

# Obtaining variance of gametic diversity with genomic models

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# Central Idea

## Breeding value inheritance components:

$$a_i = \frac{1}{2}a_s + \frac{1}{2}a_d + m_i$$

Mendelian sampling

How about future progeny?

## Additive model (QTL effect):

Values:

A +5

B +3

C +2

Sire 1		
AA	bb	cc
10	0	0

Heterozygosity

Sire 2		
Aa	Bb	Cc
5	3	2

PTA expectation/average:

+5

+5

Possible values for the gametes

+5

0,2,3,5,5,7,8,10

Probability (binomial distribution)

1

0.125, 0.125, 0.125, 0.25, 0.125, 0.125, 0.125

If linked (phased ABC|abc):  
Recombination rates: 0.2 AB|BC

> 0 (0.68)

Exactly 5

0.32, 0.08, 0.02, 0.16, 0.02, 0.08, 0.32

> 7 (0.40)

> 7 (0.25)

Exactly 5

> 0 (0.875)

# Statistics Background

## Binomial Variances and Covariances

$$\text{Var}(x) = \sum x^2 - \frac{(\sum x)^2}{N} = Np_A - \frac{(Np_A)^2}{N} = N(p_A - p_A^2) = \underline{N[p_A(1 - p_A)]}$$

$$\text{Var}(y) = \sum y^2 - \frac{(\sum y)^2}{N} = Np_B - \frac{(Np_B)^2}{N} = N(p_B - p_B^2) = \underline{N[p_B(1 - p_B)]}$$

$$\text{Cov}(x, y) = \sum xy - \frac{\sum x \sum y}{N} = Np_{AB} - \frac{Np_A Np_B}{N} = \underline{N(p_{AB} - p_A p_B)}$$

$$\sigma^2_{[A+B]} = (\sigma^2_A + \sigma^2_B + 2\sigma_{AB})$$

$$\sigma^2_{[A+B]} = (\sigma^2_A + \sigma^2_B) \quad \text{If independent !!!}$$

$$\sigma^2_{\text{gamete}} = \sigma^2_{\Sigma \text{ Nlocus}}$$

## Solutions

$$1 * 0.5 * 0.5 * S_A^2$$

$$1 * 0.5 * 0.5 * S_B^2$$

$$1 * (p_{AB} * 0.5 * 0.5) * S_A S_B$$

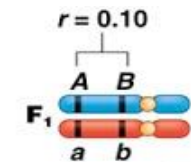
Homozygous loci:  
 $N * p * (1-p) * S^2 = 0$

Gametic phase

½ centiMorgan (0.01 Morgan)

$p_{AB} = 0.25 \Rightarrow \text{cov}_{ab} = 0 * S_A S_B$

$p_{AB} = 0 \text{ or } 0.50 \Rightarrow \text{cov}_{ab} = \pm 0.25 * S_A S_B$



Meiosis and gamete production

Gamete	Frequency	Type
A B	$(\frac{1}{2})(0.90) = 0.45$	Parental
a b	$(\frac{1}{2})(0.90) = 0.45$	
A b	$(\frac{1}{2})(0.10) = 0.05$	Recombinant
a B	$(\frac{1}{2})(0.10) = 0.05$	
	1.00	

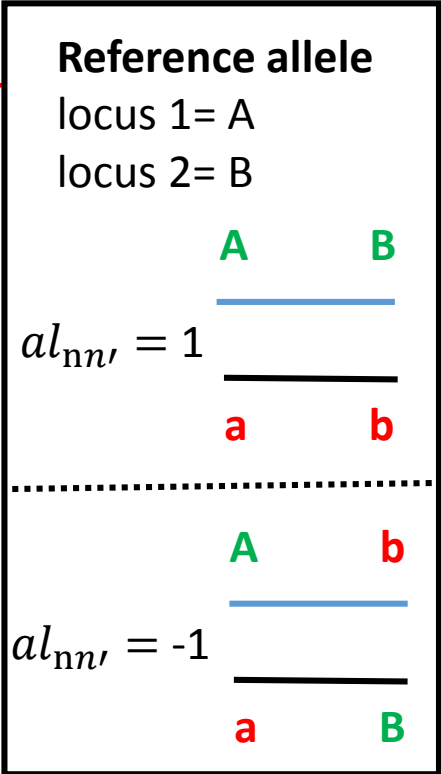
$$= \frac{\text{number of recombinant gametes}}{\text{total number of meioses}} \times 100\%$$

