



# Genomic Selection From Livestock to Aquaculture Applications

John Woolliams

Alan Archibald, John Hickey & Ross Houston

The Roslin Institute, University of Edinburgh, U.K.



THE UNIVERSITY of EDINBURGH

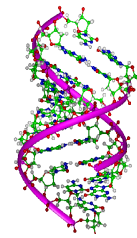


1. The State of Genomes
  - » livestock & aquaculture
2. Genomic Selection
  - » background & motivations
3. The State of the Art
  - » achievements & limitations
4. Genomic Selection 2.0
  - » sequencing populations and the final frontier?
5. Conclusions

1. The State of Genomes
  - Livestock
  - Aquaculture

- Genomic selection does not require a reference genome
  - » abbreviated GS
- BUT past & future tool development benefits from knowledge of sequence
  - » e.g. selection of SNP for spacing and coverage
- Stage of development of GS in species is associated with development of genome sequence
  - » amongst other things!

# Early Days: Towards a Sequence



**1953**  
Watson and Crick



**1977**  
DNA sequenced  
 $\Phi$ X174  
5,386 nt

**1990**  
Human Genome Project launched



**1991**  
PiGMaP project starts

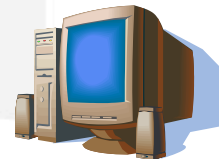
'Halothane' gene test

**2001**  
Draft human genome sequence



**1920s and 30s**  
Fisher, Lush and others Population Genetics

**1970s +**  
Advances in quantitative analysis



**1990s +**  
Quantitative trait locus (QTL) mapping

**2001**  
Genomic selection proposed



# Genomic Developments to 2011



**2003**  
Human genome  
sequence "finished"  
\$3 billion

**2004**  
Chicken  
genome  
sequenced

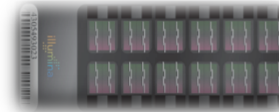


**2005**  
Dog  
genome  
sequenced

**2007**  
Cat  
genome  
sequenced



**2008**  
Bovine 50K  
SNP chip



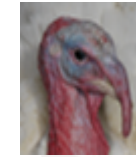
**2009**  
Cattle genome  
sequenced

Horse genome  
Sequenced

**2009**  
Pig 60K SNP chip

Sheep 60K SNP  
chip

**2010**  
Turkey genome  
sequenced



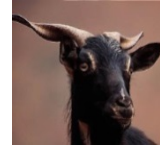
**2010**  
750K bovine  
SNP chips



# Genomic Developments to 2015



**2012**  
Chicken 600K  
SNP chip



**2013**  
Goat genome  
sequenced

**2015**  
Improved reference  
genomes – goat,  
pig, sheep, cattle,  
chicken,



**2012**  
Pig genome  
sequenced



**2012**  
Pig gene expression  
atlas



**2013**  
Duck genome  
sequenced



**2014**  
Sheep genome  
sequenced

**2015**  
Pig 650K  
SNP chip

**2015**  
Functional  
Annotation of  
Animal Genomes  
(FAANG) launched



# Tools for Genomic Selection



	Dairy Cattle	Beef Cattle	Sheep	Goats	Pigs	Layer Chick's	Broiler Chick's	Turkey	Duck
Reference genome	+++	+++	++	++	++	+++	+++	+	+
High-density SNP 'chips' available	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Genomic Selection?	+++	+	++	+	+++	++(+)	+++	No	No





# Genomic Developments to 2011



**2003**  
Human genome  
sequence "finished"  
\$3 billion

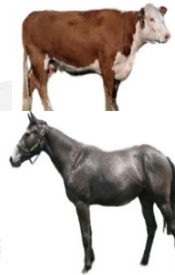
**2004**  
Chicken  
genome  
sequenced



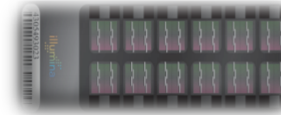
**2005**  
Dog  
genome  
sequenced



**2007**  
Cat  
genome  
sequenced



**2008**  
Bovine 50K  
SNP chip



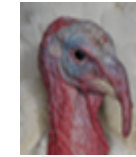
**2009**  
Cattle genome  
sequenced

Horse genome  
Sequenced

**2009**  
Pig 60K SNP chip

Sheep 60K SNP  
chip

**2010**  
Turkey genome  
sequenced



**2010**  
750K bovine  
SNP chips



**2006**  
Salmon & trout  
cDNA micro-array

**2008**  
Sea bream  
cDNA micro-array

**2009**  
Salmon 6K  
SNP chip

**2010**  
Sea bass  
cDNA micro-array

**2011**  
Cod genome  
sequenced

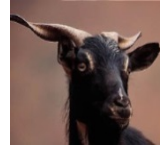
**2011**  
Salmon & trout  
RAD-sequencing



# Genomic Developments to 2015



**2012**  
Chicken 600K  
SNP chip



**2013**  
Goat genome  
sequenced

**2015**  
Improved reference  
genomes – goat,  
pig, sheep, cattle,  
chicken,



**2012**  
Pig genome  
sequenced



**2012**  
Pig gene expression  
atlas



**2013**  
Duck genome  
sequenced



**2014**  
Sheep genome  
sequenced

**2015**  
Pig 650K  
SNP chip

**2015**  
Functional  
Annotation of  
Animal Genomes  
(FAANG) launched

**2012**  
Pacific oyster  
genome sequenced

**2013**  
Salmon 130K  
SNP chip

**2014**  
Trout genome  
sequenced

Catfish HD  
SNP array

Salmon genome  
sequenced

Carp HD  
SNP array

Sea bass genome  
sequenced

Rainbow trout HD  
SNP array

Carp genome  
sequenced



# Tools for Genomic Selection



	Atlantic salmon	Rainbow trout	European sea bass	European sea bream	Turbot	Common carp
Reference genome	+	+	+	(+)	(+)	+
High-density SNP 'chips' available	Yes	Yes	No	No	No	Yes
Genomic Selection?	++	(+)	No	No	No	No



# Summary of Development



- Livestock species
  - » Sequences published, refined
  - » Expression atlases published and/or major community efforts
  - » Large number of SNP chips
    - » multiple densities for most species to suit needs
    - » imputation, GWAS etc
  - » Genomic selection firmly established in major species
- Aquacultural species
  - » Sequences at first draft
  - » Early stage annotation and expression data
  - » Some species with SNP chips
  - » Genomic selection being introduced to some species

