Extension of single-step ssGBLUP to many genotyped individuals

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### Genomic selection and single-step

$$\mathbf{H}^{-1} = \mathbf{A}^{-1} + \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{G}^{-1} - \mathbf{A}_{22}^{-1} \end{bmatrix}$$
  
lar et al., 2010



Aguilar et al., 2010 Christensen and Lund, 2010

- Simplicity
  - No DYD or DP
  - No index
  - No complexity
- Accuracy
  - Avoids double counting
  - Avoids fixed index
  - Accounts for preselection bias

### **Current implementation of SS**

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

- G and A<sub>22</sub> created explicitly
- Quadratic memory and cubic computations
- Cost per 100k genotypes 1.5 hr (Aguilar et al.,2014)



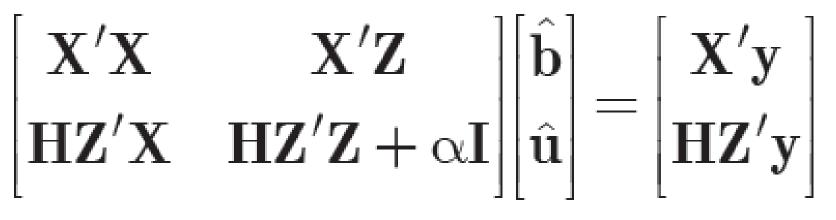
## Number of genotypes and impending problem

- > 2 M for Holsteins
- > 400k for Angus

Genomic pre-selection issue (Patry and Ducrocq, 2011; VanRaden et al., 2013)

- BLUP increasingly biased
- Need all data on preselection included

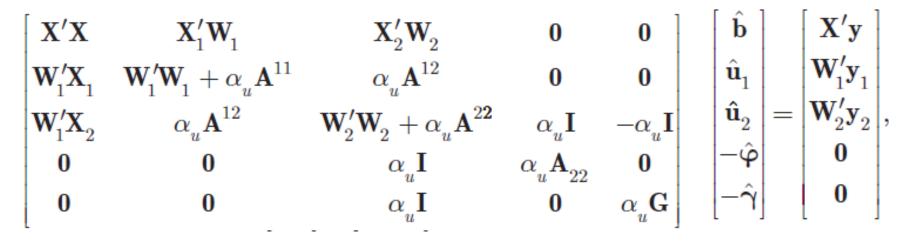
**Unsymmetric equations** 



Misztal et al., 2009

No convergence without good preconditioner No convergence with large H or A

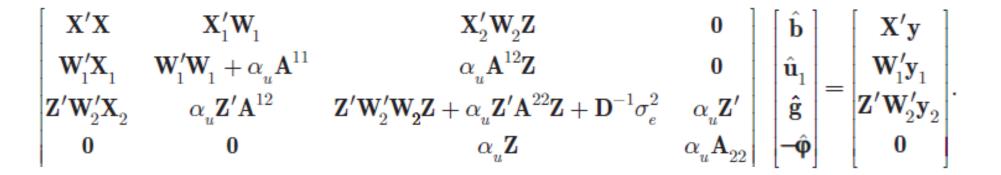
# No G or A<sub>22</sub> inverse model



Legarra and Ducrocq (2011)