# Method

## Methods for computing

$$\sigma^2_{\Sigma \text{ Nlocus}} = [S_1 \quad \dots \quad S_n] \begin{bmatrix} 0.25 & \dots & al_{n1}(-\frac{cM_{1n}}{200} + 0.25) \\ \vdots & \ddots & \vdots \\ al_{1n}(-\frac{cM_{1n}}{200} + 0.25) & \dots & 0.25 \end{bmatrix} \begin{bmatrix} S_1 \\ \vdots \\ S_n \end{bmatrix}$$

Heterozygote loci



Independent → cM=0.25 (25% for each gamete)

$$\begin{bmatrix} 0.25 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 0.25 \end{bmatrix}$$

$$\sigma^2_{\text{gamete}} = \sigma^2_{\Sigma \text{ Nlocus}}$$

> 50 cM is considered as independent (that is 50 cM)

# Application

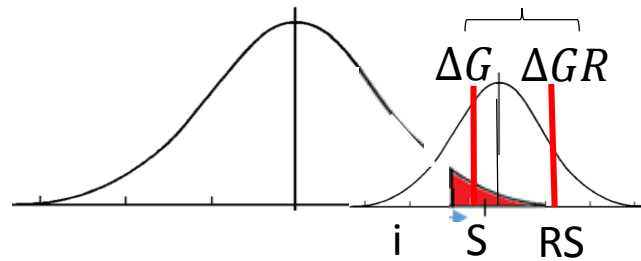
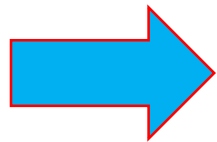
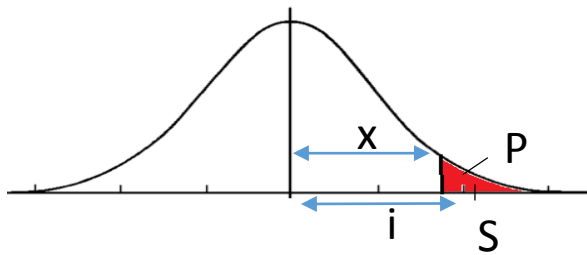
Confidence intervals

Strategies of selection

$$RPTA_i = PTA_i + \sigma_{\text{gametic}_i} * i_f$$

$$\sqrt{\sigma^2 a + 4i_f^2 \text{var}(\sigma_{\text{gametic}_i^2})} - \sqrt{\sigma^2 a}$$

Genetic Gain in Future



$$\Delta G = r * i * \sigma_a$$

$$\Delta GR = r * i * \sqrt{\sigma_a^2 + 4 * \text{var}(\sigma_{\text{gametic}_i^2}) * i_f^2}$$

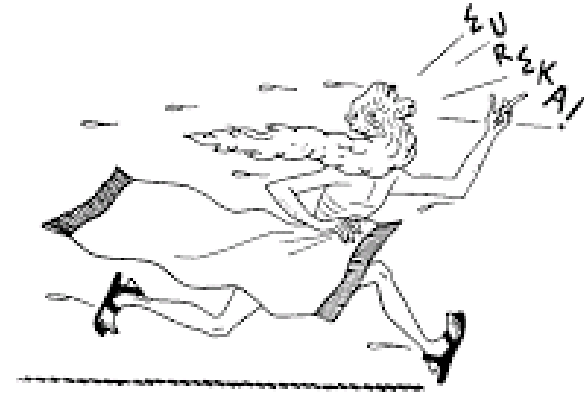
# Important Questions

**In practice, how can we obtain the variance of gametic diversity?**

**Using marker effects estimated from routine genomic evaluation!!!**

**Subsequent questions about this approach:**

- 1- Should the recombination rate also be considered (dependence) between the markers?
- 2 - What should the density panel marker be?
- 3 - Which models to use?
- 4 - What is the MAF effect?



