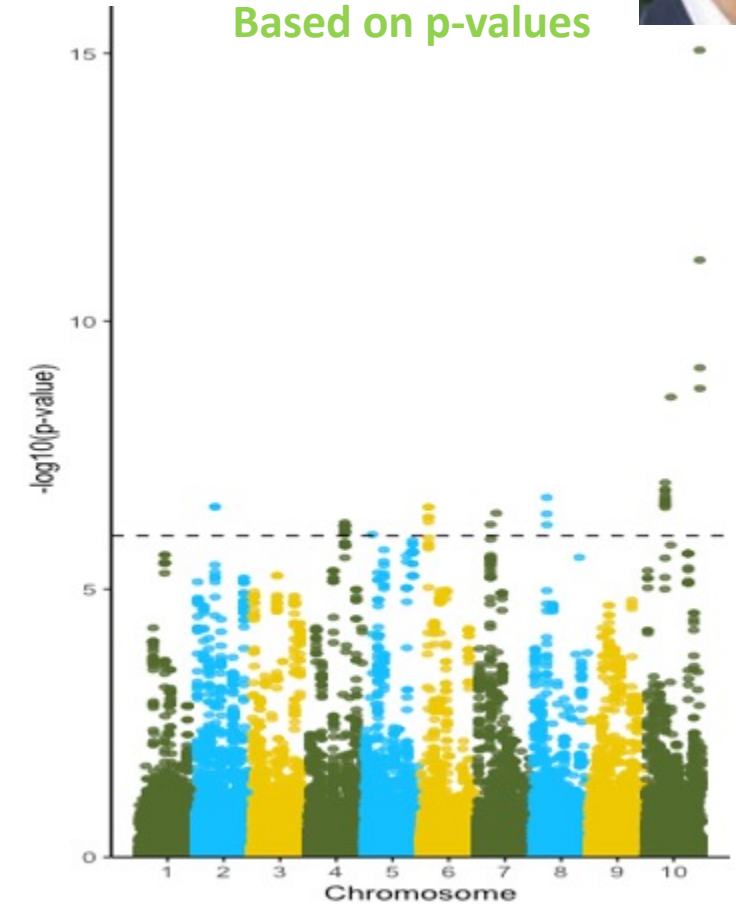
Expectation



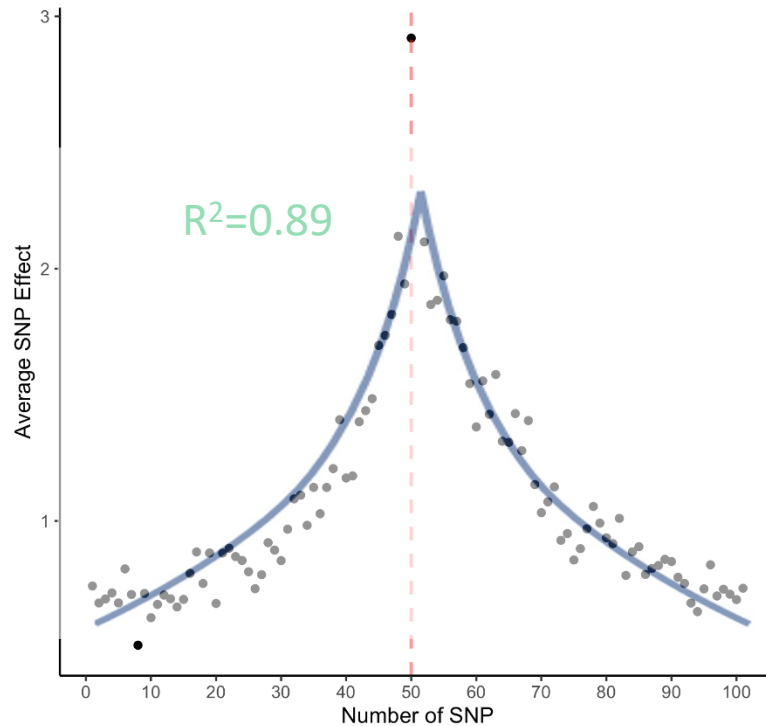
Based on SNP values



Based on p-values



Plots averaged for 100 QTN



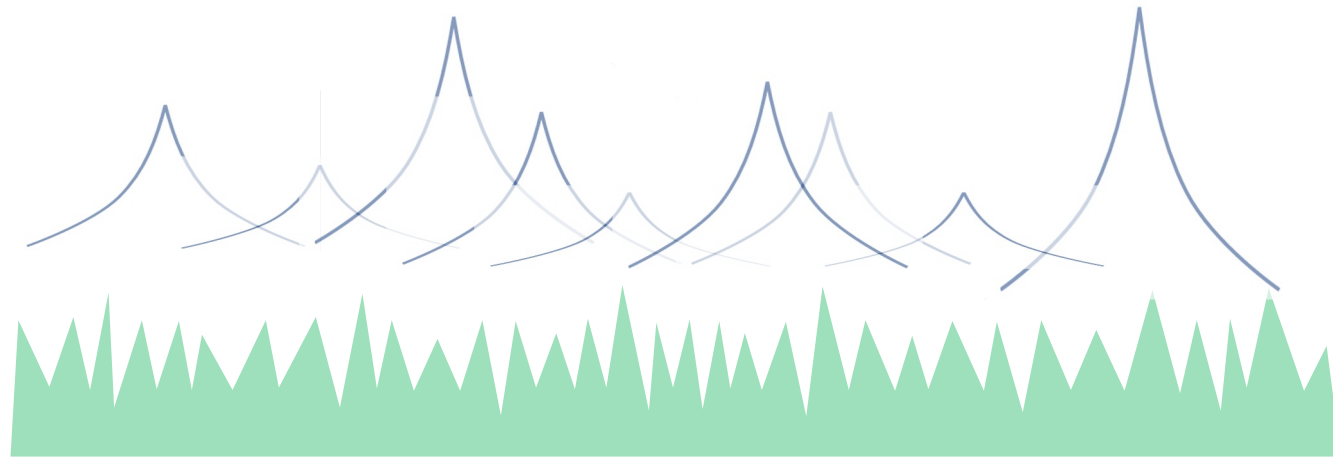
Pairwise linkage disequilibrium curve



~ 2 Mb for cattle