Slow convergence with few genotypes Divergence with many genotypes

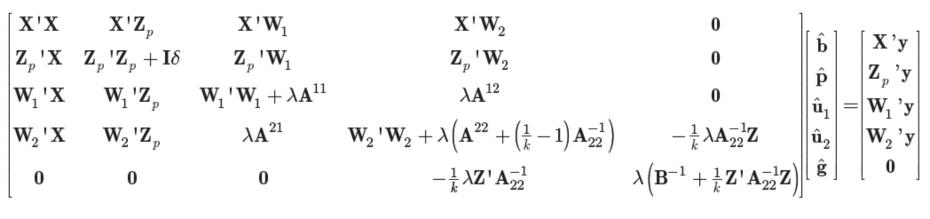
### SNP model for genotyped animals



Legarra and Ducrocq, 2011

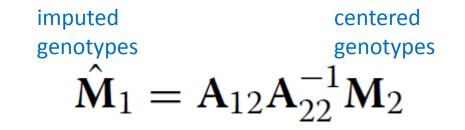
No successful programming

### SNP model for genotyped animals



Liu et al, 2014

# SNP effects for all animals (Fernando et al., 2014)



$$\begin{bmatrix} \mathbf{y}_1 \\ \mathbf{y}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1^* \\ \mathbf{X}_2^* \end{bmatrix} \boldsymbol{\beta}^* + \begin{bmatrix} \mathbf{Z}_1 & \mathbf{0} \\ \mathbf{0} & \mathbf{Z}_2 \end{bmatrix} \begin{bmatrix} \hat{\mathbf{M}}_1 \boldsymbol{\alpha} + \boldsymbol{\epsilon} \\ \mathbf{M}_2 \boldsymbol{\alpha} \end{bmatrix} + \mathbf{e}$$

Cost of imputation Requires new type of programming Extension to complex models unclear

# Can regular ssGBLUP be made more efficient?

### Scaling up A<sub>22</sub><sup>-1</sup>

$$A_{22}^{-1} = A^{22} - A^{21} (A^{22})^{-1} A^{12}$$

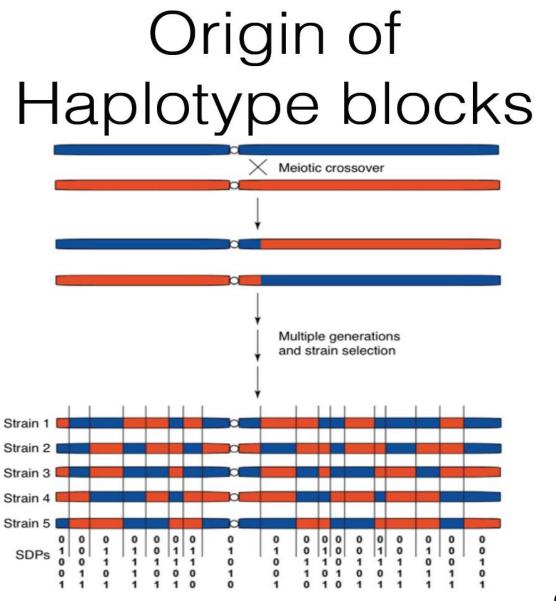
- $A_{22}^{-1}$  dense (Faux et al., 2014)
- For PCG iteration (Stranden et al., 2014)

$$A_{22}^{-1}q = A^{22}q - \left\{A^{21}\left[\left(A^{22}\right)^{-1}\left(A^{12}q\right)\right]\right\}$$

• Seconds for 500k animals with good programming (Masuda et al., 2017)

### Is dimensionality of genomic information limited?

- Regular G not positive definite past ~5k
   Blending with A (VanRaden, 2008)
- Dimensionality of SNP BLUP small (Maciotta et al., 2013)
- Success of imputation
- Manhattan plots noisy until averaged by 300k-10Mb (depending on species)



Cuppen, 2005

### Heterogenetic and homogenic tracts in genome (Stam, 1980)

.....

E(#tracts)=4NeL (Stam, 1980) Ne – effective population size L –length of genome in Morgans

> Holsteins: Ne ≈100 L=30 Me=12,000

### Inversion via SVD/eigenvalue decomposition

Assume 1 million animals genotyped with 60k chip

- G = ZZ' = UDU' Eigenvalue decomposition (1M x 1M)
- $G^- = UD^-U'$  Generalized inverse (1M x 1M)
- $Z = USV = UD^{0.5}V$  SVD decomposition (1M x 60k) 10h for 720k animals (Masuda, 2017)

**t** - index for non-negligible eigenvalues, say 10k  $\mathbf{G}^- = \mathbf{U}_t \ \mathbf{D}_t^{-1} \mathbf{U}_t' = \mathbf{U}_t \ \mathbf{S}_t^{-1} \mathbf{S}_t^{-1} \mathbf{U}_t' = \mathbf{U}_* \ \mathbf{U}_*$ 

For PCG iteration  $\mathbf{G}^{-1}\mathbf{q} = \mathbf{U}_* (\mathbf{U}_* \mathbf{q})$  - only 1 M x 10k elements