**To answer these questions, simulation study was proposed !!!**

# Simulation - Population

Historical Generations

**Phase 1 - 500 generations:**  
Constant size:  
- 500 males  
- 500 females individuals



**Phase 2 - 500 generations**  
Constant reduction:  
from 1,000 to 200 individuals  
equal proportion male/female  
LD/drift-mutation balance



**Phase 3 - 10 generations**  
Expansion:  
from 200 to 3,000 individuals.  
equal proportion male/female

200 males and 800 females (last generation)

Recent Generations

**9<sup>th</sup> Generation: Genomic evaluation**

9<sup>th</sup> and 10<sup>th</sup>:

- Estimated  $\sigma_{\text{gamete}}^2$  from the estimated marker effects;

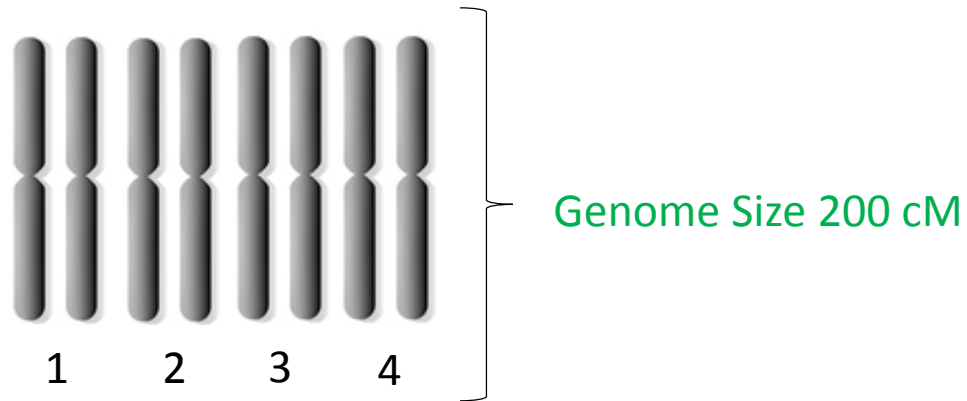
- True  $\sigma_{\text{gamete}}^2$ : effects of the QTLs and their genotypes ( $\sigma_{\Sigma \text{ Nlocus}}^2$ )



**Traditional evaluation and selection**

- 9 generations
- 5 progeny per dam
- Selection: Blup
- Mating: random
- Cutting: Blup
- Replacement rate: 20% dams and 60% for sires

# Simulation – Genome and Traits



**Scenarios:** 4 traits (QTLs x  $h^2$ ) x 2 SNPs panels

## Others Genome Parameters

Mutation Rater QTL	$2.5 \times 10^{-5}$
Mutation Rater Marker	$2.5 \times 10^{-3}$
Marker positions in genome	Evenly spaced
QTL position in genome	Random (uniform distribution)
QTL allele effect	Gamma distribution ( $\beta=0.4$ )

## Traits:

**N° of QTL:**  
20 (0.1 QTL/cM) (low density)  
200 (1 QTL/cM) (Meuwissen et al., 2001)

**$h^2$ :**  
0.1 and 0.3

$\sigma^2_{\text{phenotypic}} = 1$   
4 replicates for each trait

## Markers and Panels:

200,000 markers were simulated and randomly distributed

HD => 10% of the polymorphic markers sampled each 0.5 cM

SEQ => 20% of the markers also sampled every 0.5 cM and all QTLs

X

All simulations were performed QMSim version 1.10 (Sargolzaei & Schenkel, 2009)