~ 5 Mb for pigs/chickens
~ 15 kb for humans

$1/N_e$ Morgans for 80% QTN variance
 N_e - effective population size

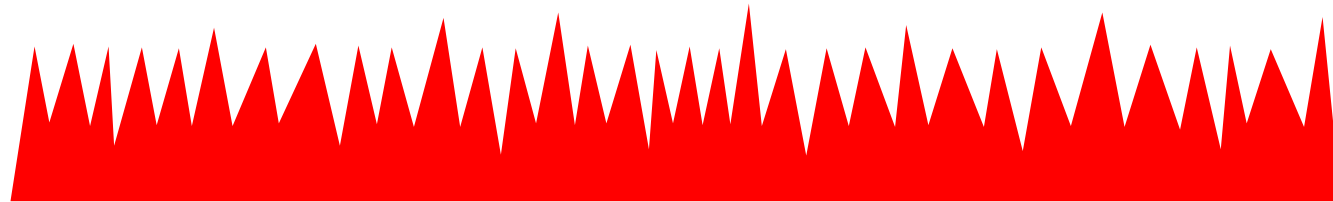
What is Manhattan plot composed of?



QTNs

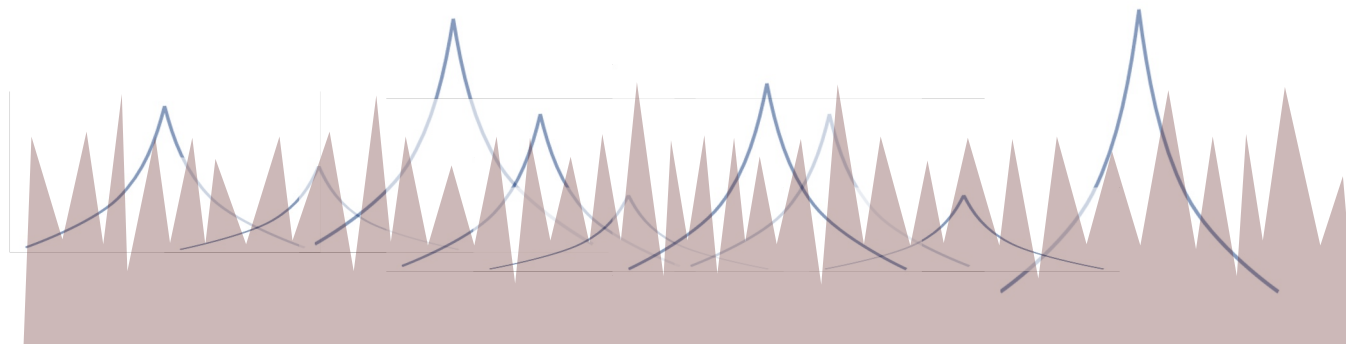
**Bigger with larger QTN
and larger data**