### Inverse by Woodbury formula

$$G = ZZ' + I\varepsilon,$$
  

$$G^{-1} = \frac{1}{\varepsilon}I - \frac{1}{\varepsilon}Z(\frac{1}{\varepsilon}Z'Z + I)^{-1}Z'\frac{1}{\varepsilon}$$
  
For PCG iteration:

Woodbury formula Z'Z 60k x 60k

Mantysaari et al., 2017

$$\mathbf{G}^{-1}\mathbf{q} = \frac{1}{\varepsilon} \{\mathbf{I} - \mathbf{Z}(\mathbf{U}\mathbf{D}\mathbf{U}')^{-1}\mathbf{Z}'\}\mathbf{q} = \frac{1}{\varepsilon} \{\mathbf{I} - \mathbf{S}\mathbf{S}'\}\mathbf{q}$$
$$\mathbf{S} = \mathbf{Z}\mathbf{U}'\mathbf{D}^{-1/2}$$
With reduced rank  $\mathbf{S} = \mathbf{Z}\mathbf{U}_t'(\mathbf{D}_t)^{-\frac{1}{2}}$  (1M x 10k)

Ostersen et al., 2017

If G has limited dimensionality, can G<sup>-1</sup> be sparse like A<sup>-1</sup>?

### Use of a la Henderson's rules?



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# A recursive algorithm for decomposition and creation of the inverse of the genomic relationship matrix

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Use of relatives for **G**<sup>-1</sup> Accuracies not good enough Theory not clear



### Assumption of limited dimensionality

S – n x 1 vector containing additive information of population (haplotypes, chromosome segments, LD blocks)?

Breeding value Very small error  $\mathbf{u} = \mathbf{Ts} + \mathbf{e}$ 

If  $\mathbf{U}_{c}$  contains n animals:

$$\mathbf{s} \approx \mathbf{T}_c^{-1} \mathbf{u}_c$$

**Breeding values of any n animals contains all additive information** 

Choose core "**c**" and noncore "**n**" animals

$$\mathbf{u}_{n} = \mathbf{P}_{nc}\mathbf{u}_{c} + \varepsilon_{n}$$
$$\mathbf{u}_{c} = \mathbf{u}_{c}$$
$$\begin{bmatrix} \mathbf{u}_{c} \\ \mathbf{u}_{n} \end{bmatrix} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{P}_{nc} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{u}_{c} \\ \mathbf{\varepsilon}_{n} \end{bmatrix}$$

 $var(\mathbf{\epsilon}_n) = \mathbf{M}_{\mathbf{nn}}$ 

$$\mathbf{G} = \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ \mathbf{P}_{nc} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{G}_{cc} & \mathbf{0} \\ \mathbf{0} & \mathbf{M}_{nn} \end{bmatrix} \begin{bmatrix} \mathbf{I} & \mathbf{P}_{cn} \\ \mathbf{0} & \mathbf{I} \end{bmatrix}$$
$$\mathbf{G}^{-1} = \begin{bmatrix} \mathbf{I} & -\mathbf{P}_{cn} \\ \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \mathbf{G}_{cc}^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{M}_{nn}^{-1} \end{bmatrix} \begin{bmatrix} \mathbf{I} & \mathbf{0} \\ -\mathbf{P}_{nc} & \mathbf{I} \end{bmatrix}$$

### How to estimate **P** and inv(**G**)?

$$\operatorname{var}\left(\begin{bmatrix}\mathbf{u}_{c}\\\mathbf{u}_{n}\end{bmatrix}\right) = \begin{bmatrix}\mathbf{G}_{cc} & \mathbf{G}_{cn}\\\mathbf{G}_{nc} & \mathbf{G}_{nn}\end{bmatrix}\boldsymbol{\sigma}_{u}^{2}$$

