Genomic selection in the era of digital phenotyping

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College of Agricultural & Environmental Sciences
Animal Breeding and Genetics Group

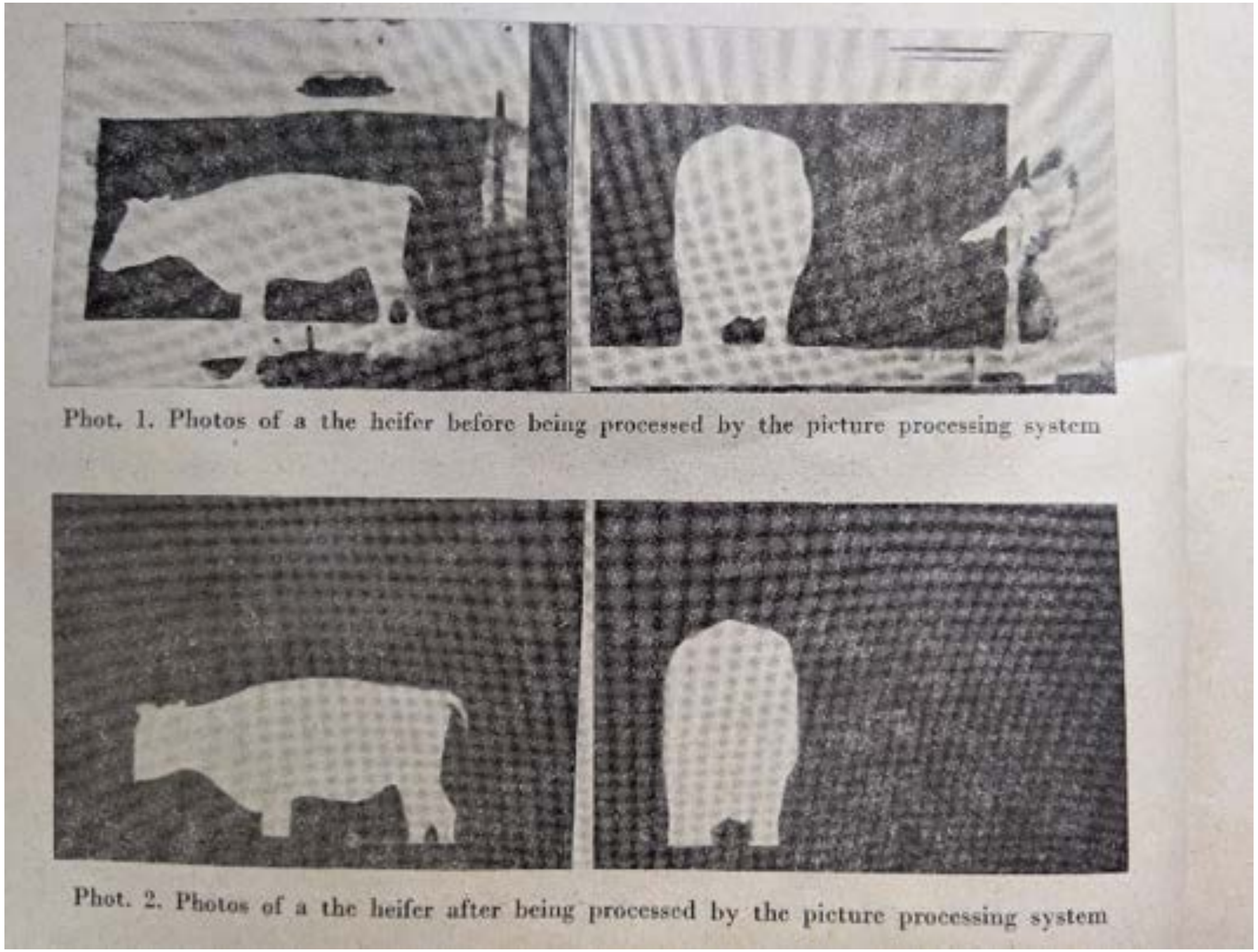
Digital phenotyping era

- Past the genomics era
  - Great job genotyping animals

- Digital phenotyping era
  - Time to invest in better phenotyping

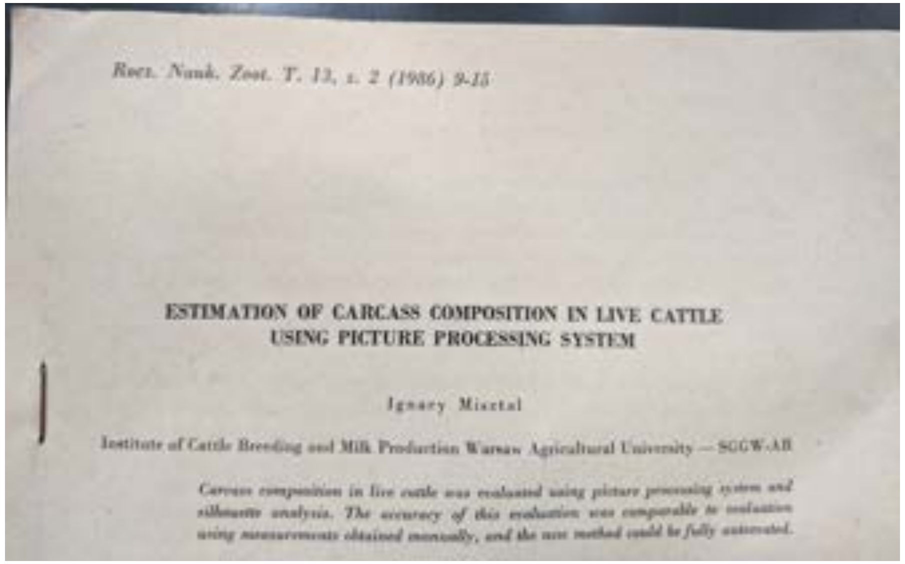
- Main goal
  - Consistent and accurate phenotypic measurements
    - Traits hard to record manually
  - Increase the rates of genetic gain
  - Several companies are investing in digital phenotyping

Digital phenotyping


Phot. 1. Photos of a the heifer before being processed by the picture processing system

Phot. 2. Photos of a the heifer after being processed by the picture processing system

Misztal (1986)