Relationships



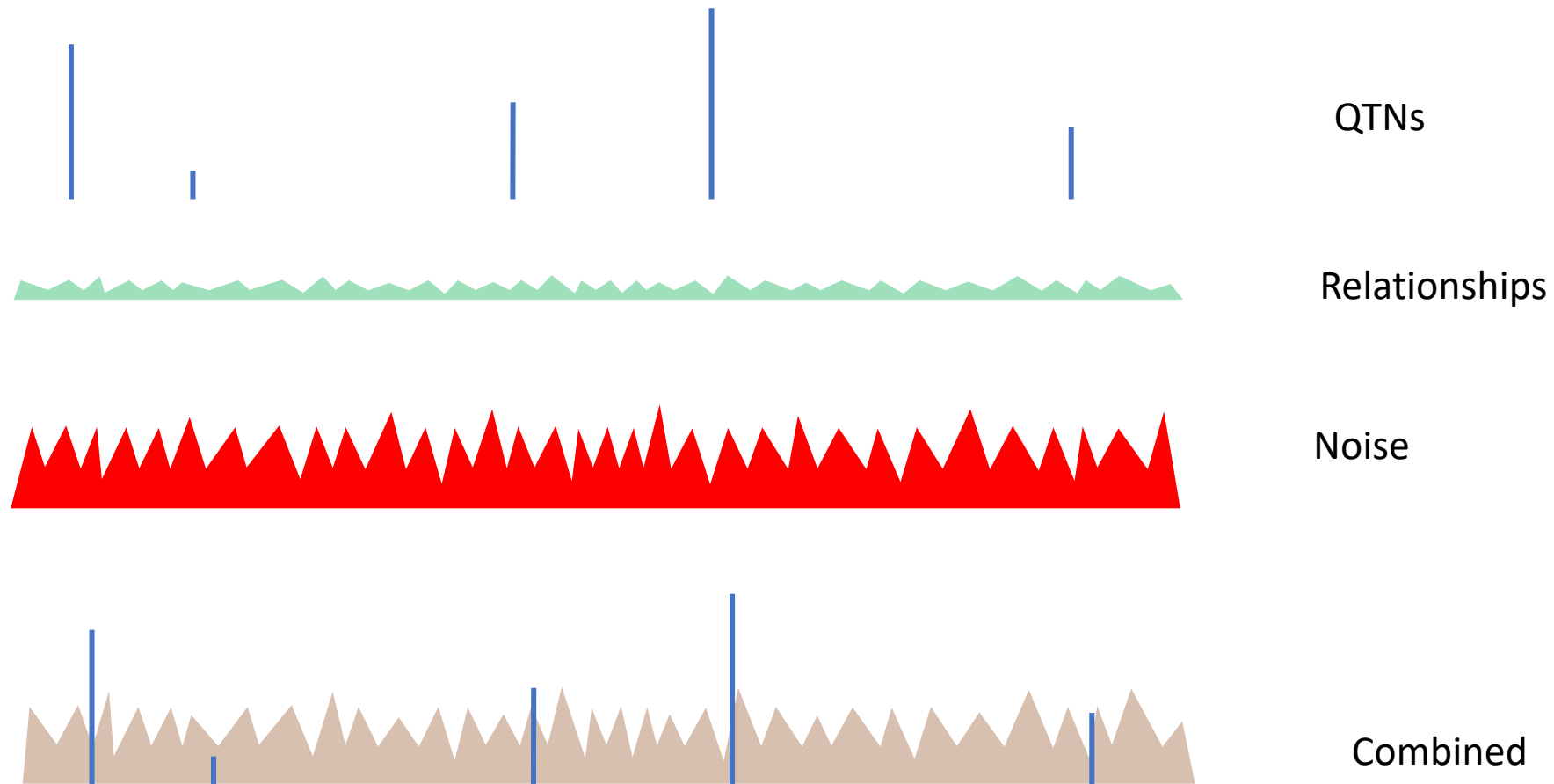
Noise

Smaller with more data