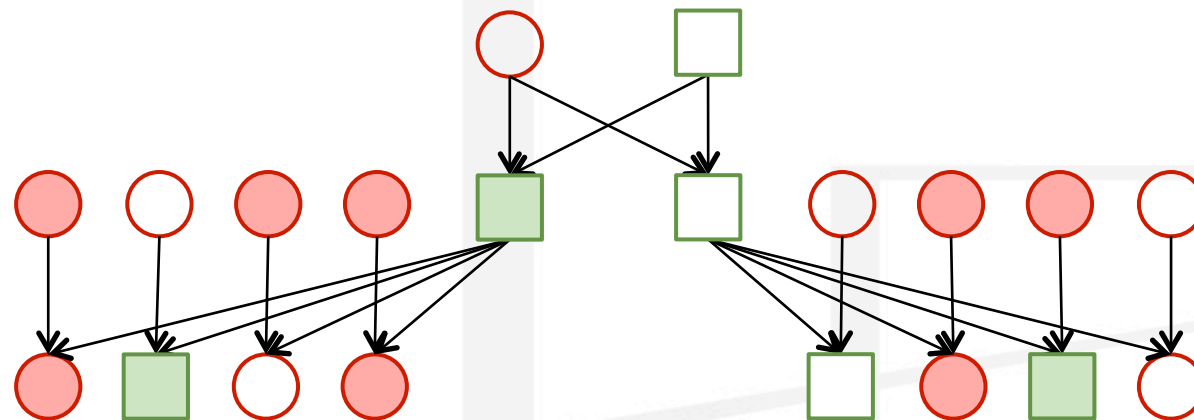


2. Genomic Selection
- Background
  - Motivations

# Traditional Breeding



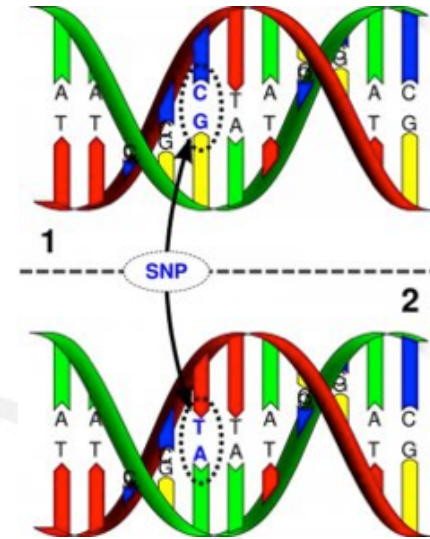
- Collect pedigree (○ □) phenotype (○ ●) information
  - » own performance (e.g. growth, ...)
  - » sib-performance (e.g. carcass and meat quality, disease, ...)
  - » progeny performance (e.g. milk yield, # eggs, ...)
- Estimate genetic values by BLUP



# Genomic Selection (1)



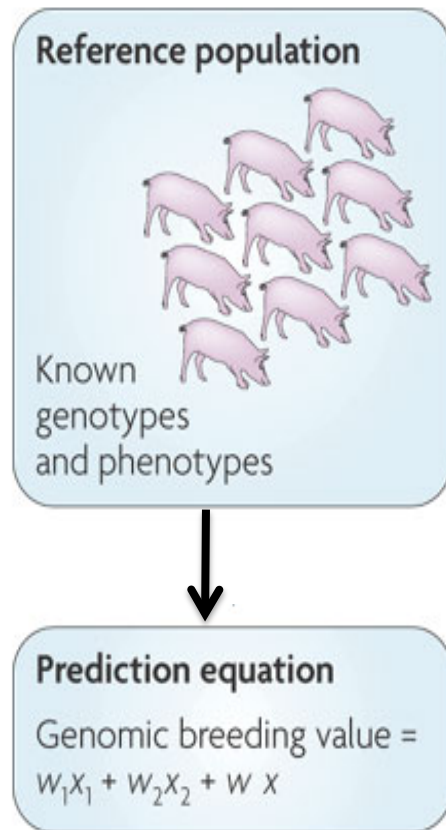
- Use abundant genome-wide markers
  - » e.g. SNP



# Genomic Selection (2)



- Obtain predictions of Marker effects from Training Set

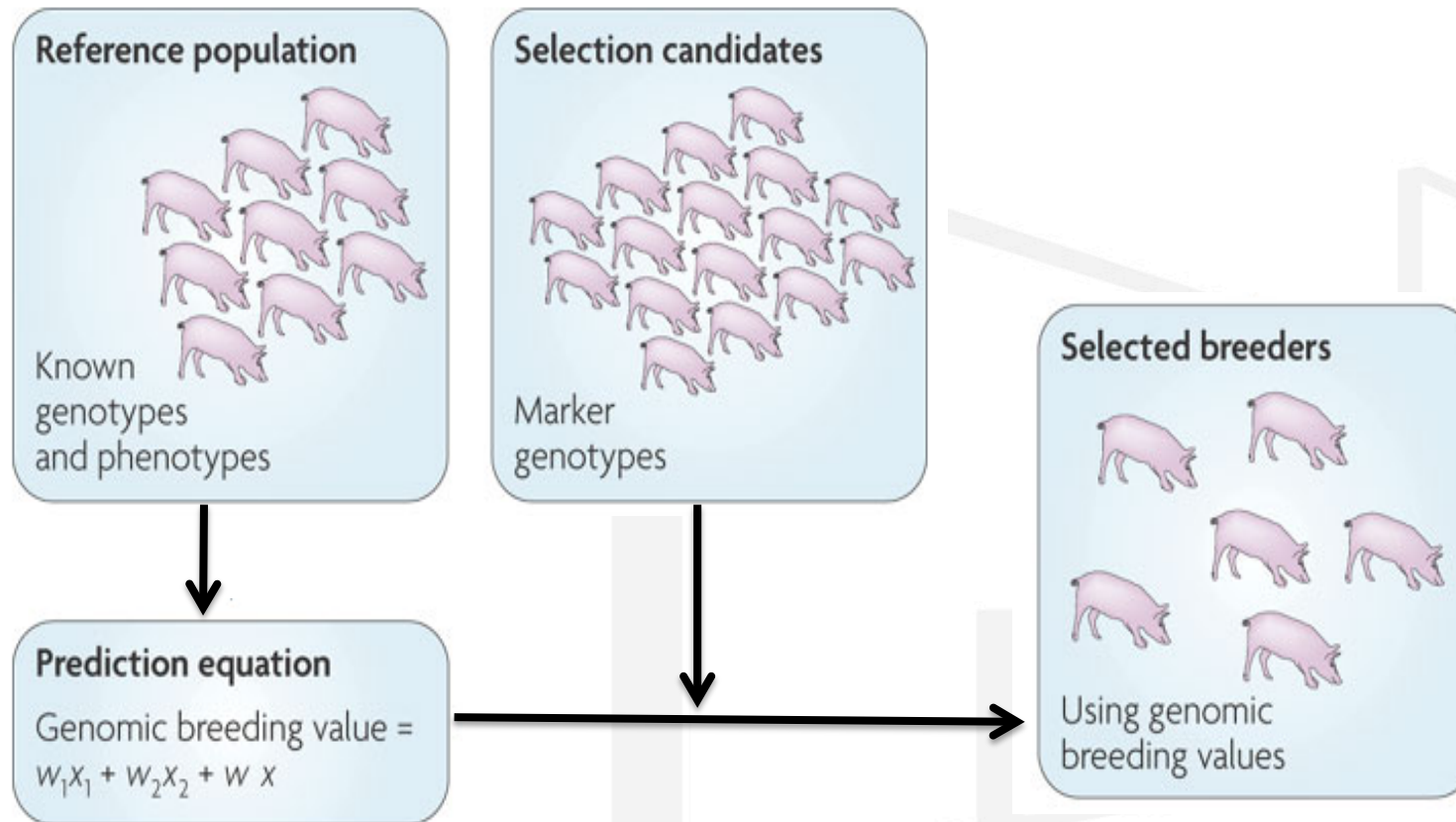




# Genomic Selection (3)



- Obtain predictions of candidates and select



Hayes & Goddard, 2009



# Some Important Properties



## 1. Accuracy of GS is dynamic

- » bigger the training set, the more accurate the prediction
- » BLUP accuracy is  $\sim$  static given structure of scheme
  - »  $f(\text{data collected on close relatives, } h^2)$



# Some Important GS Properties



- Greater accuracy of Mendelian Sampling Term
  - » what makes us unique
  - » ancestors (e.g. sire) or collateral relatives (sibs) alone cannot estimate this
  - » source of continued gain beyond best parent
  - » selective advantage when controlling inbreeding
  - » explains  $\frac{1}{2}$  (or more) of genetic variance!
    - » i.e. within-family variance



# Some Useful GS Properties



- Prediction available early in life
  - » can consider selection in the absence of phenotypes
    - » e.g. disease phenotypes
  - » reduce generation interval



$$\text{Response} = \frac{\text{Selection Intensity} \times \text{Accuracy} \times \text{Diversity}}{\text{Generation Interval}}$$

- So GS adds gain through
  - » increases accuracy
  - » decreases generation interval
  - » can in some schemes add selection intensity
    - » e.g. avoiding random culling