# Genomic Model

Depends on the effects of the markers:

$$y = \mu + Ma + e$$

Residual  $\sim N(0, I\sigma_e^2)$

Marker

MAF  $\geq 0.05$  (to mimic a conventional genomic evaluation)

1 - Traditional (**SNP-BLUP/GBLUP**)

$$a \sim N(0, \sigma^2) / u \sim N(0, G\sigma_a^2)$$

2 - Differential shrinkage (**Improved LASSO**)

$$\Pr(a_i | \tau^2) = N(0, \tau_i^2)$$

$$\Pr(\tau_i^2 | \lambda) = \lambda^2 \exp(-\lambda^2 | \tau_i^2 |)$$

**Variance components:**

- initial values = true values
- interactions: 20,000
- burn-in: 2,000.

The analyses were performed using GS3 v.3 software (Legarra et al., 2015)

# Gametic Variance

$$\left. \begin{array}{l}
 1 - \sigma_g^2 = \text{All QTL} \\
 2 - \sigma_{g\_maf}^2 = \text{QTL with } MAF \geq 0.05
 \end{array} \right\} \left[ \begin{array}{ccc}
 0.25 & \dots & al_{n1} \left( -\frac{cM_{1n}}{200} + 0.25 \right) \\
 \vdots & \ddots & \vdots \\
 al_{1n} \left( -\frac{cM_{1n}}{200} + 0.25 \right) & \dots & 0.25
 \end{array} \right]$$
  

$$\left. \begin{array}{l}
 3 - \sigma_{dia}^2 = \text{All QTL} \\
 4 - \sigma_{dia\_maf}^2 = \text{QTL with } MAF \geq 0.05
 \end{array} \right\} \left[ \begin{array}{ccc}
 0.25 & \dots & 0 \\
 \vdots & \ddots & \vdots \\
 0 & \dots & 0.25
 \end{array} \right]$$

# Results

# Correlation of True Values

Scenario			QTLs data		
$h^2$	QTL		$\sigma_{g\_maf}^2$	$\sigma_{dia}^2$	$\sigma_{dia\_maf}^2$
0.1	20	$\sigma_g^2$	0.75	0.96	0.69
	200		0.96	0.50	0.48
0.3	20		0.94	0.95	0.90
	200		0.95	0.55	0.52

Medium magnitude

High magnitude !!!

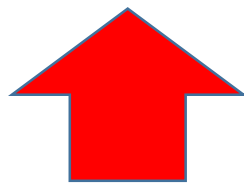
It implies that QTLs with low MAF are important for obtaining accurate estimates of  $\sigma_{gamete}^2$

$\sigma_{gamete}^2$  does not depend directly on population allele frequencies but on the individual's heterozygous state (allele carrier).

# Correlation between True and Estimated $\sigma_{\text{gamete}}^2$

Similar accuracy!

Scenario		High-sensitivity panel				Sequencing data			
$h^2$	QTL	$\sigma_{\text{gblup}}^2$	$\sigma_{\text{glasso}}^2$	$\sigma_{\text{dia\_blup}}^2$	$\sigma_{\text{dia\_lasso}}^2$	$\sigma_{\text{gblup}}^2$	$\sigma_{\text{glasso}}^2$	$\sigma_{\text{dia\_blup}}^2$	$\sigma_{\text{dia\_lasso}}^2$
0.1	20	0.49	<b>0.56</b>	0.17	0.39	0.46	<b>0.57</b>	0.20	0.40
	200	0.50	<b>0.60</b>	0.29	0.37	0.46	<b>0.61</b>	0.29	0.40
0.3	20	0.64	<b>0.83</b>	0.28	0.66	0.59	<b>0.83</b>	0.07	0.65
	200	0.63	<b>0.77</b>	0.25	0.49	0.59	<b>0.77</b>	0.29	0.48



Best accuracy Worst accuracy!