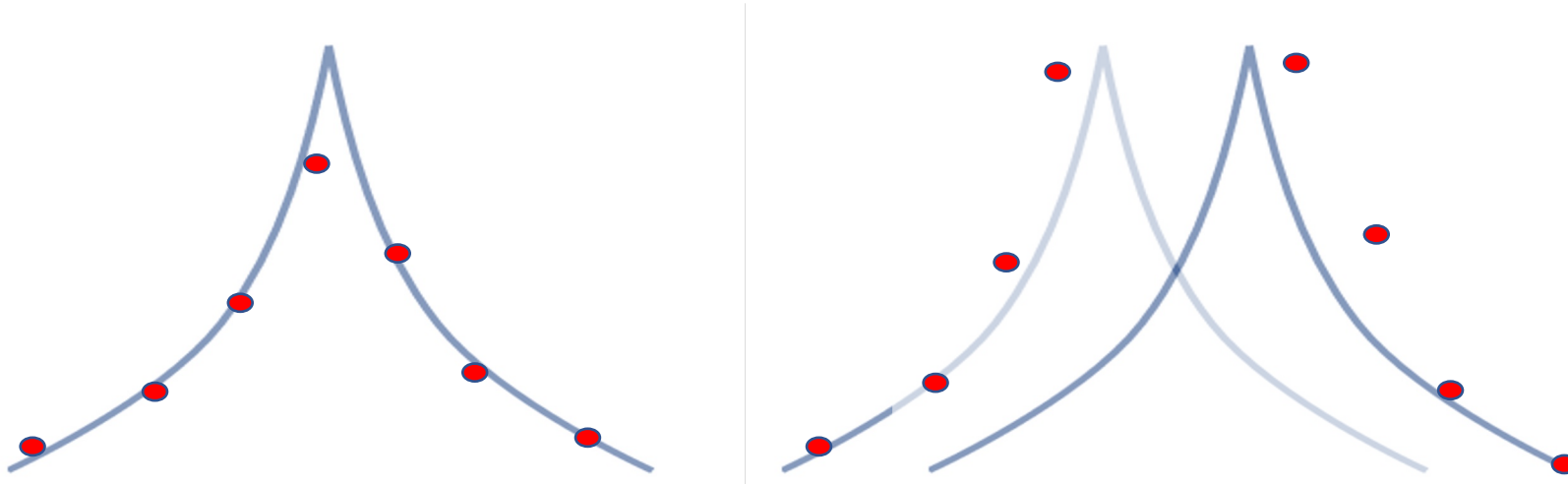


Combined

Large effective population size



Why GBLUP accounts for QTN?