3. The State of the Art
- Livestock
  - Aquaculture

- Dairy breeding
  - » traditionally relied on progeny testing
  - » long generation interval
  - » high cost per bull tested



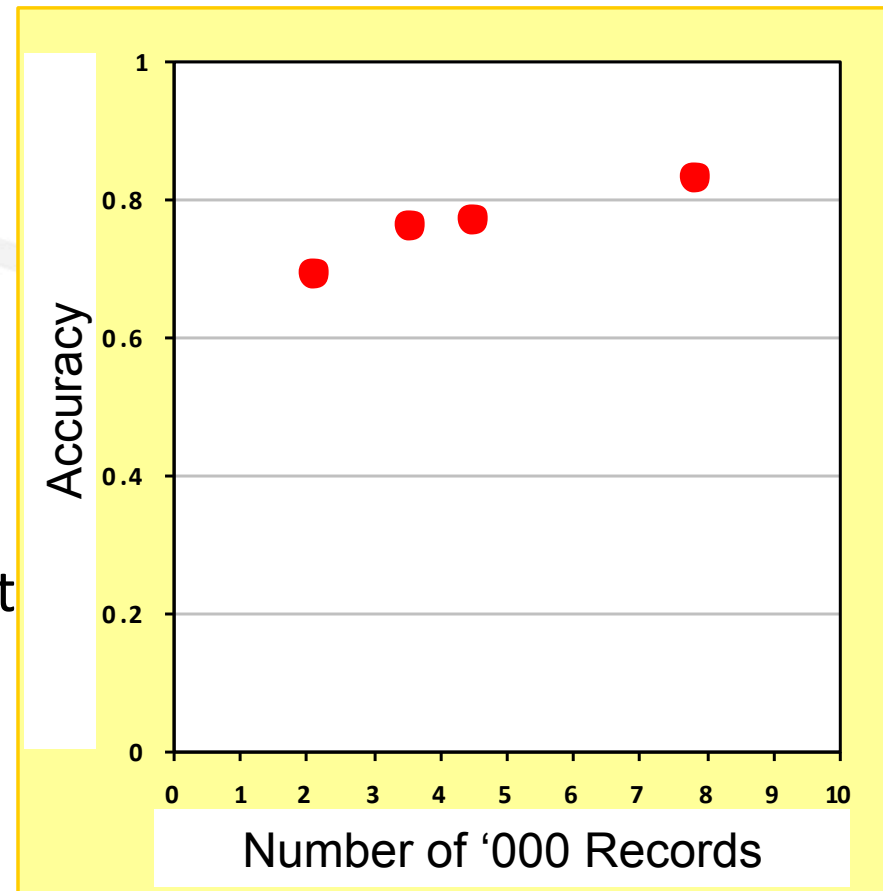
- Benefits from prediction early in life
  - » screen more bulls more accurately before entering progeny test
    - » increase selection intensity
  - » only test the best bulls
  - » if GS predictions have high accuracy might avoid progeny test
    - » decrease generation interval



# GS Accuracy for Dairy



- Note
  - » high accuracy attained
    - » source USDA
  - » dynamic accuracy
- But
  - » require large number of bulls
  - » each bull has high accuracy test



# Dairy Advantages



- Costs of genotyping are covered by savings in progeny test
- Easy availability of large numbers of high-accuracy phenotypes on bulls
  - » i.e. the progeny test proofs
- Gains are potentially very large
- Safe implementation route as predictions on bulls can be compared emerging, accurate test results
- Animals are high value compared to cost of test



# Dairy Advantages



- Costs of genotyping are covered by savings in progeny test

- Easy availability of large numbers of high-value phenotypes on bulls

» is the  
**What about sectors where animals have low individual value?**

- Genotyping is potentially very large
- Safe implementation route as predictions on bulls can be compared emerging, accurate test results
- Animals are high value compared to cost of test

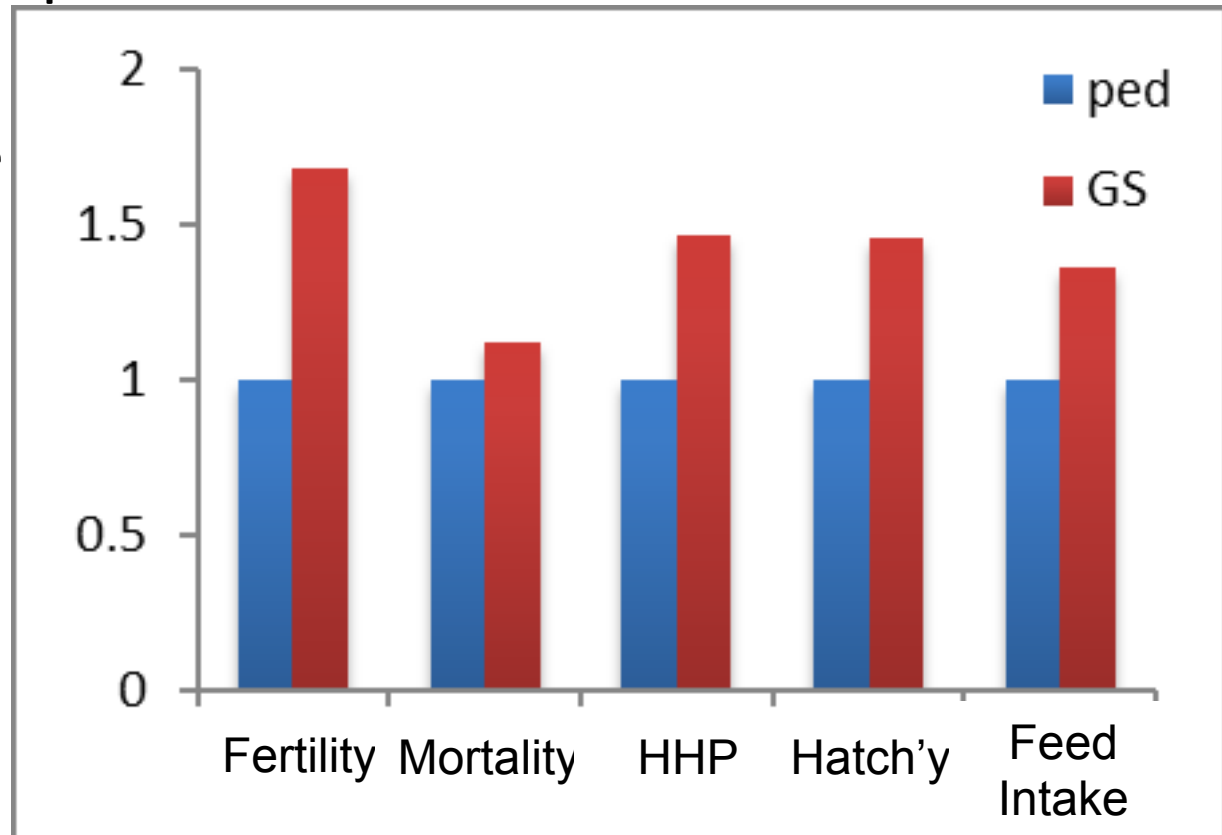


# GS Benefits in Broiler Chickens



- Accuracy of GS compared to BLUP

- » ~ 1.1 to 1.7
- » will gain with time



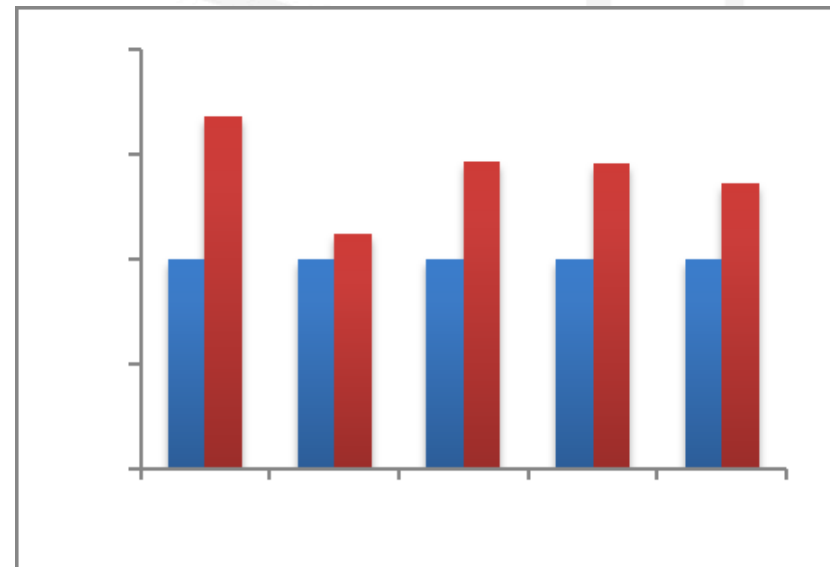
From Wolc et al. 10<sup>th</sup> WCGALP, Vancouver, 2014