Rocz. Nauk. Zoot. T. 13, z. 2 (1986) 9-15

ESTIMATION OF CARCASS COMPOSITION IN LIVE CATTLE
USING PICTURE PROCESSING SYSTEM

Ignacy Misztal

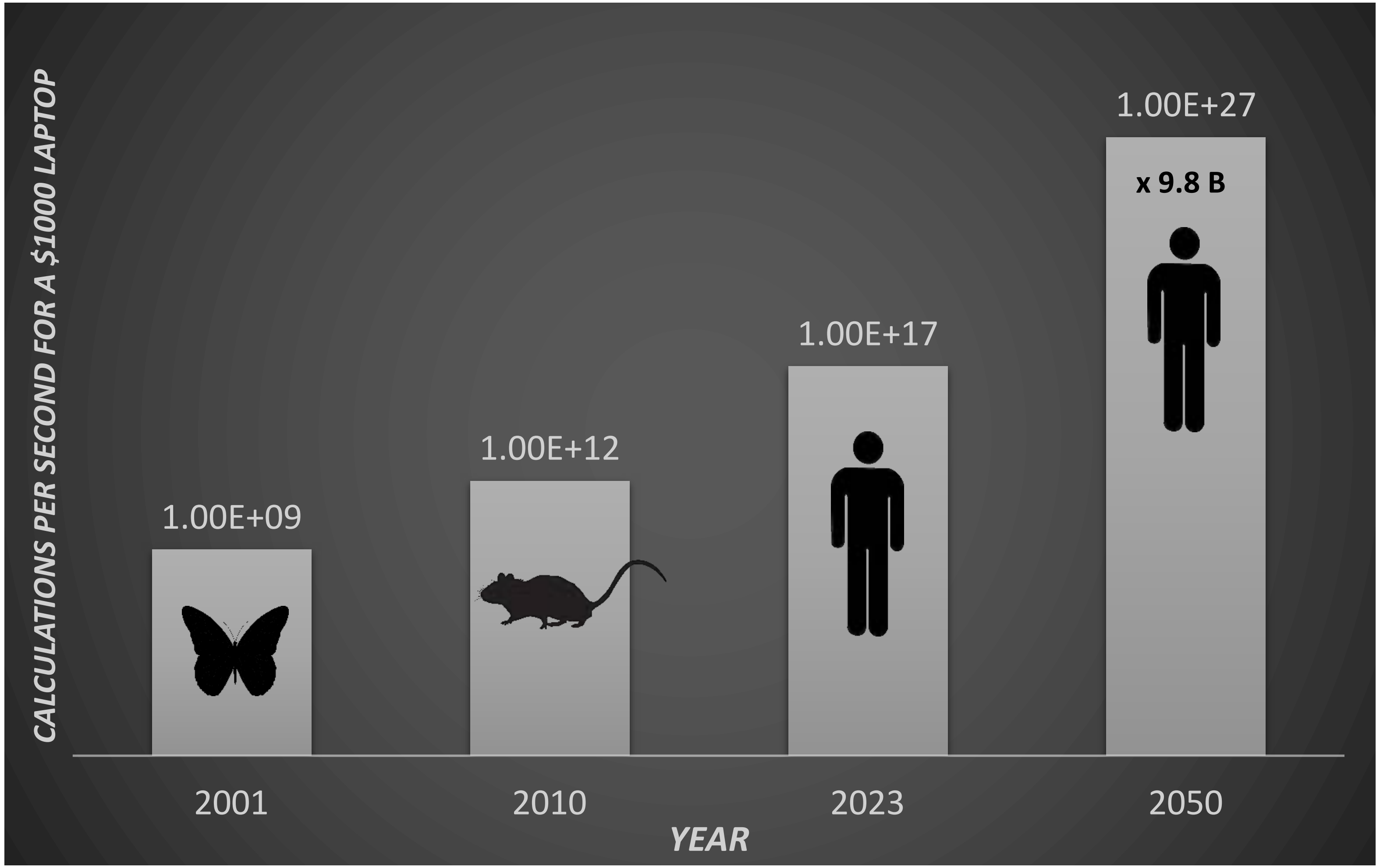
Institute of Cattle Breeding and Milk Production Warsaw Agricultural University — SGGW-AR

Carcass composition in live cattle was evaluated using picture processing system and silhouette analysis. The accuracy of this evaluation was comparable to evaluation using measurements obtained manually, and the new method could be fully automated.

Digital phenotyping - decades apart

- Cameras and sensors
  - High-throughput phenotyping (phenomics): 24/7 collecting data
  - Feed intake, grazing behavior, temperature, gas emission, fertility, weight, size, …
- Machine learning (artificial intelligence)
  - Algorithms to automatically learn from the data and make predictions
  - Expensive to teach a machine (computing resources and time)
  - Image recognition comes with an appetite for computing power

$1000 of computing power



Adapted from: Peter Diamandis https://www.youtube.com/watch?v=7XrbzlR9QmI

Digital phenotyping projects

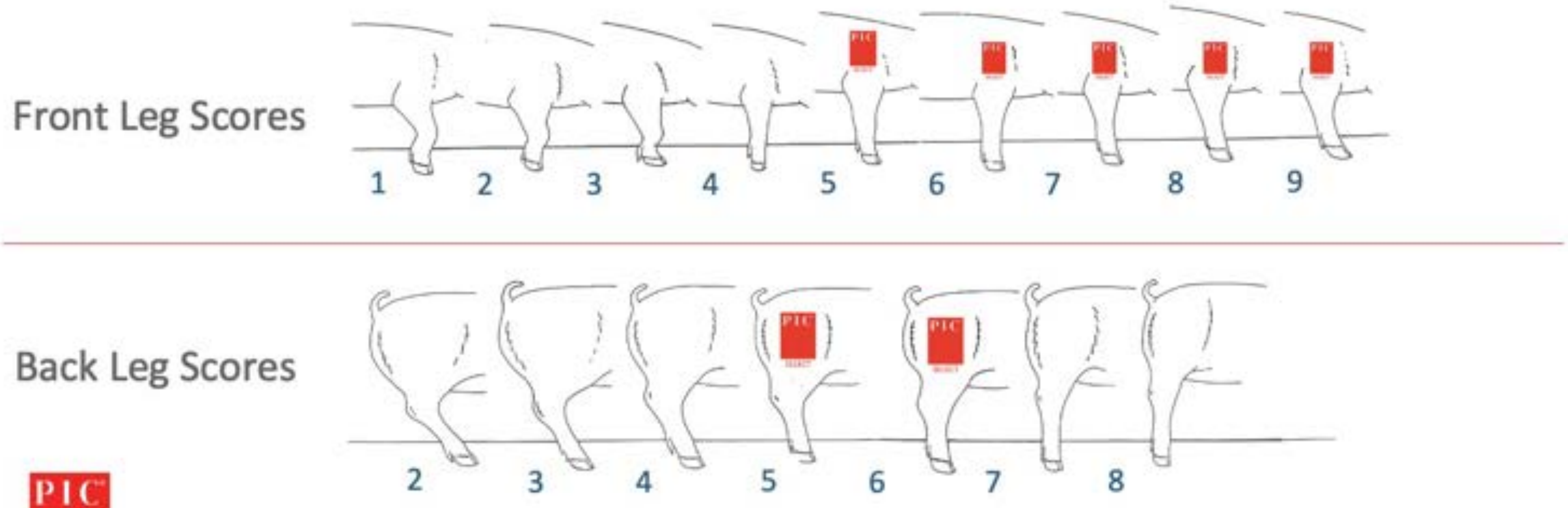
- Digital Foot and Leg Scoring (PIC -> UGA)
- Activity/Behavior Tracking (UGA + PIC)
- Predict production traits based on 2D images (UGA + PIC)

Subjective foot and leg scoring

Subjective Foot and Leg Scoring

Never Stop Improving *Your Success.*

Goal: Select pigs that are less likely to have foot and leg issues as breeding animals



PIC

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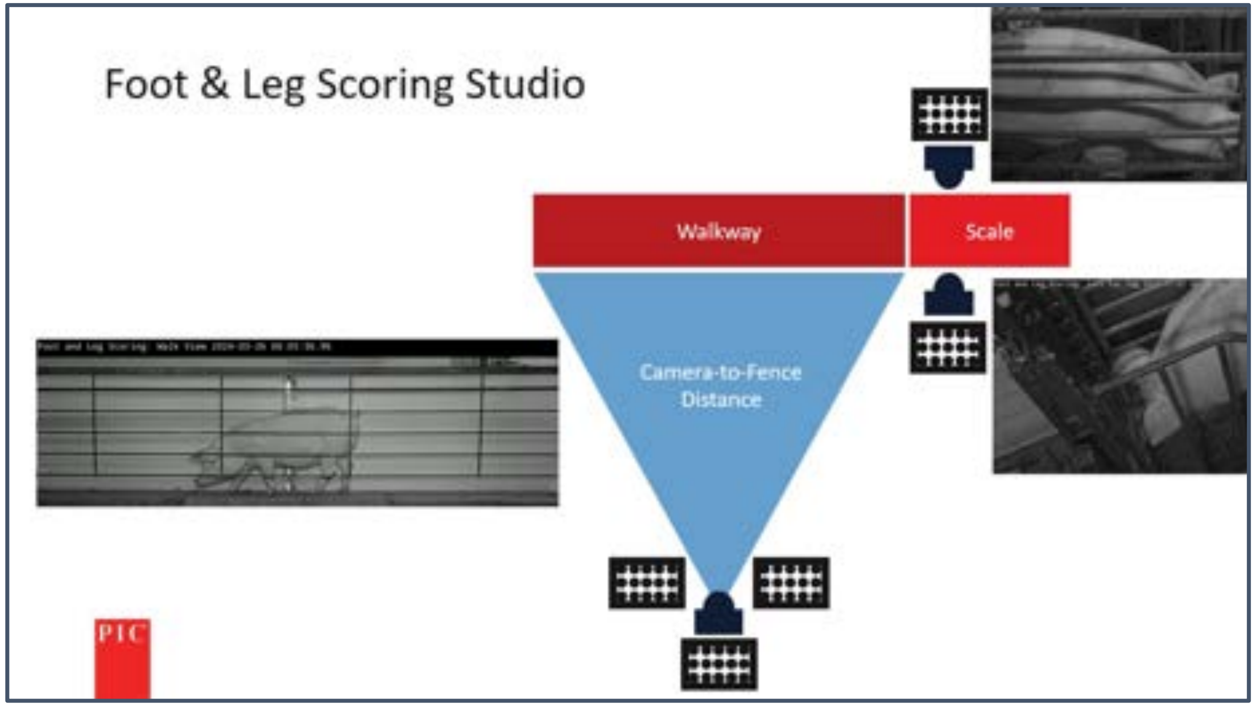
Subjective foot and leg scoring