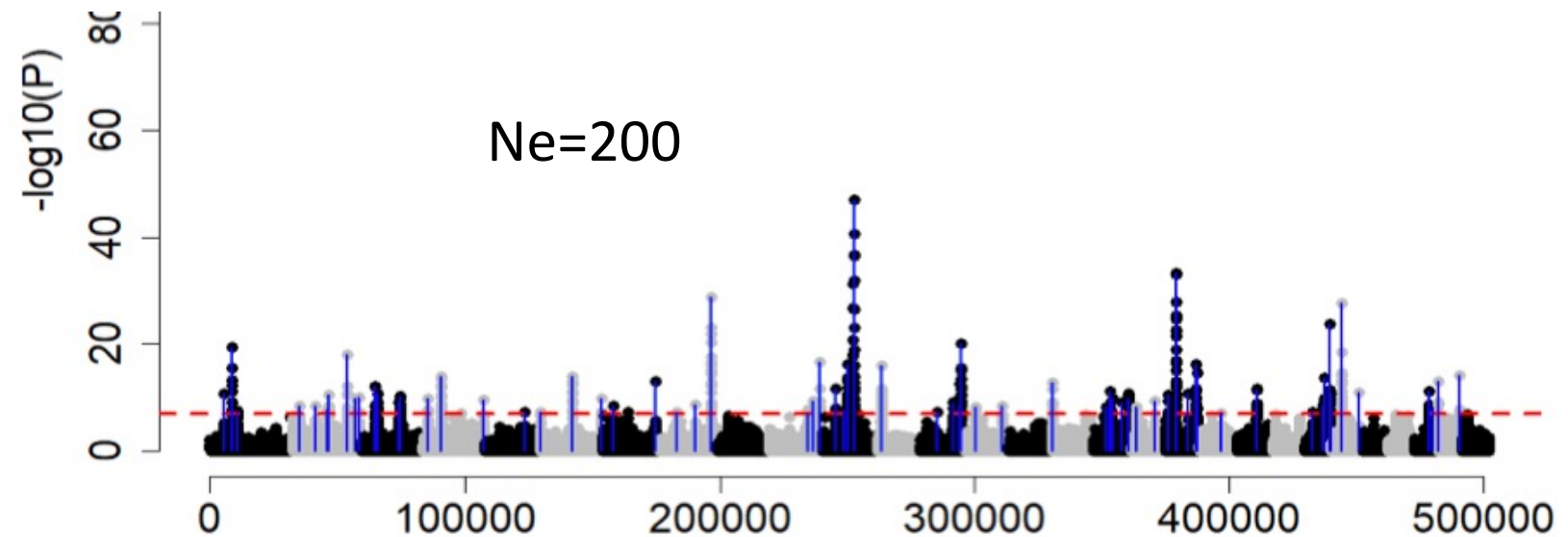
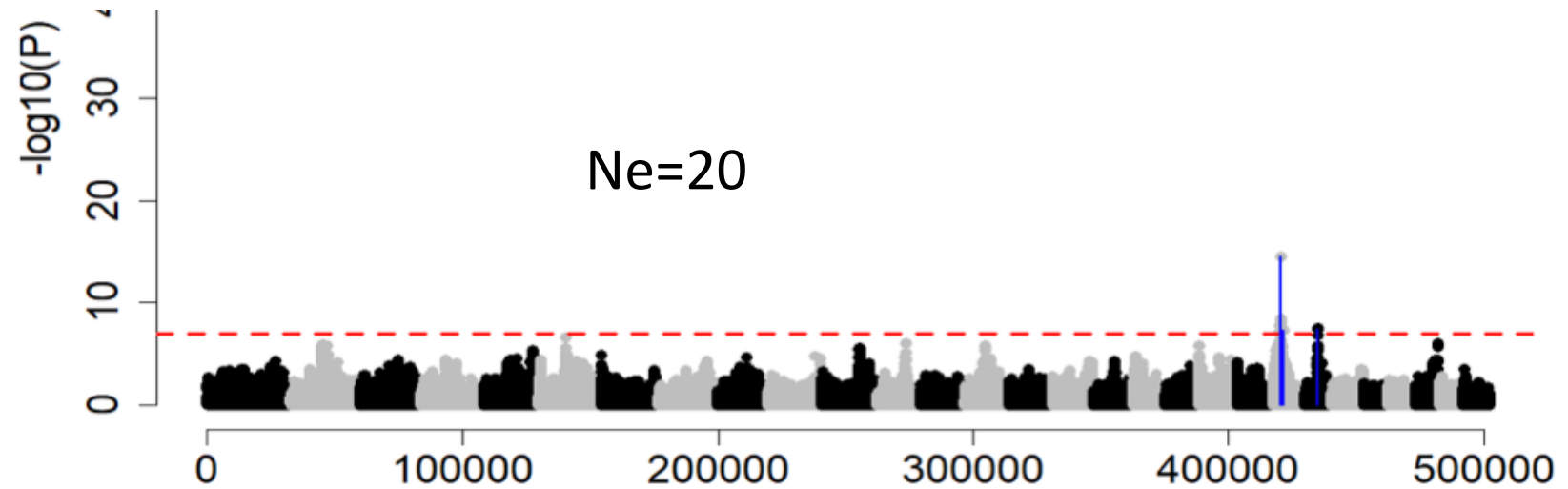