# Bias

Trait		Model	HD			SEQ		
$h^2$	QTLs		MSE	a	b	MSE	a	b
0.1	20	GBLUP	0.0014	-0.0010	0.27	0.0022	-0.00033	0.20
		LASSO	<b>8e-05</b>	0.0027	<b>1.20</b>	<b>8e-05</b>	0.00185	<b>1.26</b>
	200	GBLUP	0.0010	<b>0.0058</b>	0.23	0.0016	<b>0.00637</b>	0.18
		LASSO	<b>0.0001</b>	0.0074	<b>1.01</b>	<b>0.0001</b>	0.00681	<b>1.03</b>
0.3	20	GBLUP	0.0017	-0.00697	0.43	0.0028	-0.00625	0.35
		LASSO	<b>0.0002</b>	0.00282	<b>1.46</b>	<b>0.0002</b>	0.00247	<b>1.41</b>
	200	GBLUP	0.0021	0.00979	0.40	0.0035	0.01123	0.33
		LASSO	<b>0.0004</b>	<b>0.00945</b>	<b>1.14</b>	<b>0.0004</b>	<b>0.00950</b>	<b>1.13</b>

Mean squared prediction (MSE): ↓ values

GBLUP - higher predicted bias (overestimation)

Coefficient of the linear regression (b): close to one

HD X SEQ - Similar Bias

# Conclusions

- 1 - The  $\sigma_{\text{gamete}}^2$  can be obtained by GM using HD panels without the need to use sequencing data.
- 2 - Differential shrinkage models are preferred;
- 3 - Markers with low MAF should be also used;
- 4 - The covariance (dependence) among markers should be considered.

**For improving the accuracy  
of the estimations**

# Acknowledgement

## Financial Support

- **BARD Research Project US-4997-17**
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- **FAPESP 2017/00462-5**