Ease of movement

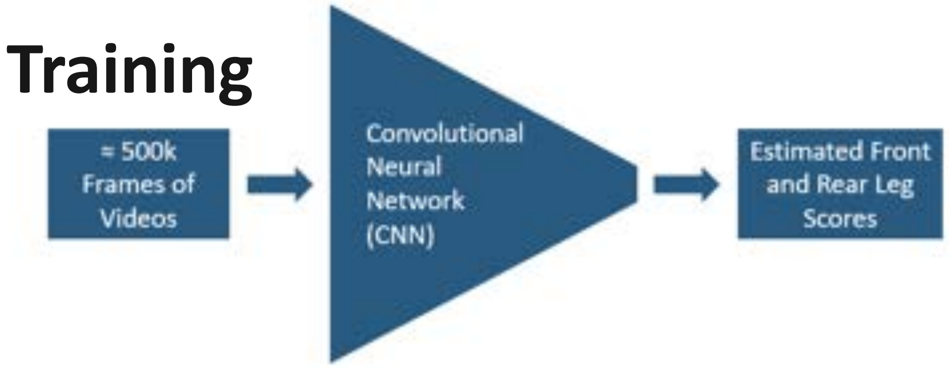
Lameness observed

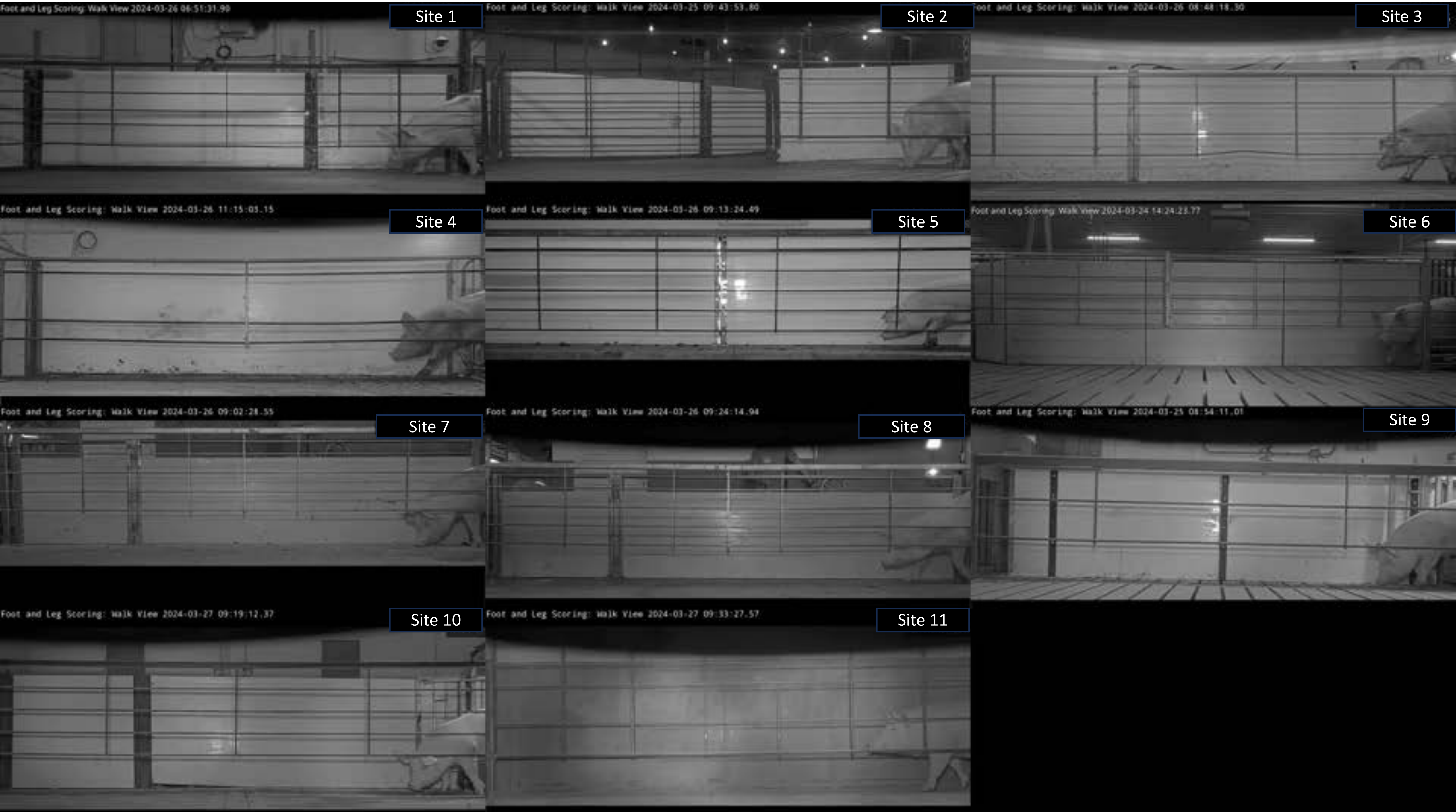
Digital foot and leg scoring

- **Over 100K records collected across sites and genetic lines**



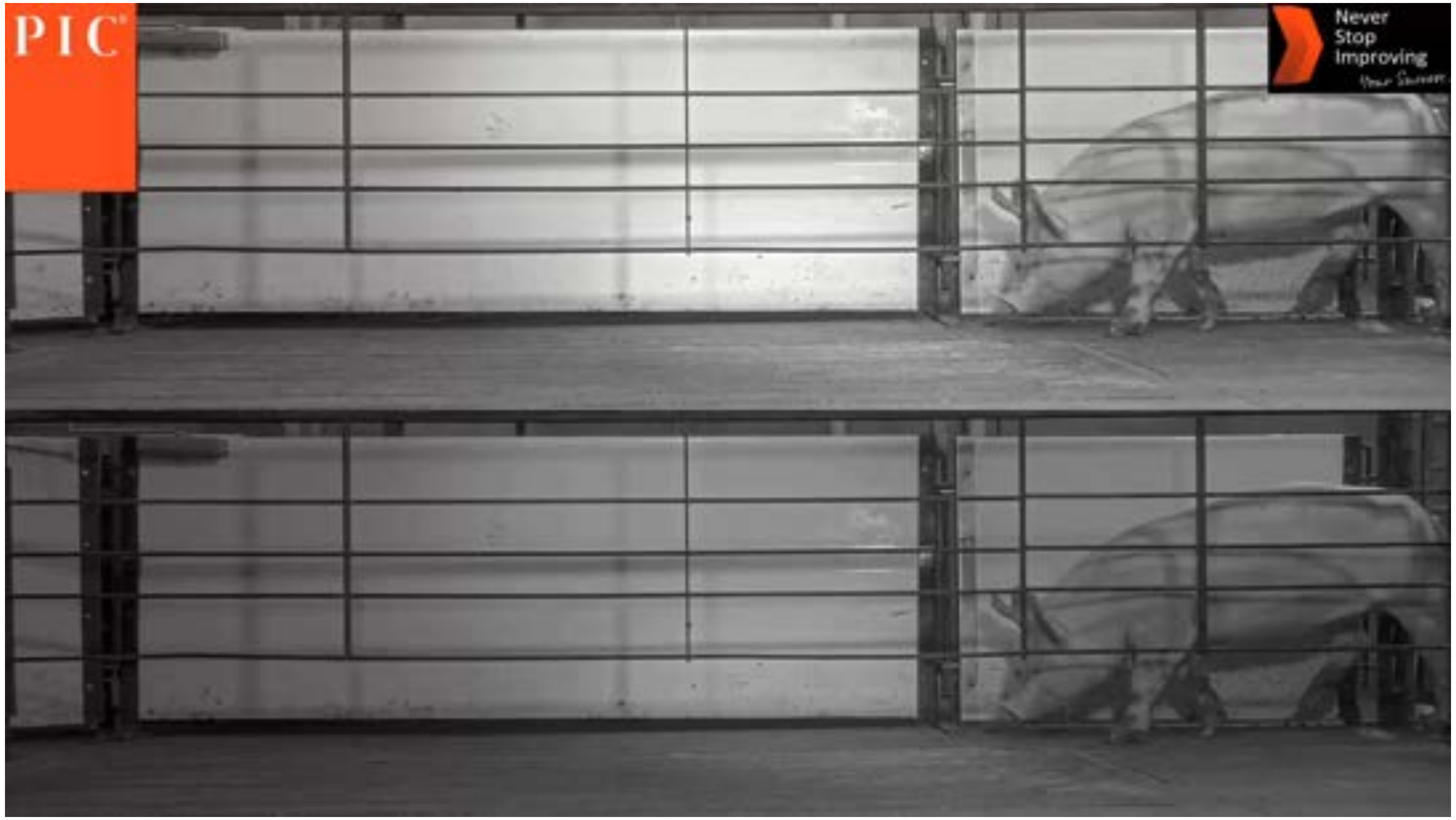
From March 2022 to March 2023
- Captured ≈23,000 walking videos with associated manual scores