# GS Benefits in Broiler Chickens



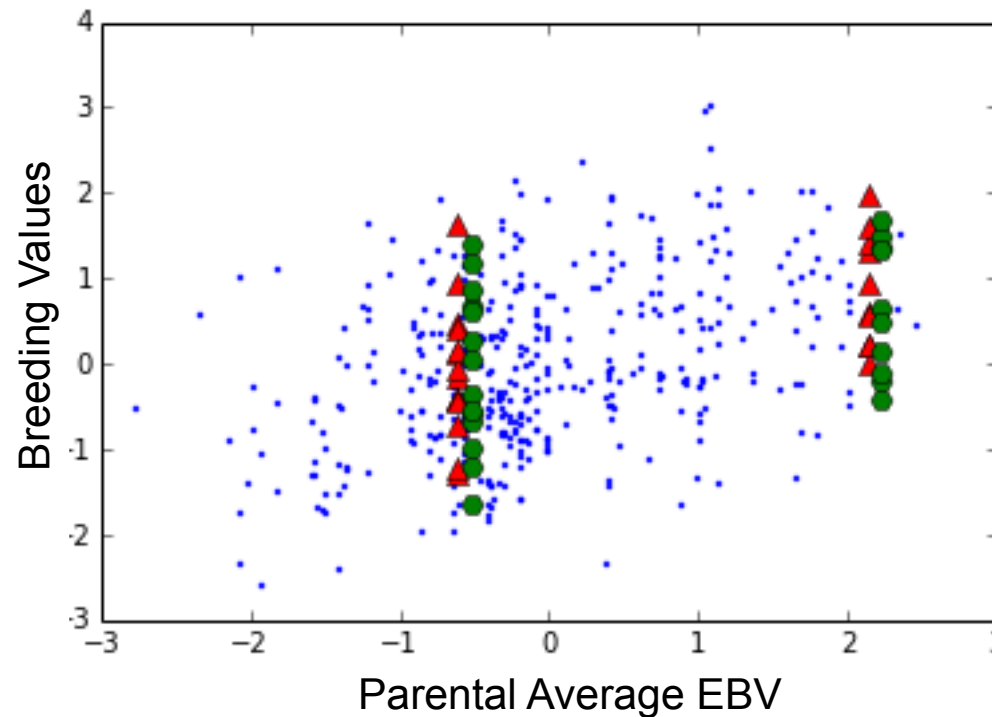
- Valuable gains in sex-limited female traits with low  $h^2$ 
  - » from estimate of Mendelian Sampling Term of males
  - » i.e. with no phenotype



# Value of Mendelian Sampling



- Red triangles: Mendelian genomic predictions
- Green circles: Validation from progeny means



From Wolc et al. 10<sup>th</sup> WCGALP, Vancouver, 2014



# Salmon Breeding



- Published results on GS are few
- Major study by Ødegård (2014)
  - » presenting this conference



# Salmon Breeding



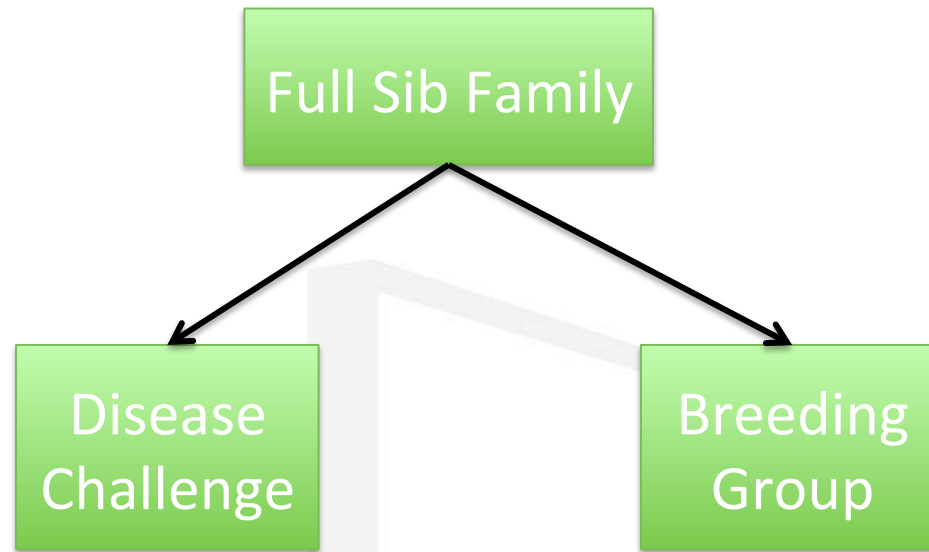
- Small to moderate training set size of 2000
- Accuracies from GS were better than BLUP
  - » 1.2-fold for Lice Resistance
  - » 1.1-fold for Fillet Colour
    - » BLUP for both traits was  $\sim 0.6$

Ødegård et al. *Frontiers in Genetics* 5 (2014)