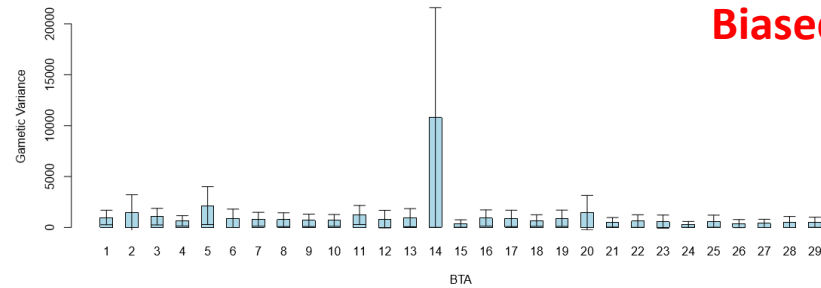
**Thank you!!!**





# Real Data: USDA/Jersey

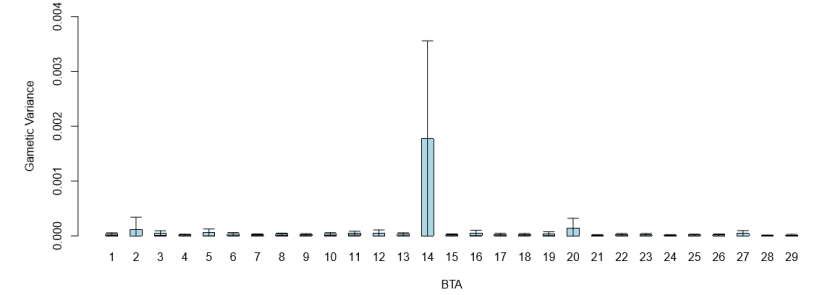
Milk Yield



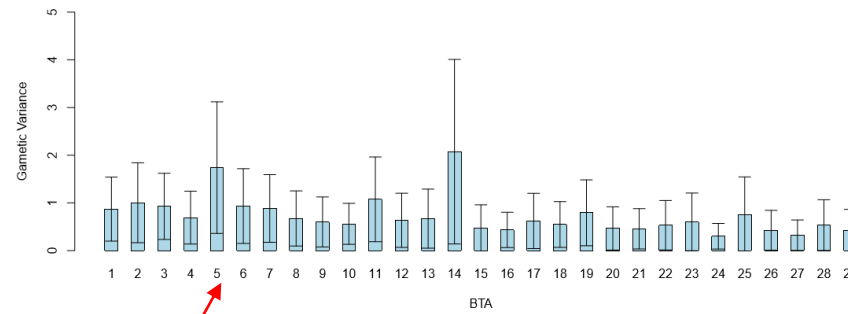
Biased distribution among chromosomes



Fat (%)



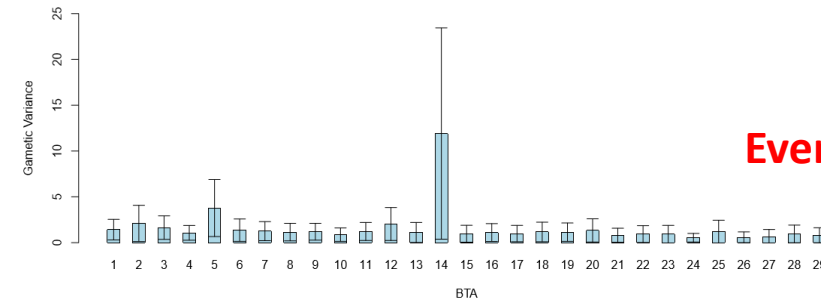
Protein Yield



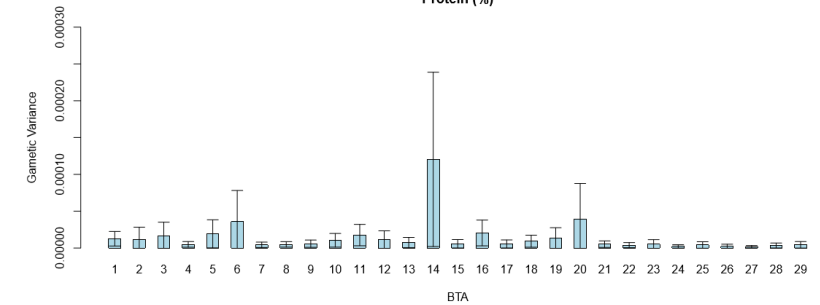
Even distribution among chromosomes



Fat Yield

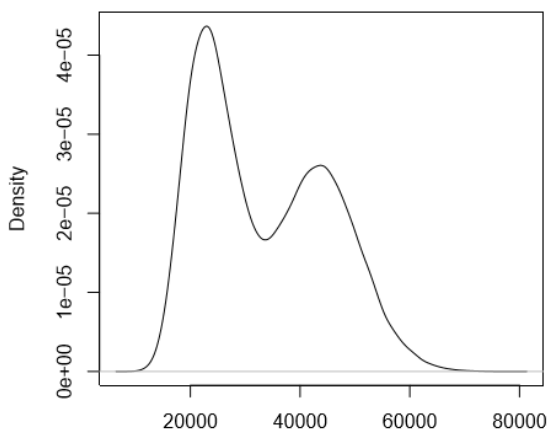


Protein (%)



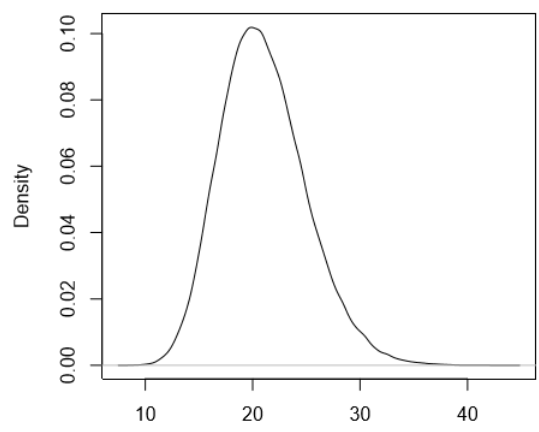
# Distribution of $\sigma_{\text{gamete}}^2$ for Production Traits