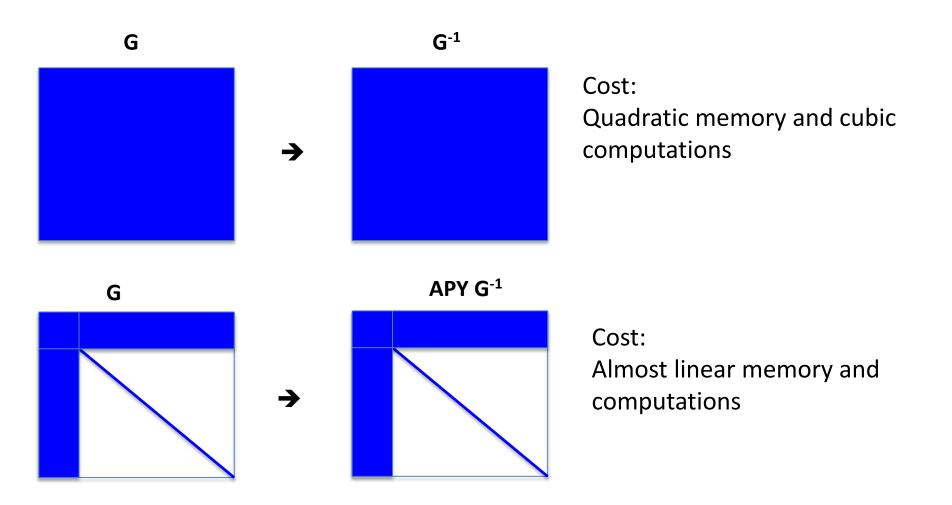
**G** is "true" relationship matrix

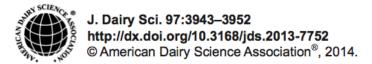
$$\mathbf{u}_n \mid \mathbf{u}_c = \mathbf{G}_{nc} \mathbf{G}_{cc}^{-1} \mathbf{u}_c, \quad \mathbf{P} = \mathbf{G}_{nc} \mathbf{G}_{cc}^{-1}$$

$$\mathbf{G^{-1}} = \begin{bmatrix} \mathbf{G}_{cc}^{-1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix} + \begin{bmatrix} \mathbf{G}_{cc}^{-1} \mathbf{G}_{cn} \\ \mathbf{I} \end{bmatrix} \mathbf{M^{-1}} \begin{bmatrix} \mathbf{G}_{nc} \mathbf{G}_{cc}^{-1} & \mathbf{I} \end{bmatrix}$$

APY algorithm (Algorithm for Proven and Young)

### **Properties of APY algorithm**





#### Using recursion to compute the inverse of the genomic relationship matrix

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### *Hot topic:* Use of genomic recursions in single-step genomic best linear unbiased predictor (BLUP) with a large number of genotypes

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

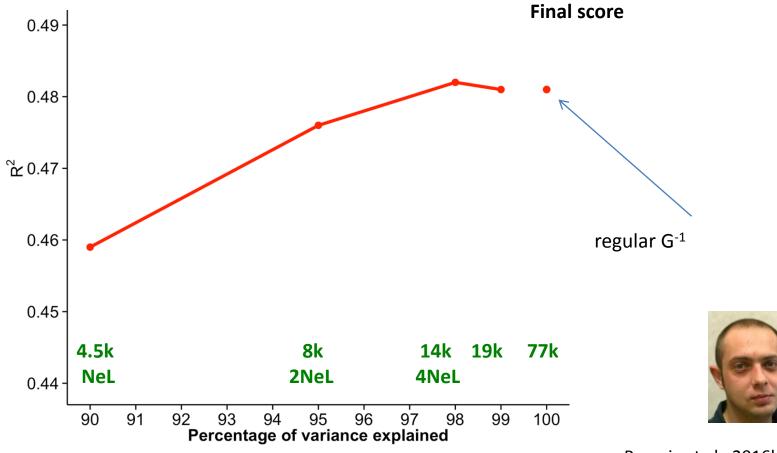
> Ignacy Misztal<sup>1</sup> Animal and Dairy Science, University of Georgia, Athens, Georgia 30602

> > The Dimensionality of Genomic Information and Its Effect on Genomic Prediction

> > Ivan Pocrnic,\*.<sup>1</sup> Daniela A. L. Lourenco,\* Yutaka Masuda,\* Andres Legarra,<sup>†</sup> and Ignacy Misztal\* \*Department of Animal and Dairy Science, University of Georgia, Athens, Georgia 30602, and <sup>†</sup>Institut National de la Recherche Agronomique, GenPhySE, F-31326 Castanet-Tolosan, France