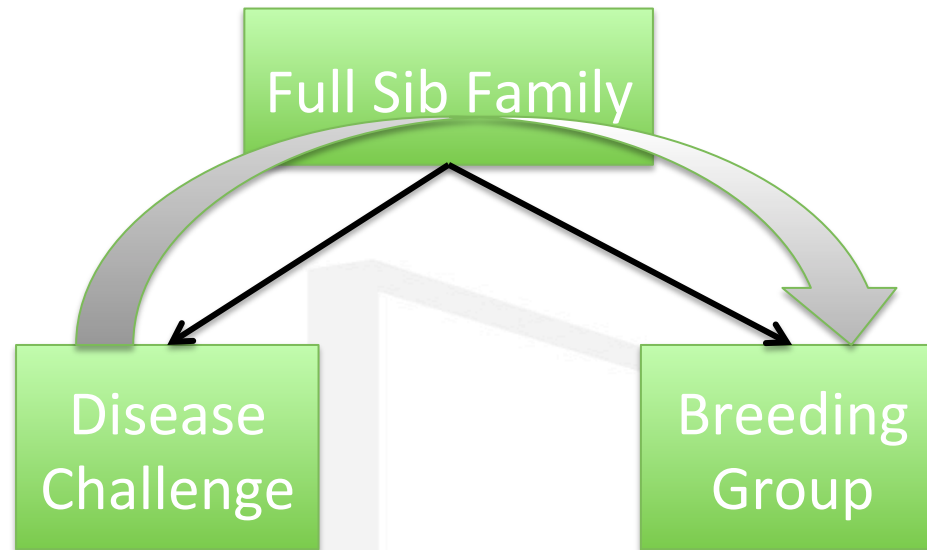




# Sib Testing

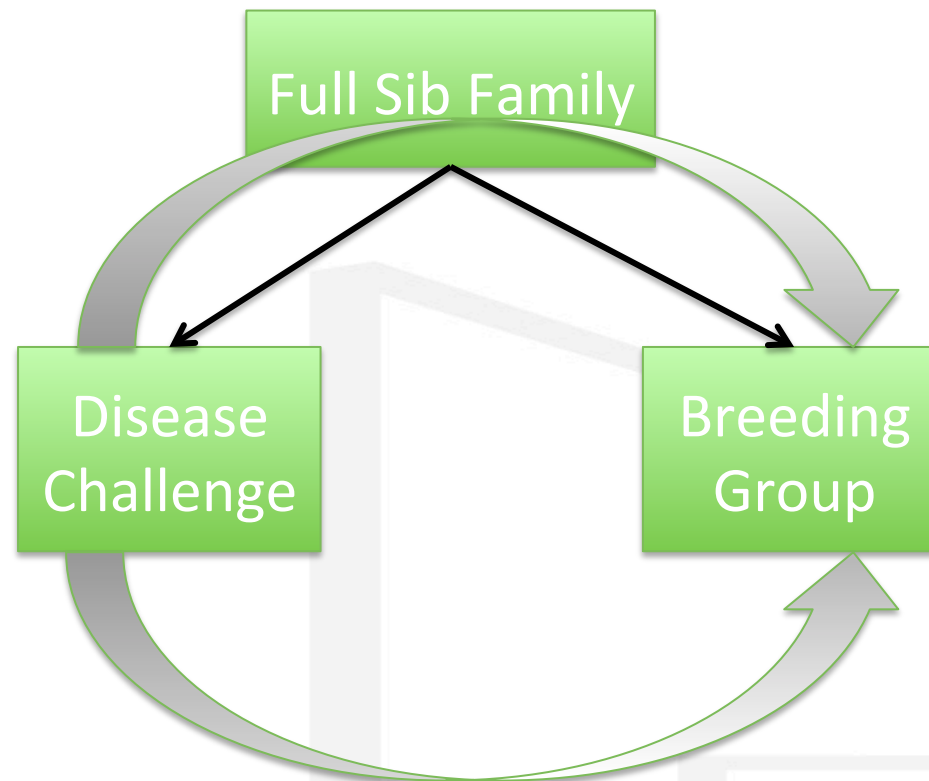


# Sib Testing with BLUP



- Information gained from test is only family mean





- Information on family mean and desirable marker alleles within family both transferred to breeding group

- Simulations show important benefits in accuracy
  - » estimate of Mendelian Sampling Term from markers
  - » require relatively few markers per chromosome (10-20)

Lillehammer et al (2013), Genet Sel Evol. 45

# Summary of Applications



- GS has been implemented or is being implemented in all livestock species
  - » benefits over BLUP demonstrated
  - » benefits come from
    - » early prediction & reduced generation time
    - » better Mendelian sampling estimates, particularly for sex-limited traits
- Emerging evidence of benefits in salmon breeding
  - » exploits family structure in sib-testing
    - » c.f. livestock: more efficient training sets, lower SNP density needed
  - » GS models may benefit from separating within-family and between-family LD



4. Genomic Selection 2.0
- Why isn't GS 1.0 Perfect?
  - Sequencing Populations
  - The Final Frontier?

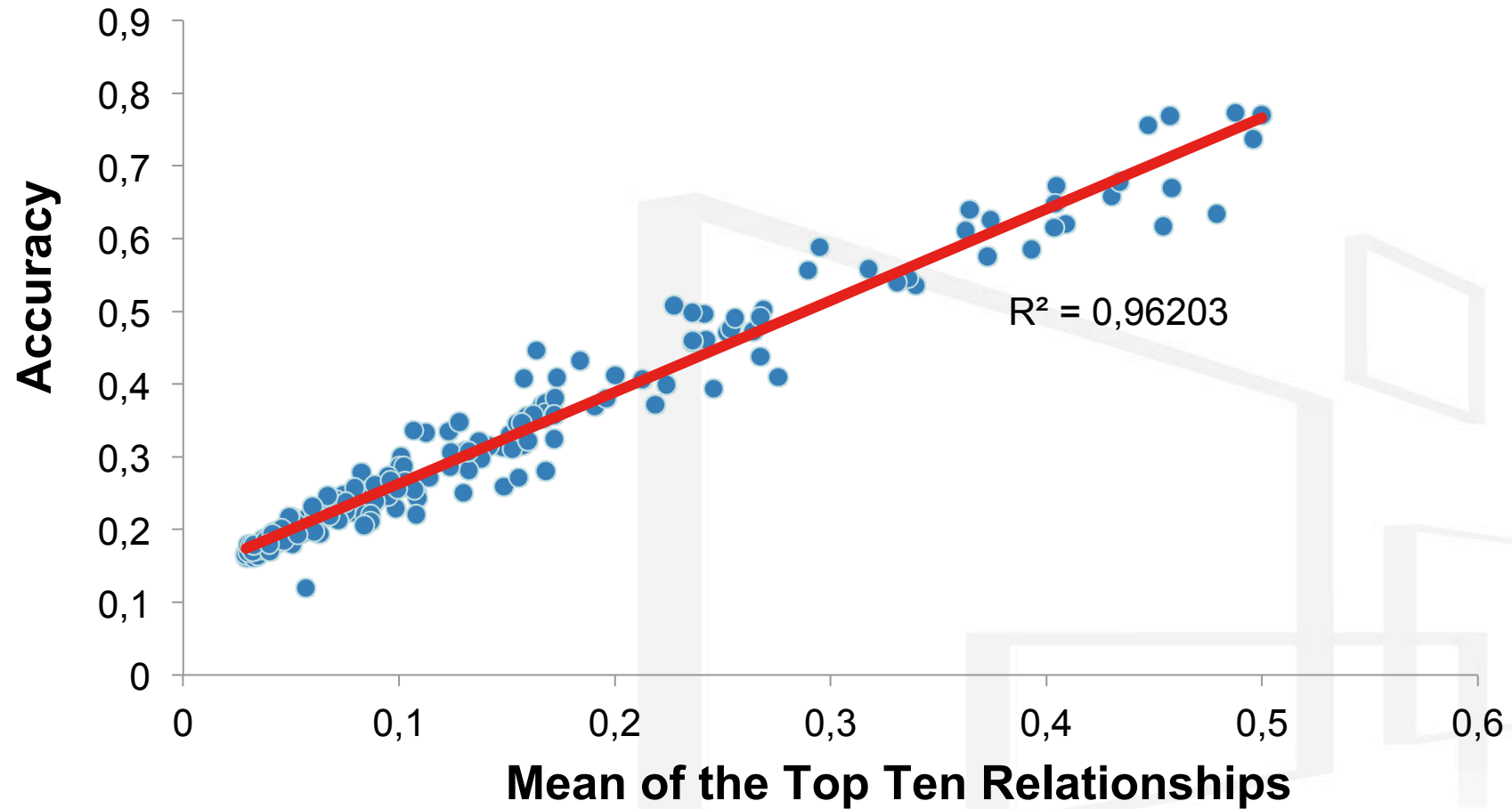
# Why isn't GS 1.0 Perfect



- Markers effects are 'blind' predictions, not causal
  - » unable to predict unknown genetic correlations, e.g. GxE
  - » less than required for Precision Breeding
- Relies on linkage and LD, unlikely to capture full variance
  - » bovine 50k chip only captures 80% variance
- Can't predict well across breeds or lines
- Need large training sets for very good accuracies
  - » order 10,000s in livestock
  - » accuracy depends on how many close relatives
  - » but aquaculture populations often have many close relatives



# Accuracy and Relationships



Clark et al. (2012)