Milk Yield

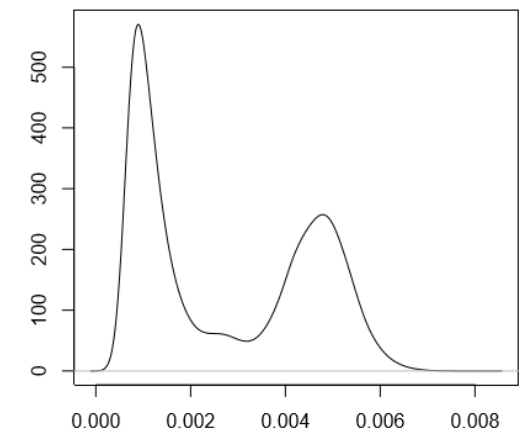


Atypical Gaussian curve

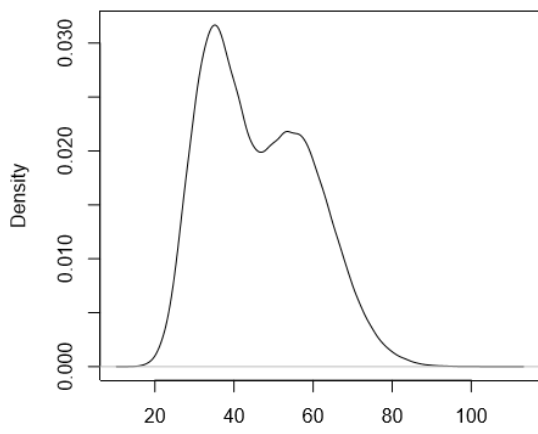
Protein Yield



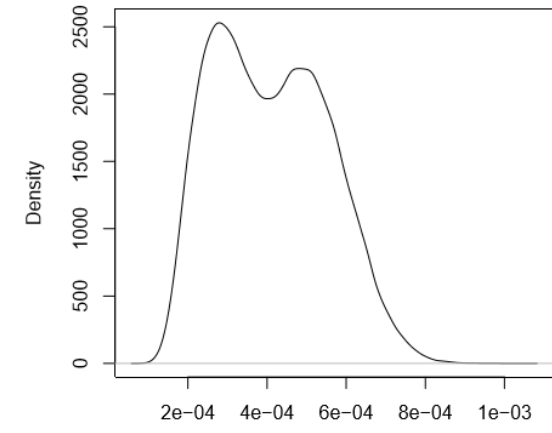
Fat (%)



Fat Yield



Protein (%)



Close to typical Gaussian curve

# Applied example: USDA/Jersey

Correlation ( $r$ ) between  $\sigma_{\text{gamete}}^2$  and variance of progeny GEBV for different traits per minimum number of offspring per sire.

Increasing

Minimum n° of offspring	N° Sires	$r_{\text{Milk Yield}}$	$r_{\text{Fat Yield}}$	$r_{\text{Protein Yield}}$	$r_{\text{Fat \%}}$	$r_{\text{Protein \%}}$
10	1109	0,24	0,20	0,16	0,58	0,30
50	451	0,40	0,46	0,33	0,75	0,50
100	311	0,53	0,47	0,34	0,85	0,60
200	183	0,64	0,49	0,31	0,95	0,77
300	128	0,68	0,55	0,40	0,96	0,86
400	97	0,66	0,61	0,43	0,97	0,90
500	77	0,66	0,62	0,51	0,97	0,90
600	66	0,69	0,66	0,54	0,97	0,92