Foot and Leg Scoring: Walk View 2024-03-26 06:51:31.90
Site 1
Foot and Leg Scoring: Walk View 2024-03-25 09:43:53.80
Site 2
oot and Leg Scoring: Walk View 2024-03-26 08:48:18.30
Site 3
Foot and Leg Scoring: Walk View 2024-03-26 11:15:03.15
Site 4
Foot and Leg Scoring: Walk View 2024-03-26 09:13:24.49
Site 5
Foot and Leg Scoring: Walk View 2024-03-24 14:24:23.77
Site 6
Foot and Leg Scoring: Walk View 2024-03-26 09:02:28.55
Site 7
Foot and Leg Scoring: Walk View 2024-03-26 09:24:14.94
Site 8
Foot and Leg Scoring: Walk View 2024-03-25 08:54:11.01
Site 9
Foot and Leg Scoring: Walk View 2024-03-27 09:19:12.37
Site 10
Foot and Leg Scoring: Walk View 2024-03-27 09:33:27.57
Site 11

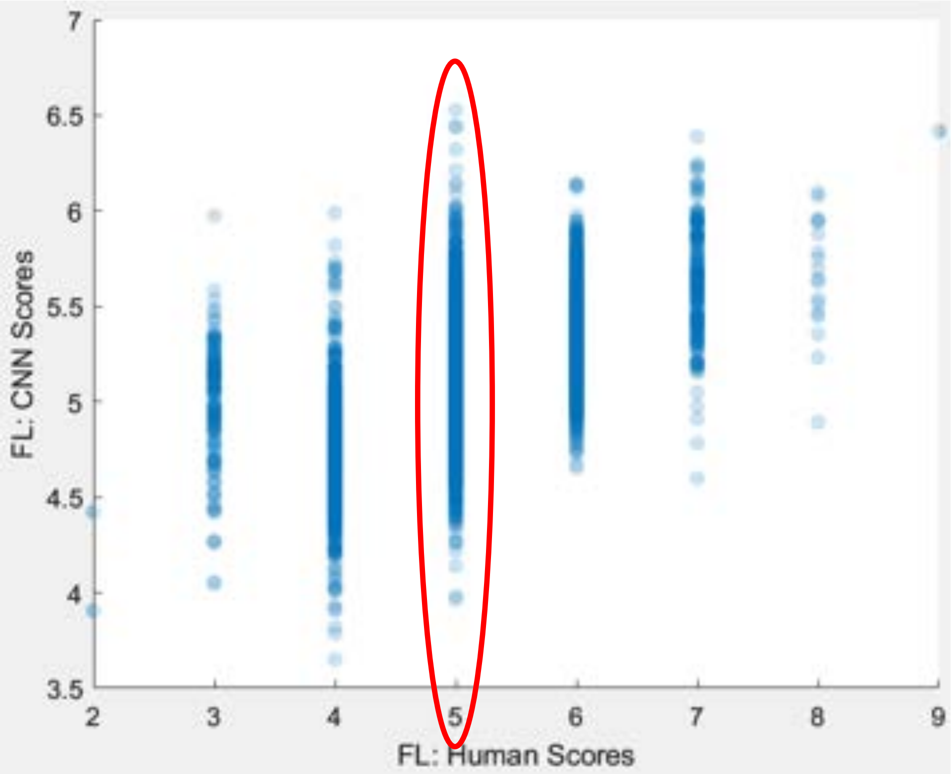
Digital foot and leg scoring

- Many features can be extracted from video
- Continuous values for digital leg scoring vs. discrete categorical scale from 1 to 9
- Helps on-site culling decisions



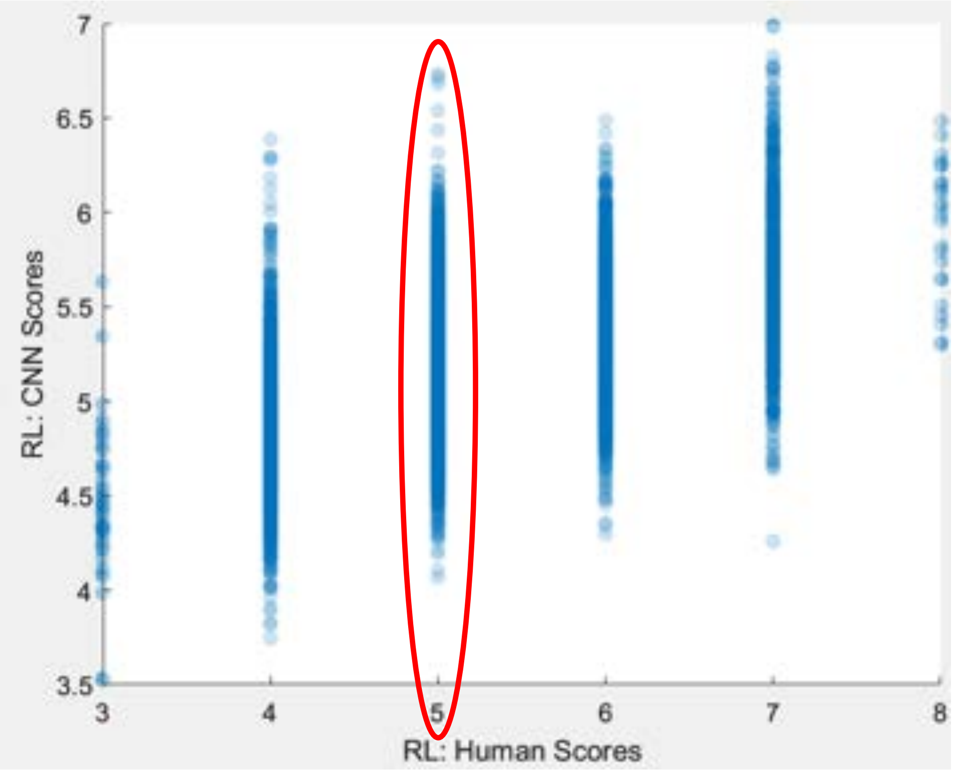
Subjective vs. digital leg scoring

- Front Leg Scores
- Correlation Coefficient = 0.50



Rear Leg Scores

Correlation Coefficient = 0.57



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Subjective vs. digital leg scoring

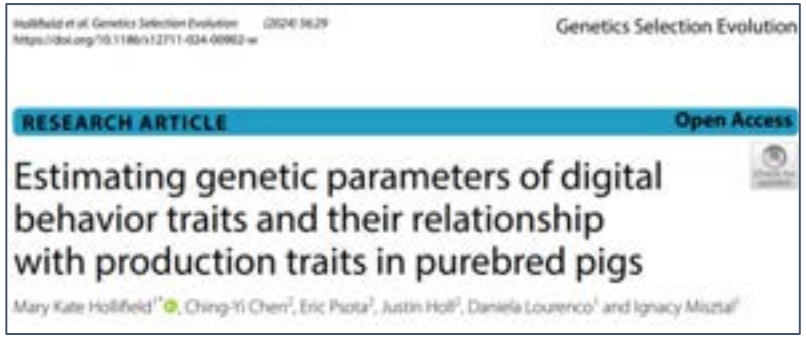
Trait	Subjective	Digital (CNN)
Front leg	0.21	0.60
r_g	0.93	
Rear leg	0.18	0.45
r_g	0.96	

Heritability increased almost 3x!