If 4 SNP per segment, 32 SNP account for 80% of QTN variance

Need chip with 16 NeL SNP to mostly account for QTN

About 20k for pigs/broilers, 60k for cattle, 5m for humans

Effective population size affects GWAS



Sungbong et al., 2021

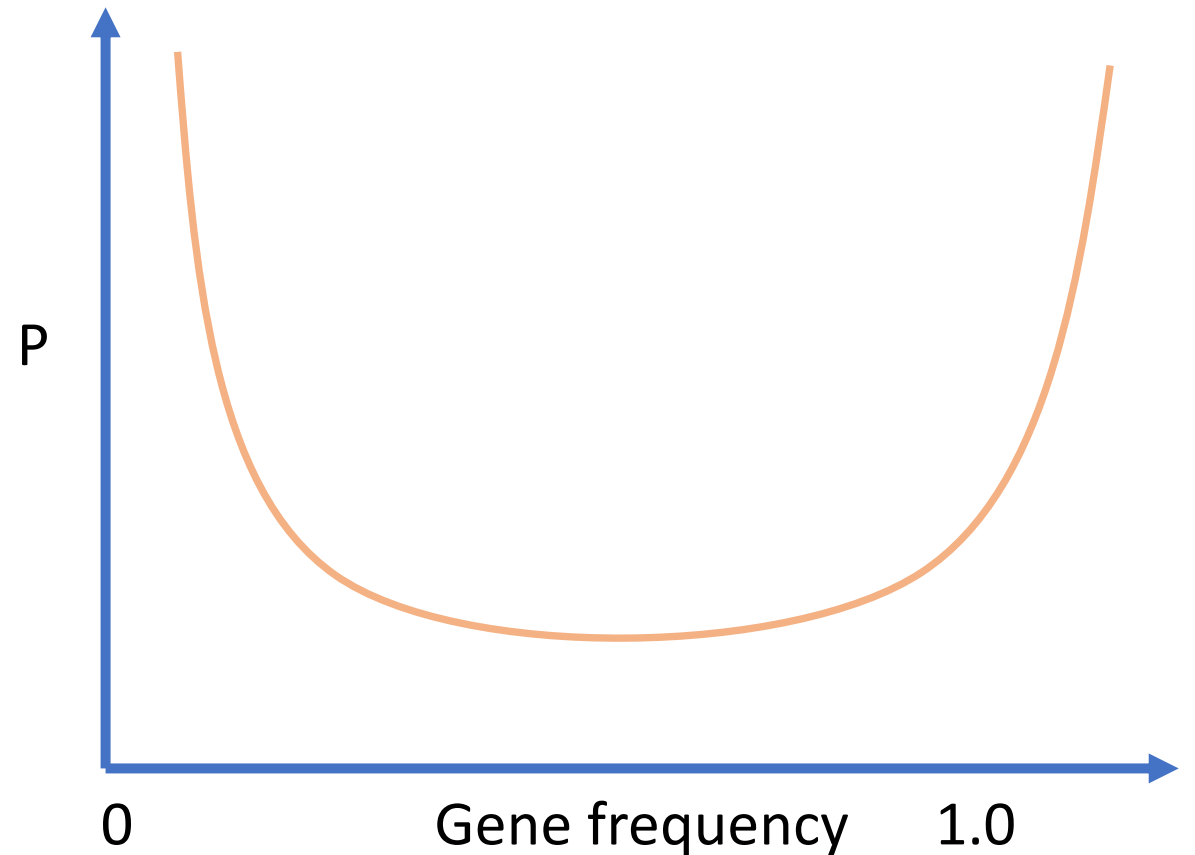
Why few QTN detected?