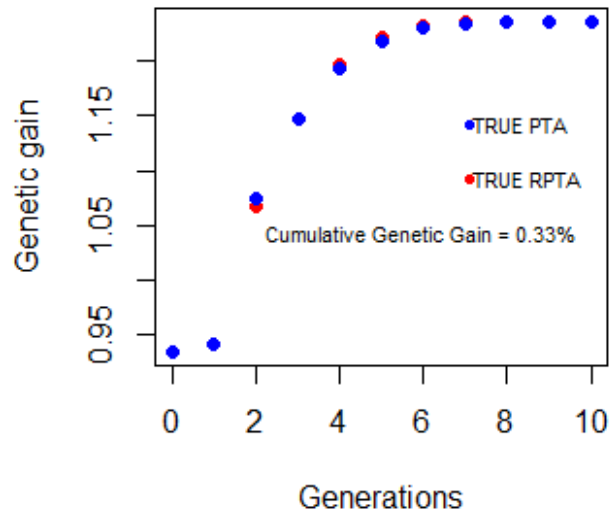
Lowest Protein Yield

Greatest Fat %

# Motivating Results – TRUE RPTA / PTA

Simulation: Future generations; sires ( $i=1.75$ ) and Dam ( $i=0.97$ ).

**TRUE RPTAs** were corrected for number of offspring;

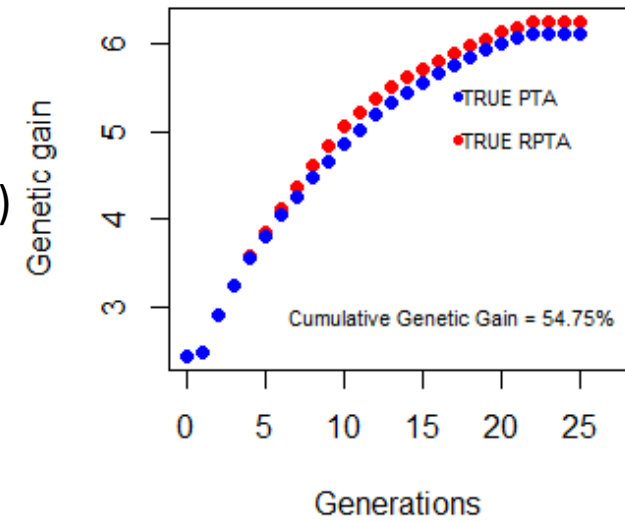


**0.1 QTL/cM**  
 $\sigma^2_a=0.3(h^2=0.3)$

**$\Delta G=0.33\%$**   
**7 generations**

**1 QTL/cM**  
 $\sigma^2_a=0.3(h^2=0.3)$

**$\Delta G=54.75\%$**   
**25 generations**



# Applied example: USDA/Jersey

## Genetic summary for Top 10 Sires for Milk Yield.

Sire_ID	Year	$\sigma_{gamete}^2$	CRV	N	PTA	rankPTA	RPTA_1.5	rankRPTA	Pr>1,100
59250449	2010	27,905	0.50	96	1,057	1	1.308	1	0.40
62902902	2012	23,724	0.47	83	1,027	2	1.259	4	0.32
56893061	2009	23,526	0.47	85	1,021	3	1.251	5	0.30
63345061	2012	30,756	0.53	107	1,004	4	1.267	3	0.29
54319065	2008	29,600	0.52	103	983	5	1.241	6	0.24
63561482	2012	39,800	0.65	164	973	6	1.272	2	0.26
68432385	2014	25,722	0.50	95	963	7	1.204	8	0,20
66011155	2013	26,721	0.50	97	958	8	1.203	9	0,19
65096622	2013	20,532	0.45	78	928	9	1.142	25	0,11
66009958	2013	26,503	0.49	93	927	10	1.171	14	0,14

$$CRV = \frac{\sigma_{gamete}}{0.5\sqrt{E[u^2]}}; N = \frac{(1.96)^2 + (CRV)^2}{(0.1)^2}; RPTA_{1.5} = PTA + \sigma_{gamete} * 1.5$$