# What can be done?



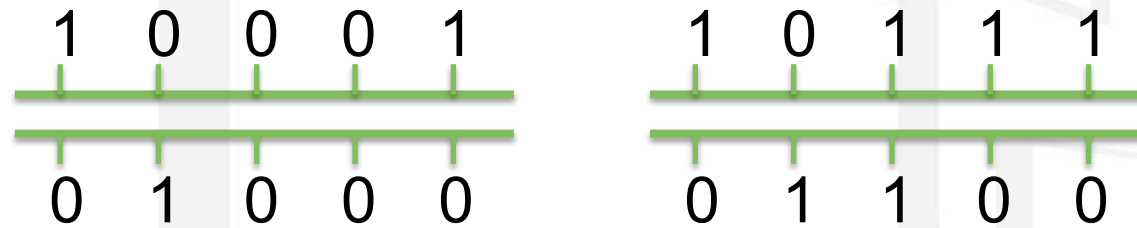
- Reduce cost of genotyping an individual
  - » obtain huge data



# Driving Down Unit Costs



- Imputing genotypes
  - » High density information for key individuals (e.g. sire)
  - » Low density information for candidates
  - » Exploit pedigree



Low Density Genotypes



Imputed Genotypes



# Power of Genotype Imputation



#Sires = 480  
 #Dams = 11,884  
 #Candidates = 100,000

60k chip = \$120  
 6k chip = \$48  
 3k chip = \$35  
 384 chip = \$20

Scenario	MGD + PGD	Sire	Dam	Candidates	Individual cost	Accuracy of Imputation R <sup>2</sup>
SC1	0	60K	0	384		0.878
SC2	384	60K	384	384	\$20.58	0.929
SC3	3K	60K	3K	384	\$24.74	0.950
...						
SC16	60K	60K	60K	60K	\$120.00	1.000

Huang et al. (2012)

- AlphaImpute <http://www.alphagenes.roslin.ed.ac.uk>



# Driving Down Unit Costs



- Imputation
  - » High density information for key individuals (e.g. sire)
  - » Low density information for candidates
  - » Exploit pedigree
- Impute to what density?
  - » cost of sequencing data reducing!
  - » can we get it to \$10 /individual with sequencing?



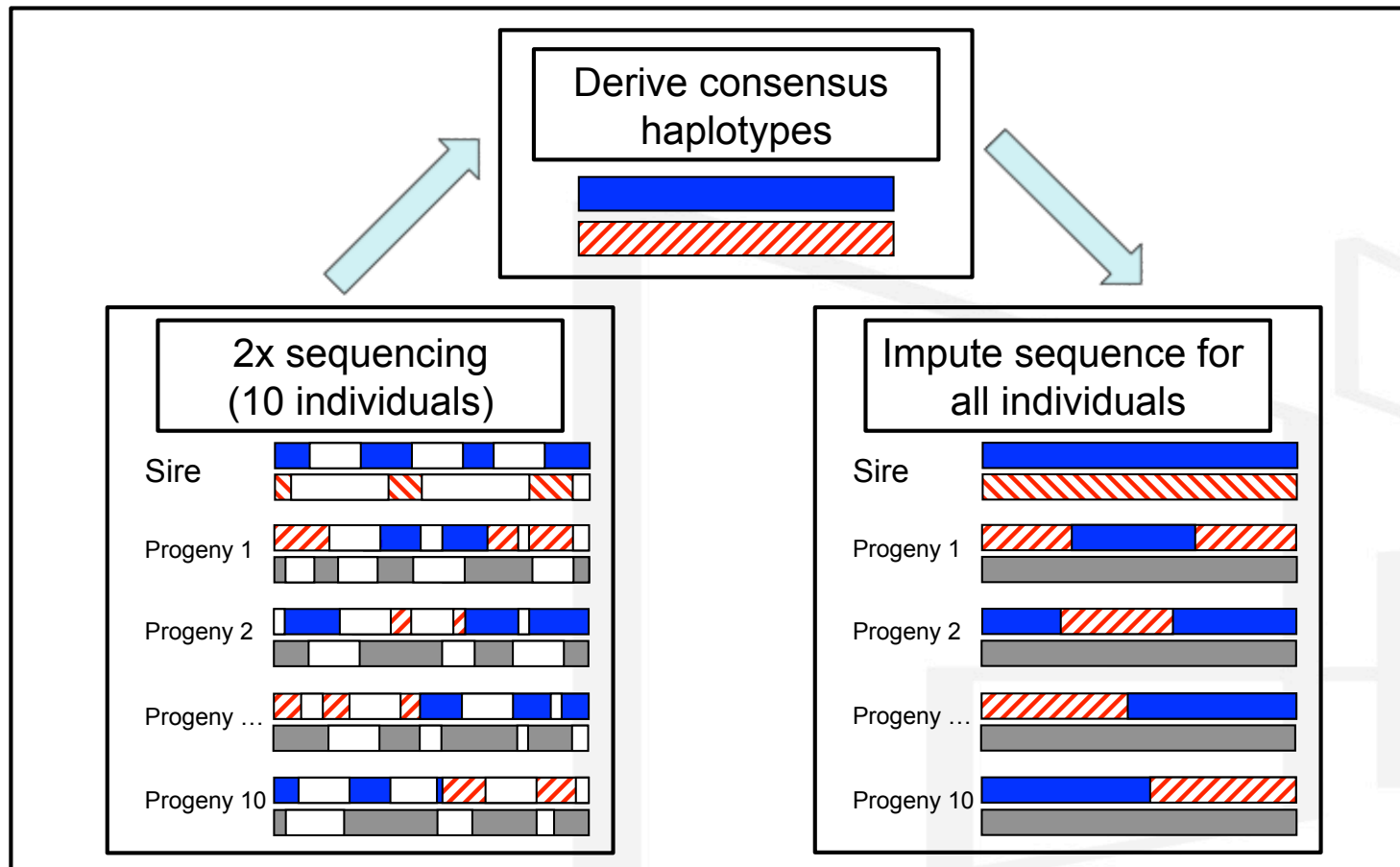
# Sequencing a Population



- ‘Traditional’ sequencing of individuals
  - » 10x or 30x coverage, still expensive
  - » therefore only sequence a few
- Sequencing a population
  - » how best to use total coverage available?
  - » genotyping by sequencing approach, 1x
  - » exploit pedigree and low  $N_e$  of livestock
    - » haplotype of key individuals are repeated many times in population
    - » sequence everyone at low coverage
    - » need new generation of imputation tools to cope with probabilistic nature of the sequencing at any locus



# Sequencing a Population



# Sequencing Populations



- Feasible to develop training sets in real populations of 300,000 animals all with sequence information
  - » before the next ISGA?



# The final frontier?



- Feasible to develop training sets in real populations of 300,000 animals all with sequence information
- Two orders of magnitude greater than '1000 Bulls' project in sequence data
- Order of magnitude greater than publically reported training sets for GS
- Will this be the final frontier?
  - » with our finite populations?





# What will final frontier look like?



- Will accuracy be 1?
  - » it should be close
  - » if not, why not
    - » what is wrong with our models?
- How many QTN will be detected?
  - » 100's or 1000's?
  - » How much variation do detected QTN explain?



