An imputation pipeline for cost effective genomic selection in commercial pig breeding

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Background

- Genomic selection has the potential for increasing genetic gains in pigs
 - Increased accuracy of selecting replacements

- Genomic approaches require large amounts of data
 - Genotypes increase breeding value accuracy
 - Improvement constrained when dense genotypes on young selection candidates are unavailable

- Cost prohibitive to genotype selection candidates
 - Large number of progeny per litter
 - 120k @ \$100 = \$12m per year

Cost effective genomic selection

Strategies for dense and sparse genotyping

Other	Grandparents		Pai	rents	Testing individuals	Cost,	r²				
MGS+PGS MGD+PGD Sire Dam											
Н	Н	L384	Н	L384	L384	20.58	.935				
Н	Н	L3k	Н	L3k	L384	24.74	.955				
Н	Н	L6k	Н	L6k	L384	26.28	.956				
Н	Н	Н	Н	Н	L384	34.84	.967				
Н	Н	Н	Н	Н	Н	120.00	1.000				

Huang Y, JM Hickey, MA Cleveland and C Maltecca. 2012. Assessment of alternative genotyping strategies to maximize imputation accuracy at minimal cost. Genet. Sel. Evol. 44:25.

- Impute dense genotypes from small SNP panel
- Perform genomic evaluation with complete dense genotypes – gEBV for all selection candidates

Low-density genotyping

 Developed low-density SNP panel to be used across traits and lines

- SNPs selected based on 7 lines
 - Filtering based on genotype coverage, MAF and HW chisquare statistic
 - High confidence in map position
 - Even spacing (based on map position), accounting for LD

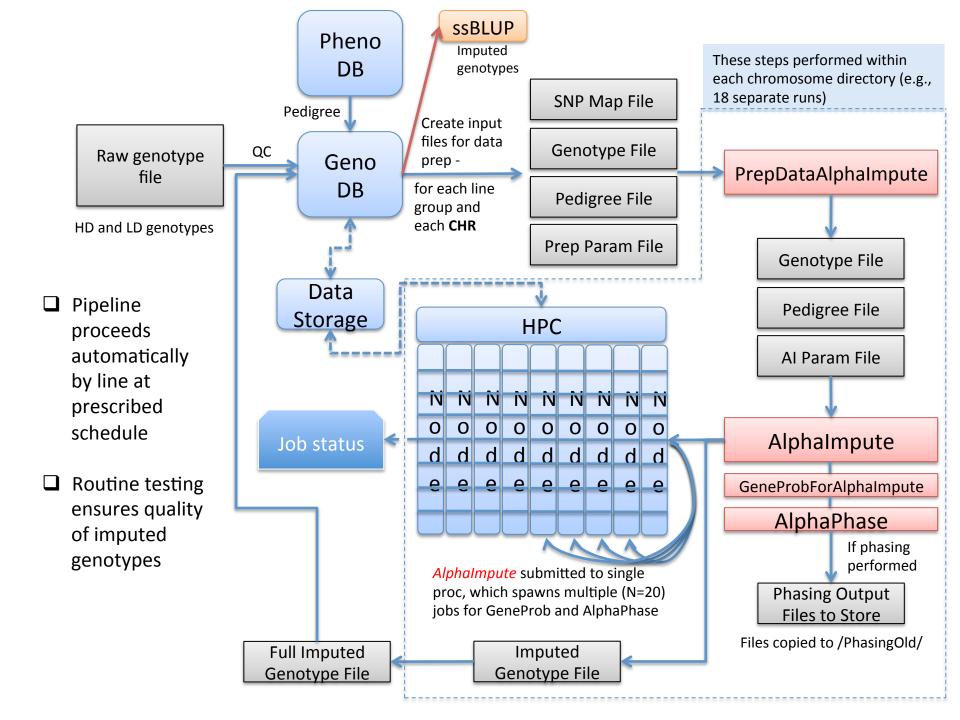
Final panel <450 SNPs

Imputation

- Alphalmpute¹
 - Combines simple phasing rules, long-range phasing, haplotype libraries, segregation analysis and recombination modeling
 - Imputes genotypes for all loci at the highest genotype density for animals in the analysis
 - Imputed genotypes are the sum of fully imputed alleles or the sum of allele probabilities

- Automated pipeline
 - Extract raw data, prepare files, impute genotypes, upload probable genotypes

¹Hickey JM, BP Kinghorn, B Tier, JHJ van der Werf and MA Cleveland. 2012. *A phasing and imputation method for pedigreed populations that results in a single-stage genetic evaluation method.* Genet. Sel. Evol. 44:25.