Digital behavior traits

Tracking individual-level activities for 14-hours per day for on-test group

- Eating
- Drinking
- Walking
- Posture (Standing, Sitting, Lying sternally, Lying laterally)
- 70-day tracking data on 2008 pigs = 140,560 data points



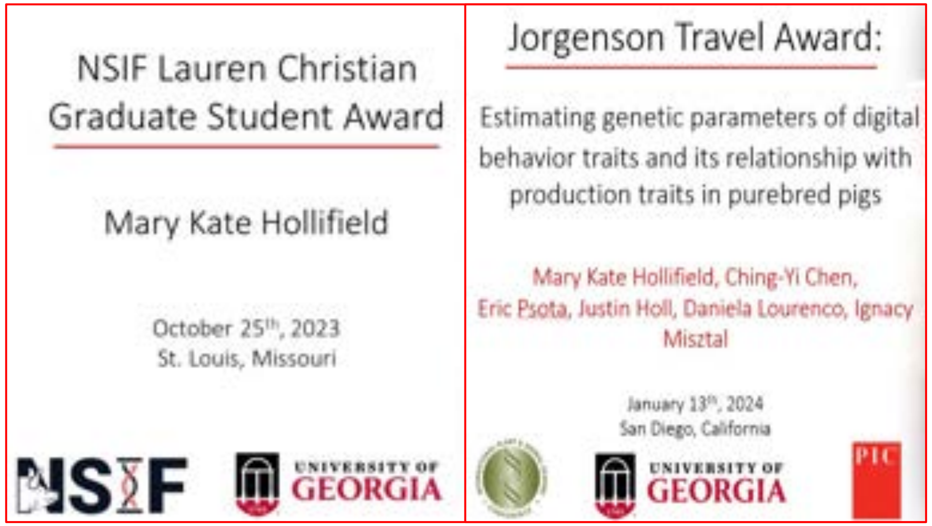
Hollifield et al. Genetics Selection Evolution (2024) 56:29
https://doi.org/10.1186/s12711-024-00902-w

Genetics Selection Evolution

RESEARCH ARTICLE — Open Access

Estimating genetic parameters of digital behavior traits and their relationship with production traits in purebred pigs

Mary Kate Hollifield[1*], Ching-Yi Chen[2], Eric Psota[3], Justin Holl[2], Daniela Lourenco[1] and Ignacy Misztal[1]

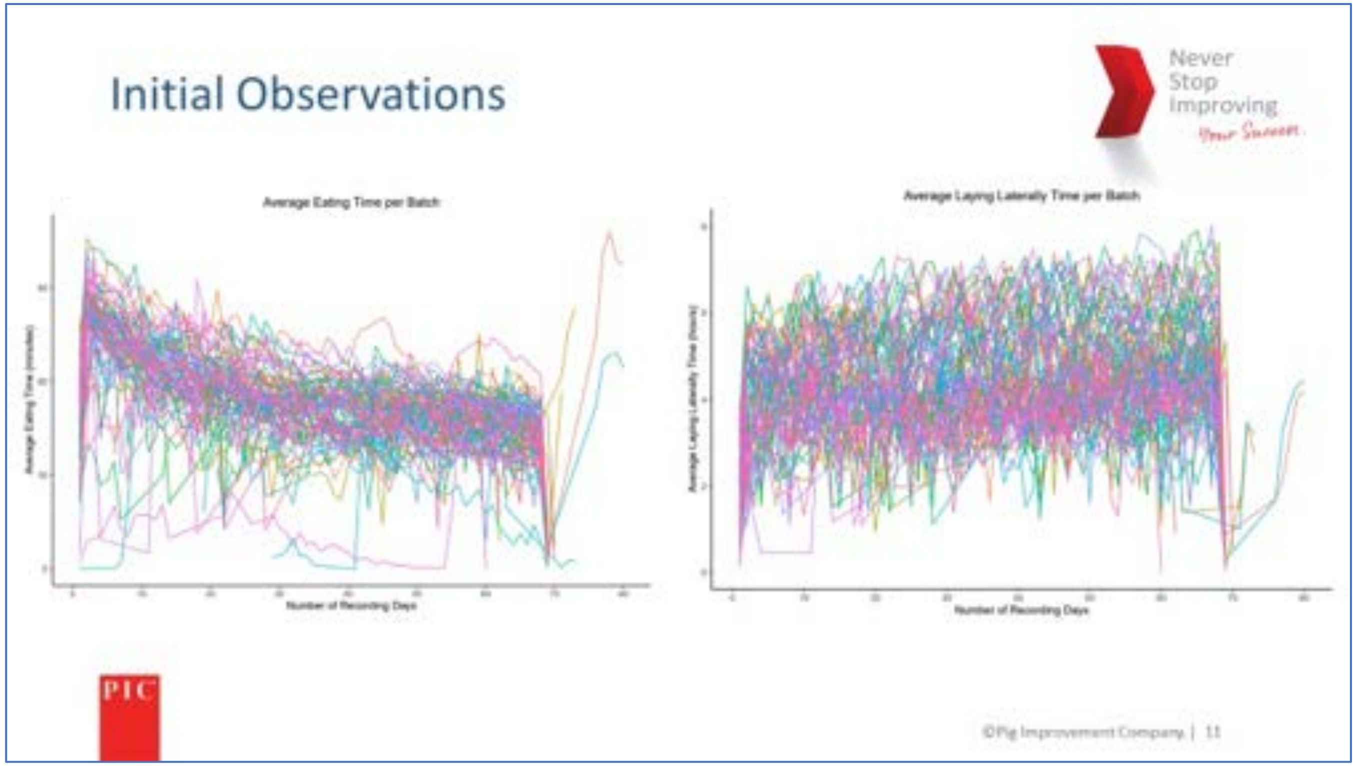


Objectives

- Quality control
- Identify behavior patterns
- Estimate genetic parameters
- Genetic correlations with ADG, BF, LD