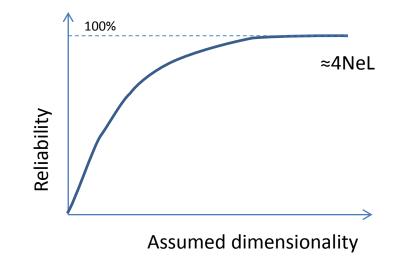
EAAP meeting 20

### Reliabilities – Holsteins (77k)



Pocrnic et al., 2016b

### Distribution of segments/haplotypes/..



# Costs with 720k genotyped animals

- 30 M Holsteins
- 50 M records
- 764k 60k genotypes



ltem	BLUP	ssGBLUP
APY G	-	7 h
A22-1	-	10 min
rounds	402	464
Time/round	51 s	83 s
Total time	6 h	17 h

### Which core animals in APY?

Bradford et al. (2017)



- Simulated populations (QMSim; Sargolzaei and Schenkel, 2009)
- Ne = 40
- #genotyped animals = 50,000
- Core animals:
  - Random gen 6 || gen 7 || gen 8 || gen 9 || gen 10 (y)
  - Random all generations

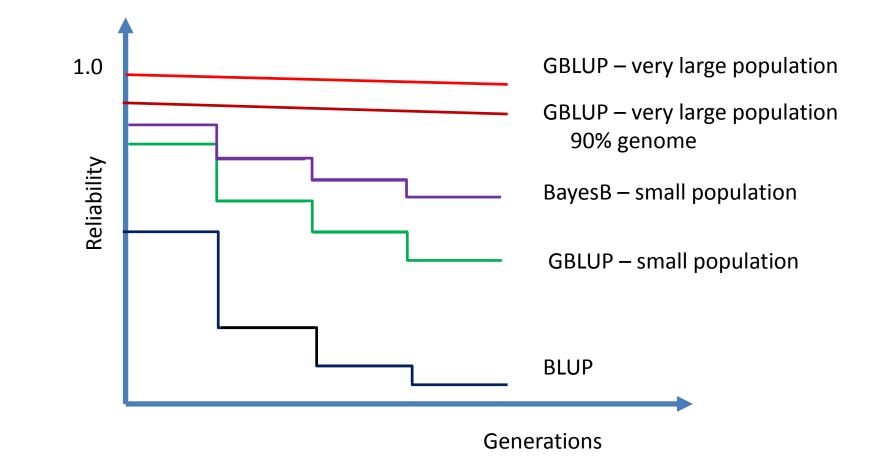
### Which core animals in APY?

Accuracy 1 **G**<sup>-1</sup> 0.9 Т 0.8 0.2 0.1 0 98% 95% 90% NeL 4NeL Percent of variation explained in G

Gen 6 Gen 7 Gen 8 Gen 9 Gen 10 Random

Bradford et al. (2016)

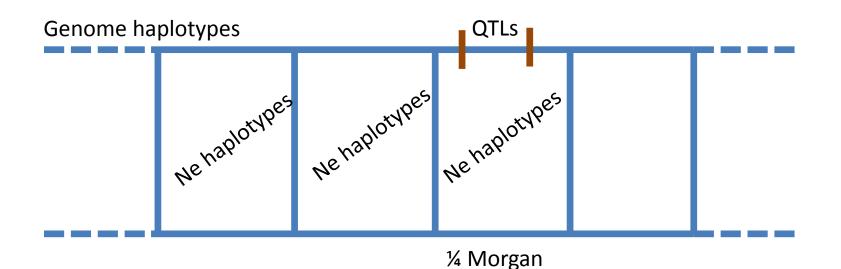
### Persistence over generations



Very large – equivalent to 4NeL animals with 99% accuracy Are SNP effects from Holstein national populations converging