# Challenge of Precision Breeding



- Require to understand genetic correlation
  - » including GxE interactions
- Need to map QTN closely
  - » need sequence data, lots of it
  - » annotation of sequence
- To move from sequence to consequence need to understand expression and regulation
  - » to build the systems biology underling the consequences



- Functional Annotation of ANimal Genomes
  - » new international community consortium
- Target tissues
  - » musco-skeletal
  - » immune tissues
- Assays
  - » DNaseI, FAIREseq, ATAC-seq
  - » histone marks (promoters, enhancers)
  - » Methylation (BS-seq, RRBS)
  - » RNAseq (stranded), CAGE



# Conclusions



- Major expansion of aquaculture genomes and tools emerging, while livestock are in a stage of refinement



# Conclusions



- Major expansion of aquaculture genomes and tools emerging, while livestock are in a stage of refinement
- Success of GS is determined by the quality and size of training set



# Conclusions



- Major expansion of aquaculture genomes and tools emerging, while livestock are in a stage of refinement
- Success of GS is determined by the quality and size of training set
- **GS proven to be successful in key livestock species**



# Conclusions



- Major expansion of aquaculture genomes and tools emerging, while livestock are in a stage of refinement
- Success of GS is determined by the quality and size of training set
- GS proven to be successful in key livestock species
- **GS in aquaculture may be particularly beneficial due to sib testing**



# Conclusions



- Major expansion of aquaculture genomes and tools emerging, while livestock are in a stage of refinement
- Success of GS is determined by the quality and size of training set
- GS proven to be successful in key livestock species
- GS in aquaculture may be particularly beneficial due to sib testing
- **Genomic advances may allow us to boldly go to the final frontier**





# Acknowledgements



- Sponsors of the presentation
  - » Red de Excelencia de Biotecnología en Acuicultura
  - » Aquagenomics-Net - Ministerio de Economía y Competitividad
- Sponsors of work presented
  - » EC FP7
  - » Biotechnology and Biological Sciences Research Council, UK
  - » Aviagen, Genus PIC



# Precision Breeding Goals



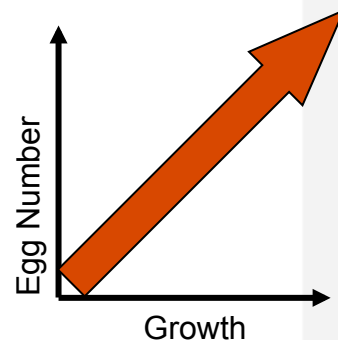
- To increase the scope and precision of predictions of the outcomes of breeding
- To avoid the introduction and advance of characteristics deleterious to animal well-being or, more generally, the well-being of the species
- To manage genetic resources and diversity between and within populations in accordance with the principles set out in the Convention on Biological Diversity

Flint & Woolliams, 2008, Proc.Roy.Soc.B

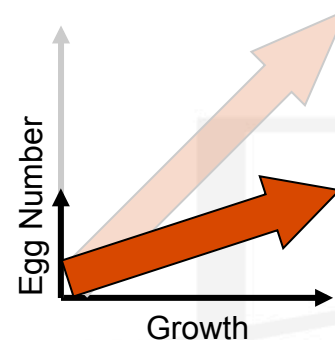


- Differences in accuracy among traits arise from differences in amount of genetic information
  - » one trait sex-limited, one not
  - » different heritabilities
- Such differences create divergence from gains achieved using economic indices and desired gains