Digital behavior traits – noisy data

2,008 pigs x 70 days = 140,560 data points

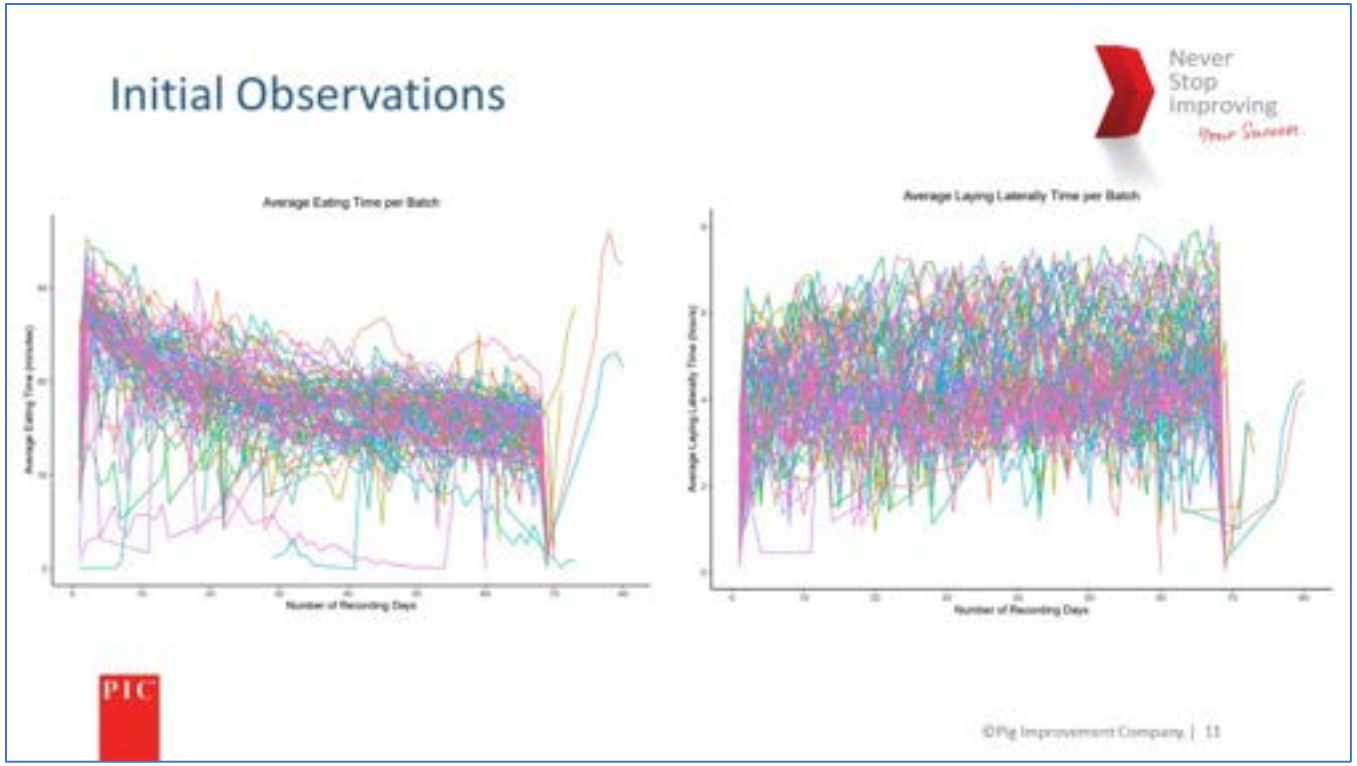


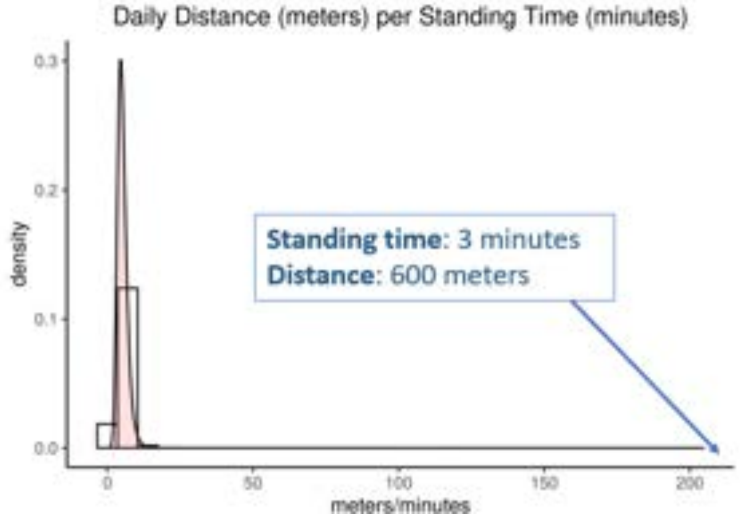
- Removed:
  - Start and end day records
  - Culling day
  - Days with < 8 hours

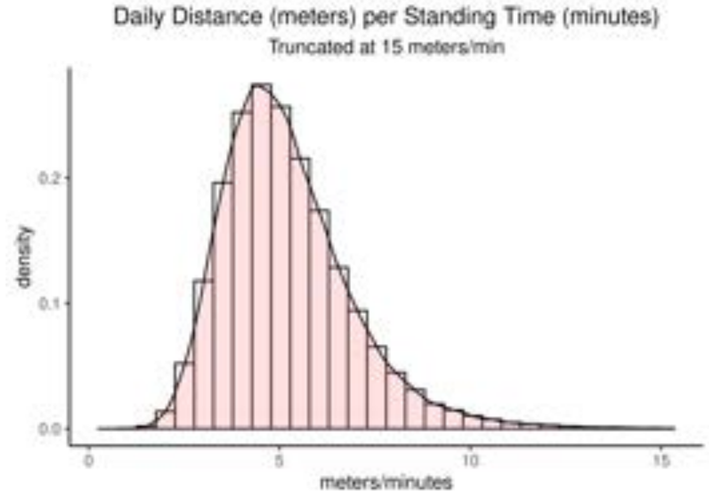
	Before Cleaning	After Cleaning	After Cleaning + Off-test
# Individuals	2008	1327	1079
# Records	140,560	77,423	71,873

Digital behavior traits – noisy data

2,008 pigs x 70 days = 140,560 data points







	Before Cleaning	After Cleaning	After Cleaning + Off-test
# Individuals	2008	1327	1079
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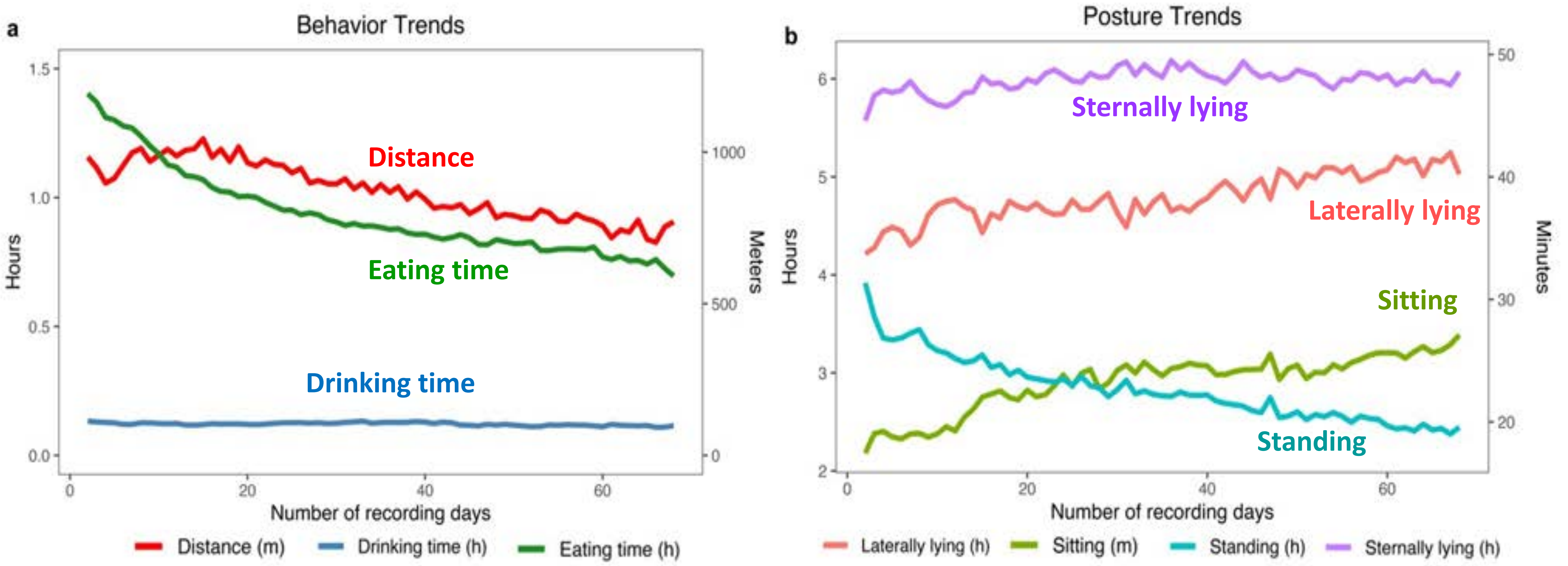
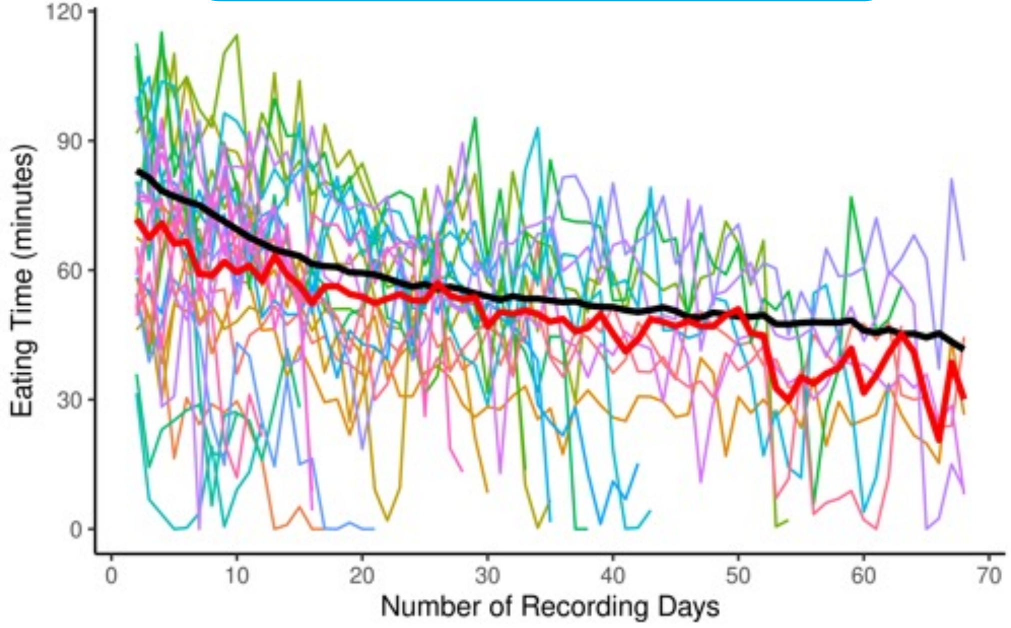
Average digital behavior over 70 days