High Performance Computing Cluster

216 cores 1,664GB RAM 114TB Storage

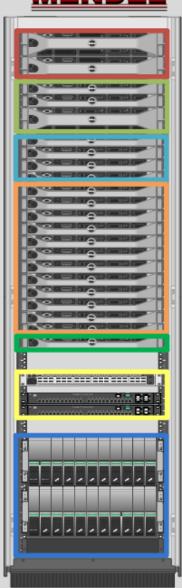
<u>MENDEL</u>

Redundant Head-nodes
2 with 8 cores & 48GB RAM

Production Compute-nodes 4 with 8 cores & 48GB RAM

> Genotype Database 12 cores & 96GB RAM

Panasas ActiveStor 11 pNFS Storage
2 Shelves
Triple Redundant Director Blades
114TB RAW Storage
Mounted on all Cluster Nodes



High Memory Compute-nodes

2 with 8 cores & 96GB RAM 1 with 32 cores & 512GB RAM

All-purpose Compute-nodes

Production and R&D 8 with 8 cores & 48GB RAM 4 with 12 cores & 48GB RAM

Network Connectivity

2 x Brocade Turbolron 24x 10GbE (Cluster Mgmt & Storage) 1 x Qlogic InfiniBand QDR 32-port (MPI)



Computational considerations

- >5k animals with 60k genotypes in multiple lines (>21k 60k genotypes overall)
 - Dense genotyping continues to grow

- Large number of selection candidates genotyped for low-density panel
 - Following imputation all have 60k genotypes

- Routine pipeline runs
 - <13 hours per line (in serial)</p>
 - Probable genotype files ~600Mb per line

Imputation testing

Investigate imputation and gEBV accuracy using alternative genotyping scenarios

- Data
 - N=4,579 60k genotyped
 - N=183 full parent/grandparent genotypes; no progeny
 - Three low-density panels: 450, 3k, 6k
 - 33k SNPs after filtering (chr 1-18)

Results: imputation accuracy

 Implementation considering 4 approaches to genotyping close relatives

	Genotyping Scenario								Imputation accuracy		
	Other	PGS+MGS	PGD+MGD	Sire	Dam	Progeny	-				
	4220	74	108	70	107	184	450	3k	6k		
S 1	Н	Н	Н	Н	Н	L	0.97	0.99	1.00		
S2	Н	0	0	Н	Н	L	0.95	0.98	0.99		
S 3	Н	Н	0	H	0	L	0.91	0.97	0.98		
S4	Н	Н	L	H	L	L	0.94	0.99	0.99		
S1_r	0	Н	Н	Н	Н	L	0.96	0.99	0.99		
S2_r	0	0	0	Н	Н	L	0.92	0.97	0.97		
$S3_r$	0	Н	0	Н	0	L	0.85	0.94	0.95		
S4r	0	Н	L	Н	L	L	0.90	0.97	0.98		

Results: gEBV accuracy

- Calculate gEBV using single-stage evaluation¹
- Compare gEBV from full dense genotyping to gEBV from low-density genotyping/imputation

									Imputed gEBV		
		Genotyping Scenario						Accuracy			
	N HD		PGS+	PGD+							
	Geno.	Other	MGS	MGD	Sire	Dam	Progeny	450	3 k	6k	
S 1	2519	Н	Н	Н	Н	Н	L	0.94	0.97	0.97	
S2	2344	Н	0	0	Н	Н	L	0.89	0.95	0.96	
S 3	2318	Н	Н	0	Н	0	L	0.87	0.92	0.93	
S 4	2318	Н	Н	L	H	L	L	0.90	0.96	0.97	
S1_r	323	0	Н	Н	Н	Н	L	0.79	0.81	0.80	
S2_r	148	0	0	0	Н	Н	L	0.71	0.73	0.71	
S3_r	122	0	Н	0	Н	0	L	0.69	0.76	0.75	
S4_r	122	0	Н	L	Н	L	L	0.75	0.80	0.80	

¹Aguilar et al., 2009

Summary

An imputation pipeline has been implemented in routine production

Continued optimization will stabilize runtimes as data size increases

 Imputation accuracy for very low-density panel was high

 gEBV accuracy was high, but appropriate genotyping strategies are needed



Thank you!

"Pioneering animal genetic improvement to help nourish the world."