JOURNAL ARTICLE

AlphaSimR: an R package for breeding program simulations

R Chris Gaynor , Gregor Gorjanc, John M Hickey

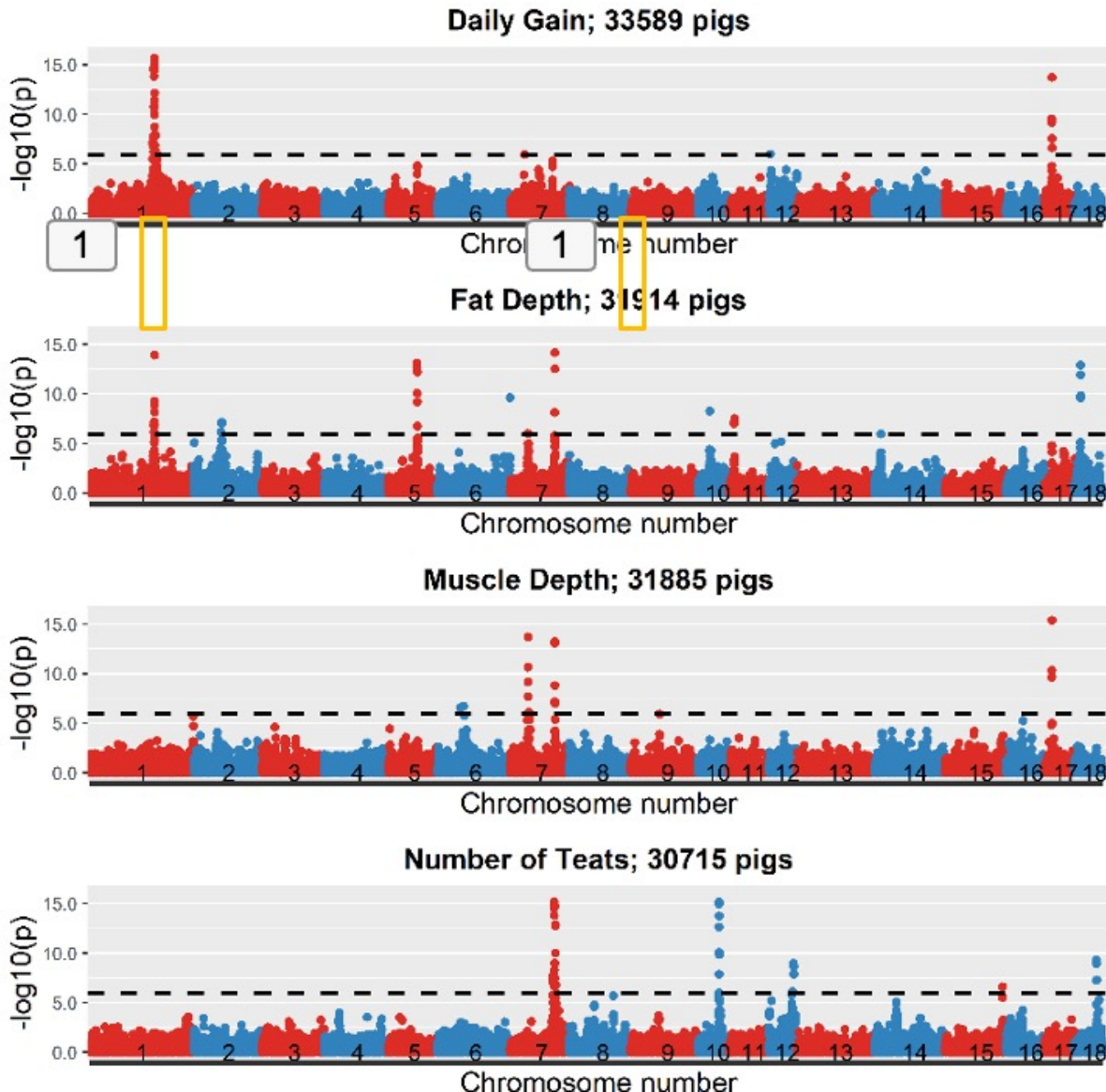
Only 20-30% QTN with $p > 0.3$



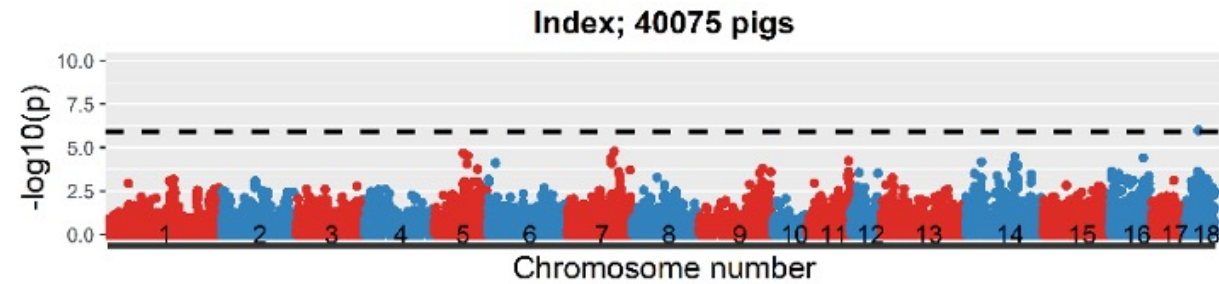
GWAS for various traits and index in pigs



Bijma, EAAP 23



Index



- Different peaks in different lines
- Antagonistic pleiotropy

Conclusions

- GWAS in farm animals affected by small effective population size
- Optimal window size 1-2 Mb for $N_e=100$
- Large signals in GWAS due to QTN, relationships and noise (incl. Imputation)
- Large QTL show pleiotropy – QTL not visible in index
- GWAS by single-step GBLUP for any data size with option for p-values

UGA AB&G team