Uncovering individual variations

By Group

By Individual
(within a group)

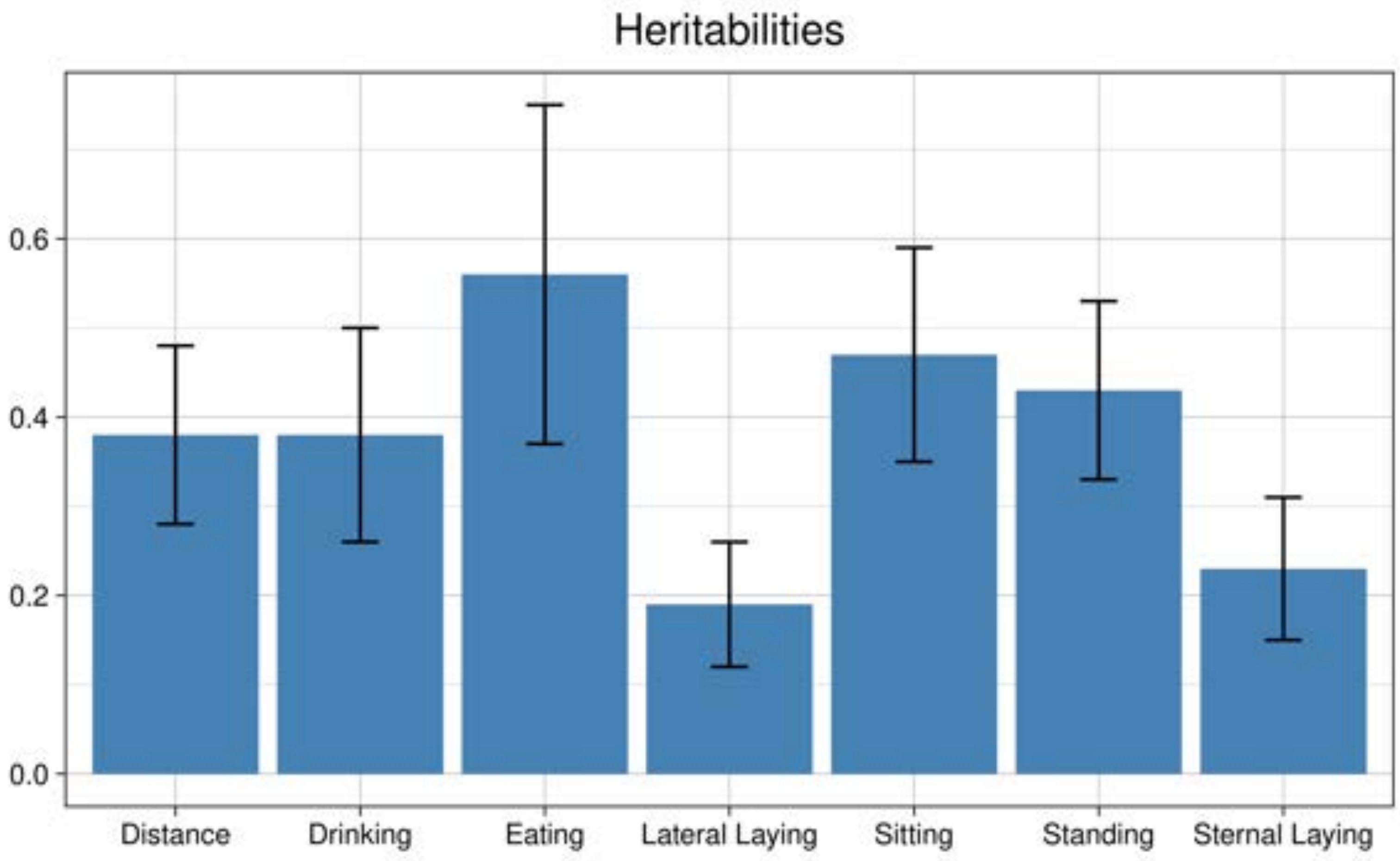


Phenotypic correlations

	Eat	Drink	Lat. Lying	Stern. Lying	Sitting	Standing	Distance	ADG	BF	LD
Eat		0.15	-0.31	-0.01	-0.04	0.59	0.26	0.06	0.05	0.05
Drink			0.03	-0.19	0.05	0.20	0.16	-0.02	0.05	-0.09
Lat. Lying				-0.82	-0.20	-0.52	-0.23	-0.07	-0.00	-0.14
Stern. Lying					0.09	-0.03	-0.14	0.13	0.01	0.19
Sitting						-0.14	-0.06	0.11	-0.02	0.09
Standing							0.63	-0.10	0.00	-0.06
Distance								-0.18	-0.01	-0.14
ADG									0.29	0.52
BF										0.10
LD										

Heritabilities

- *y = line + CG + litter + animal + residual*
- CG: Off-TestDay_Year
- blupf90+



Heritability:
Growth rate: 0.25 to 0.35
Litter size: 0.10 to 0.15

Genetic correlations

- **Quantifying the influence of selection for production traits on behavior traits**

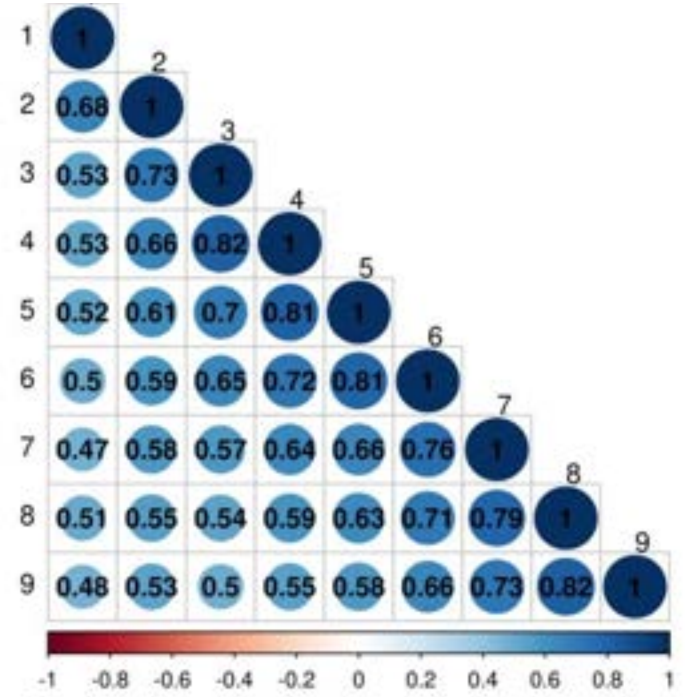
	Eat	Drink	Lat. Lying	Stern. Lying	Sitting	Standing	Distance	ADG	BF	LD
Eat		0.38	-0.40	-0.41	*	0.69	0.45	*	0.18	*
Drink			-0.33	-0.43	0.26	0.62	0.44	0.32	0.18	*
Lat. Lying				-0.84	-0.23	-0.72	-0.68	0.50	0.19	0.24
Stern. Lying					-0.25	-0.62	-0.58	0.26	*	*
Sitting						-0.48	*	0.26	*	0.19
Standing							0.93	-0.56	-0.17	-0.37
Distance								-0.57	-0.27	-0.48
ADG									0.56	0.84
BF										0.21
LD										

*Estimates with high SE

How many days of recording?

- Can we reduce the recording time?
- When is the right time to record: early or late?