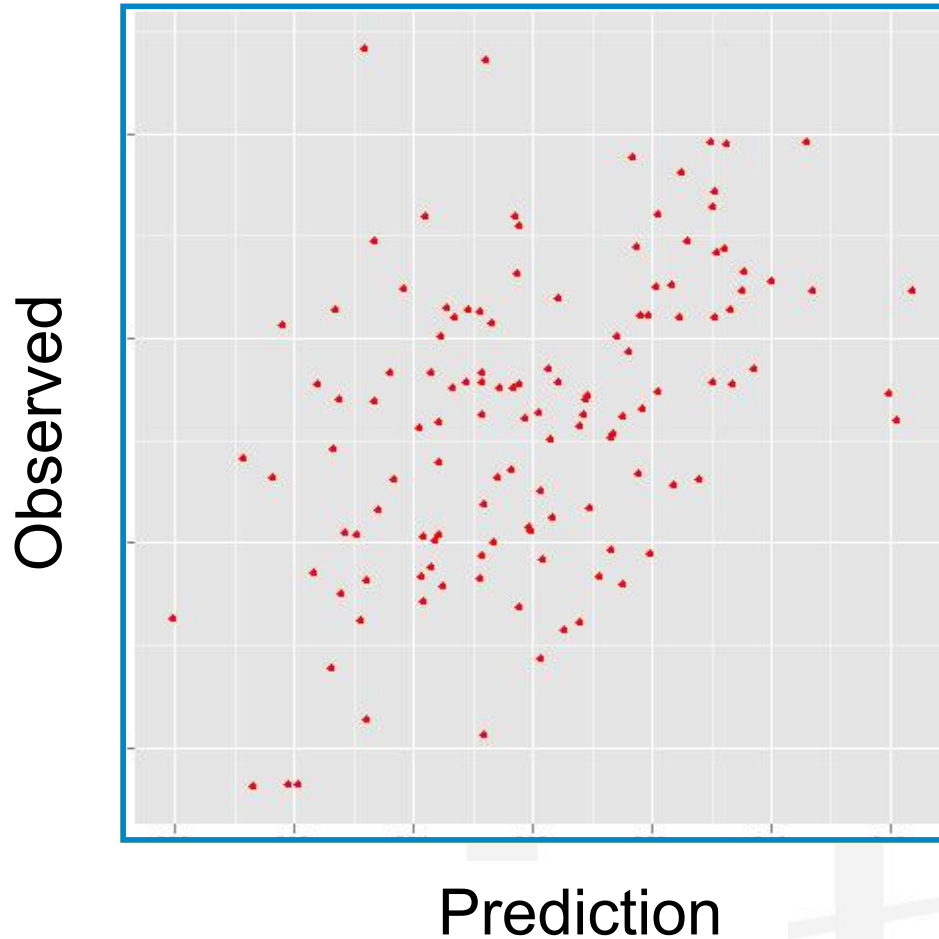
Desired Gain



Achieved Gain



# Cross Validation: Height



Set 1  
 $r = 0.455$

Set 2  
 $r = 0.426$

Set 3  
 $r = 0.317$

Set 4  
 $r = 0.335$

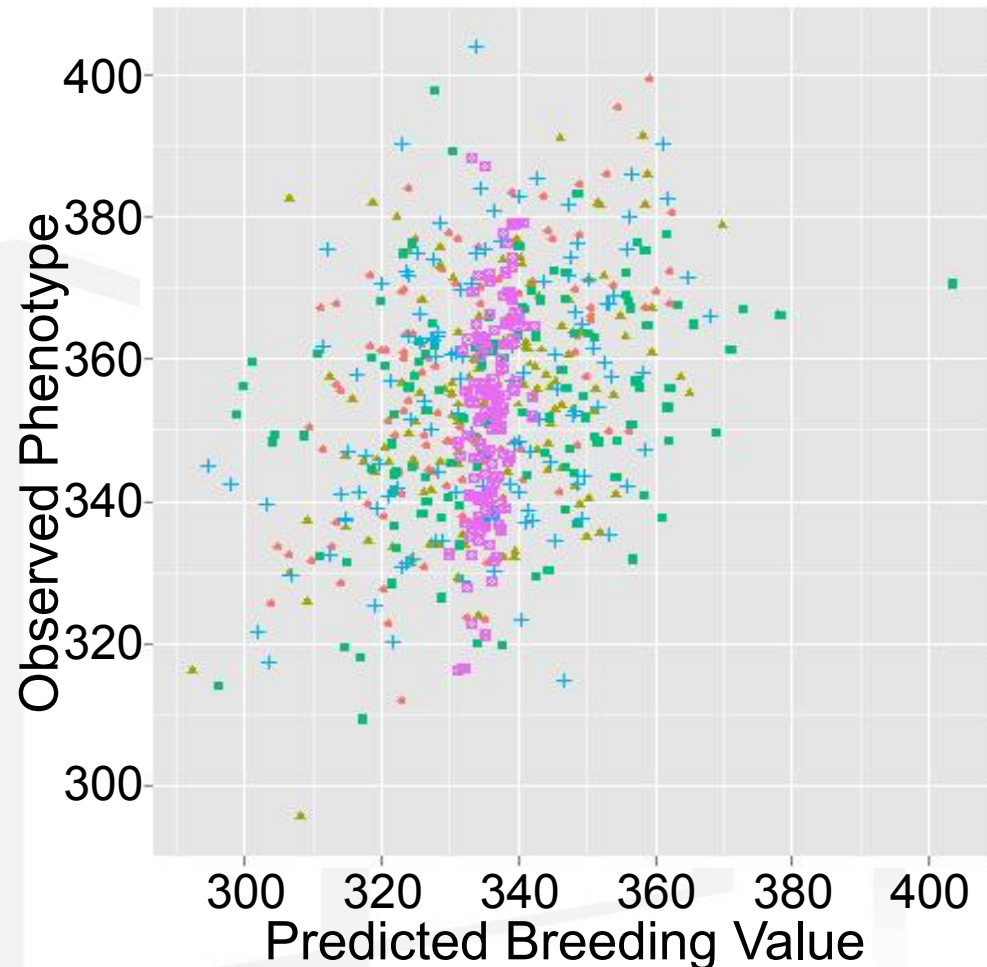
Set 5  
 $r = 0.447$



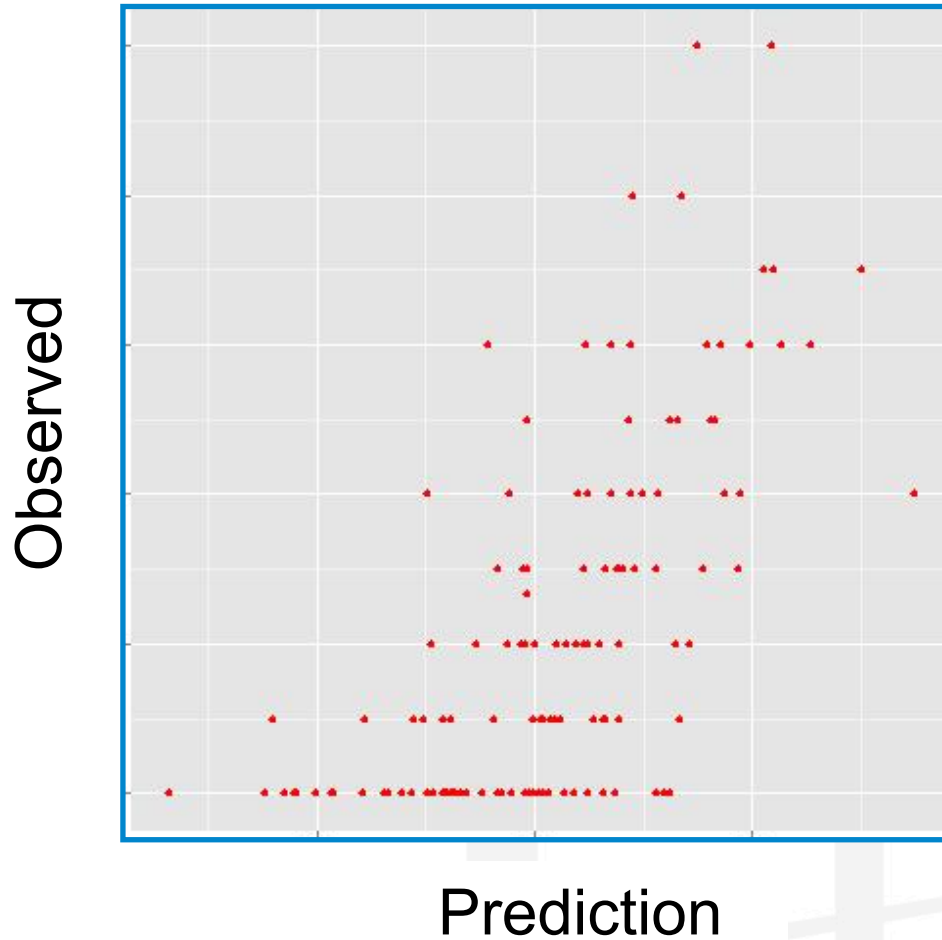
# Prediction of Height



- Accuracy = 0.400
- Max accuracy for predicting phenotype from BV is 0.548
  - » within families
  - »  $\sqrt{0.3}$
- Corrected accuracy = 0.73
  - » from 497 phenotypes



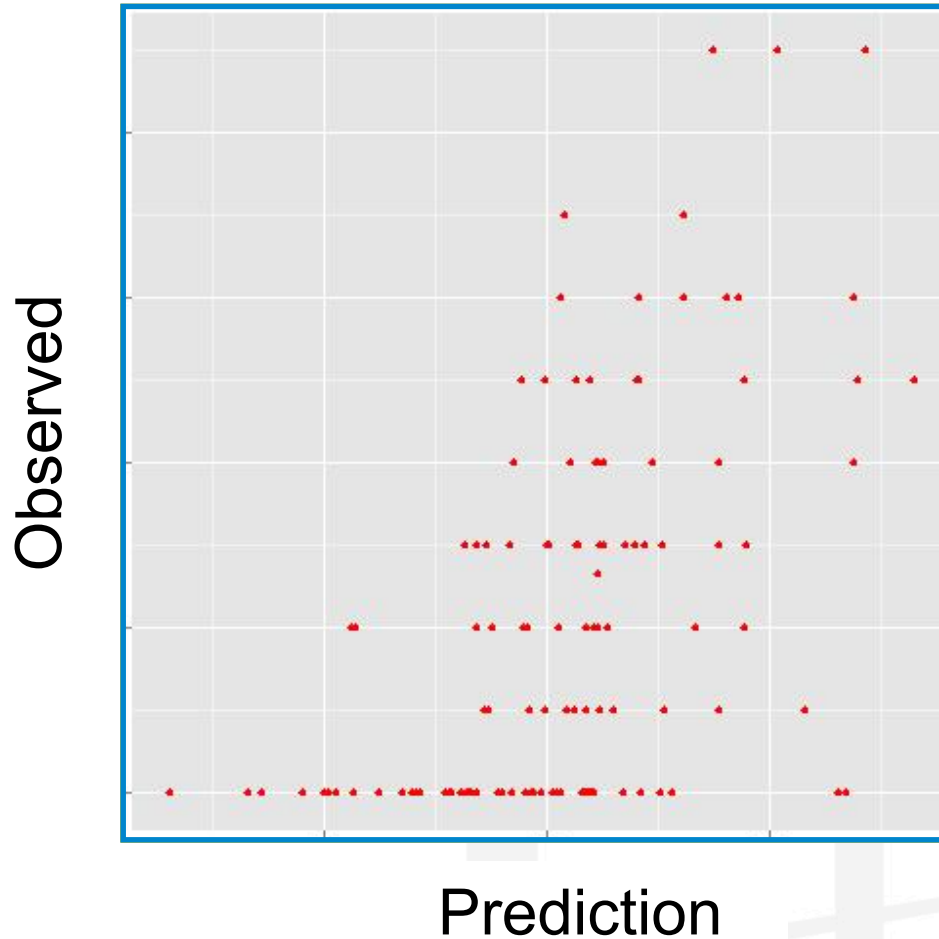
# Cross Validation: Bud Burst



Set 1  
 $r = 0.646$



# Cross Validation: Bud Burst



Set 1  
 $r = 0.646$

Set 2  
 $r = 0.615$

Set 3  
 $r = 0.618$

Set 4  
 $r = 0.502$

Set 5  
 $r = 0.526$



# Prediction of Bud Burst

- Accuracy = 0.581
- Max accuracy for predicting phenotype from BV is 0.632
  - within families
  - $\sqrt{0.4}$
- Corrected accuracy = 0.92
  - from 497 phenotypes