# Theory of limited dimensionality

Number of haplotypes: 4 Ne L Ne within each ¼ Morgan segment



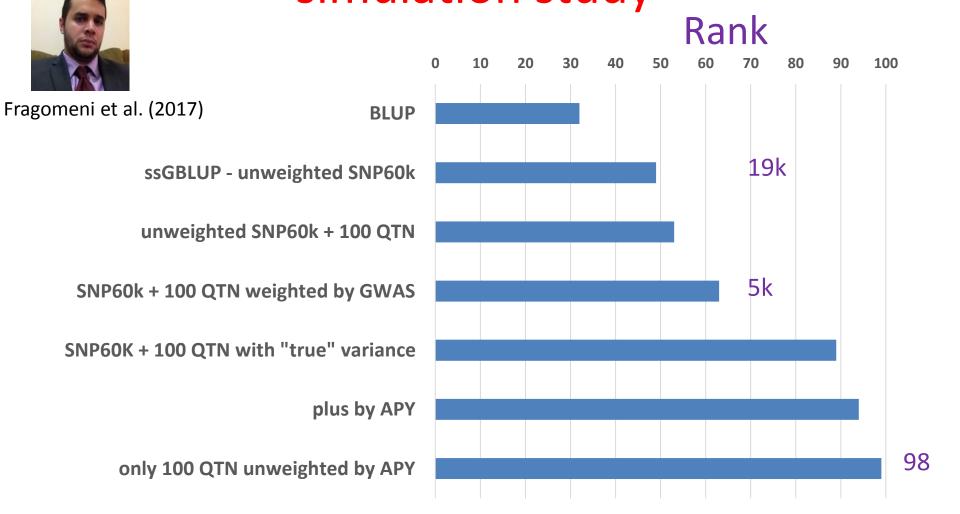
Dimensionality of ¼ Morgan case: Ne

or number of identified QTLs

Reduced dimensionality with weighted GRM

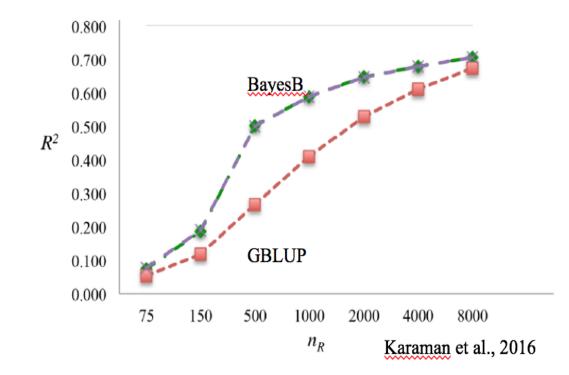
Fragomeni et al., 2018

# ssGBLUP accuracies using SNP60K and 100 QTNs – simulation study



### Multitrait ssGBLUP or SNP selection?

- SNP selection/weighting (BayesB, etc.)
  - Large impact with few genotypes
  - Little or no impact with many



### Variance components

- Based on SNP
  - limitations
- REML based on relationships
  - Equations no longer sparse
  - YAMS sparse matrix package –up to 100 times speedup (Masuda et al., 2017)
  - APY for REML
- Method R (Legarra and Reverter, 2017)

### Extra topics

- Matching pedigrees and genomic relationships
- Missing pedigrees
- Crossbreeding
- Causative SNP
- Haplotypes for crossbreds (Christensen et al., 2016)
- Metafounders (Legarra et al., 2016)
- Approximation of reliabilities

### Conclusions

- Limited dimensionality of genomic information due to limited effective population size
- ssGBLUP suitable for any data set and model
- With large data sets for Holsteins:
  - Good persistence of predictions
  - Convergence of predictions from different countries



**United States** Department of Agriculture

National Institute of Food and Agriculture





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Tom Lawlor, Holstein Assoc Paul VanRaden, AGIL USDA

### zoetis





Pocrnic



## Theory for APY

- Breeding values of core animals linear functions of:
  - Independent chromosome segments (Me)
  - Independent effective SNP
- E(Me)=4 Ne L (Stam, 1980; VanRaden, 2008)

Ne –effective population size

L – length of genome in Morgans

Me = 4 (Ne=100) (L=30) = 12,000

# Accuracy and distance from markers to QTL

Fragomeni et al. (2017)