Distance – Recording Weeks



Genetic correlations between ADG and behavior trait time intervals

Time Period	Eating Time	Drinking Time	Lateral Lying	Sternal Lying	Sitting	Standing	Distance
All	0.14 ± 0.23	0.32 ± 0.21	0.50 ± 0.14	-0.10 ± 0.15	0.26 ± 0.15	-0.56 ± 0.11	-0.57 ± 0.10
Days 1-13	0.36 ± 0.17	0.41 ± 1.75	0.48 ± 0.21	-0.06 ± 0.16	0.32 ± 0.26	-0.41 ± 0.10	-0.55 ± 0.14
Days 14-26	0.23 ± 0.18	0.45 ± 0.36	0.52 ± 0.25	-0.01 ± 0.24	0.16 ± 0.15	-0.40 ± 0.10	-0.47 ± 0.12
Days 27-40	0.12 ± 0.21	0.35 ± 0.27	0.49 ± 0.15	-0.22 ± 0.22	0.21 ± 0.15	-0.43 ± 0.09	-0.46 ± 0.11
Days 41-54	-0.05 ± 0.14	0.27 ± 0.23	0.50 ± 0.66	-0.05 ± 0.14	0.30 ± 0.20	-0.51 ± 0.08	-0.63 ± 0.14
Days 55-68	-0.09 ± 0.21	0.05 ± 0.66	0.55 ± 0.19	-0.13 ± 0.16	0.36 ± 0.24	-0.55 ± 0.10	-0.70 ± 0.11

Predicting production traits – 2D images

Masum Billah

- Same videos as for the foot and leg scoring
- Uncontrolled 2D side view of pigs
  - 9K individuals at 60 frames per second
  - Average recording duration was 7.19 seconds

- Develop a low-cost machine learning pipeline based on 2D images to predict
  - Body weight
  - Backfat thickness
  - Loin depth

Image processing

body segmentation (OpenCV)

Image processing

body segmentation (deep learning)

Illustration of a corner case handled by deep learning

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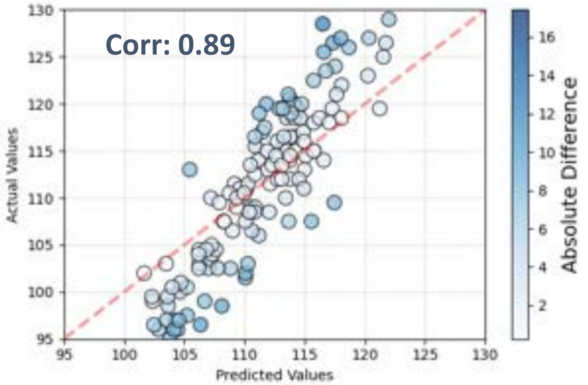
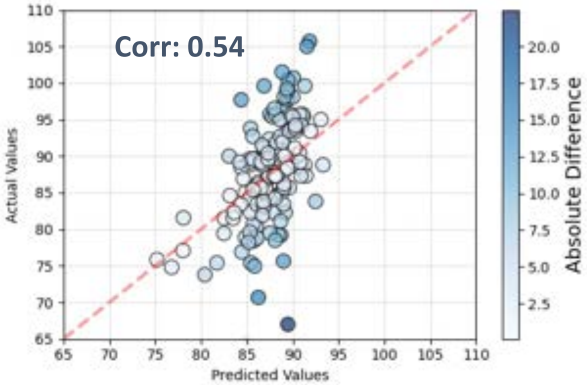
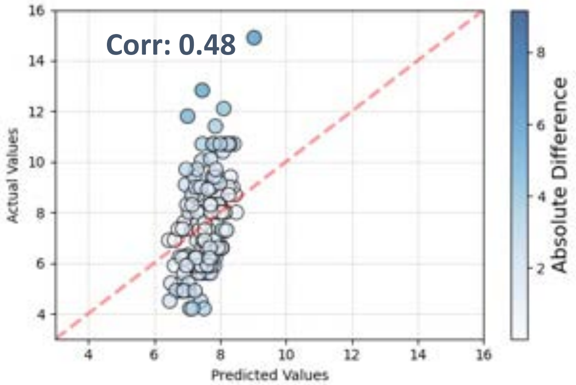
Actual vs. predicted phenotype



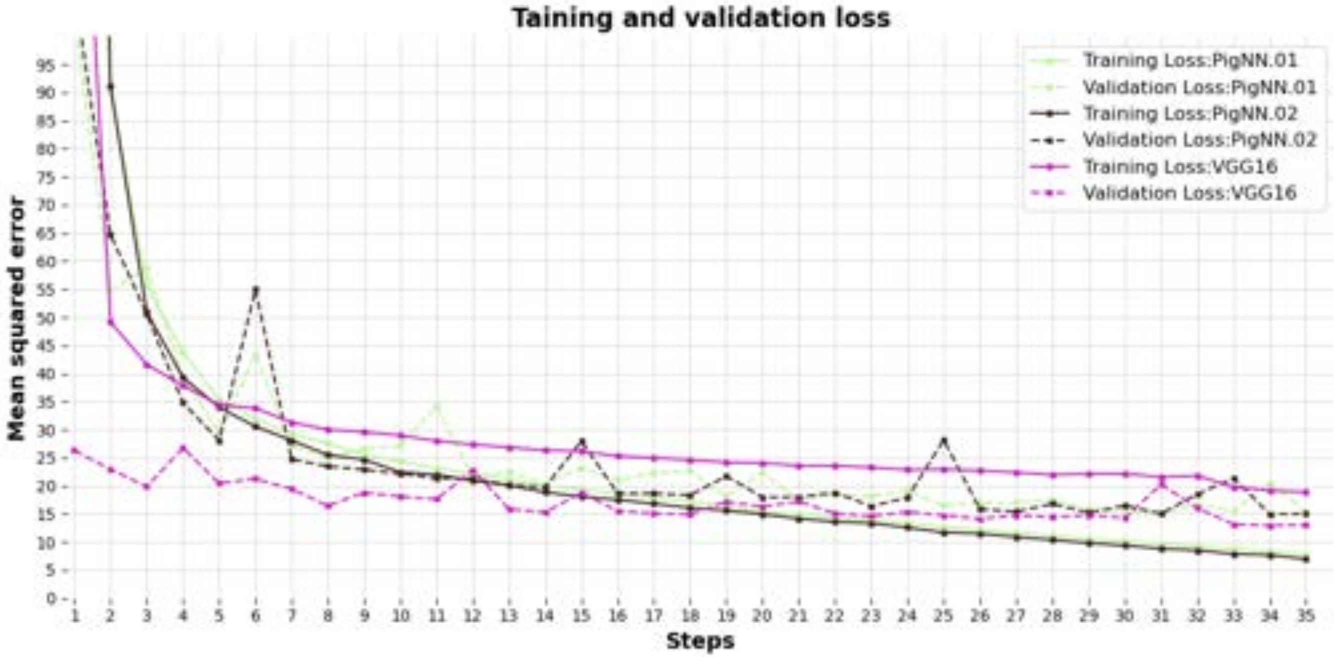
Predicted average body weight

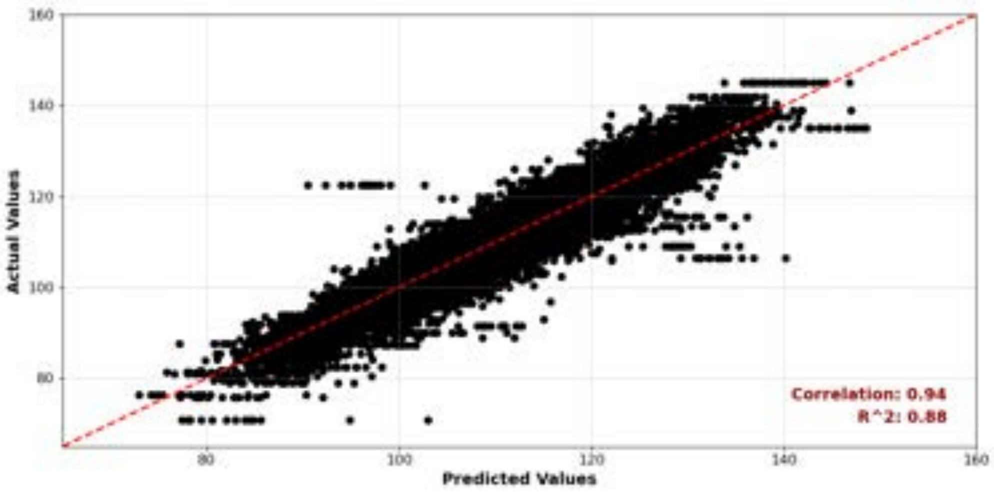


Predicted average loin depth

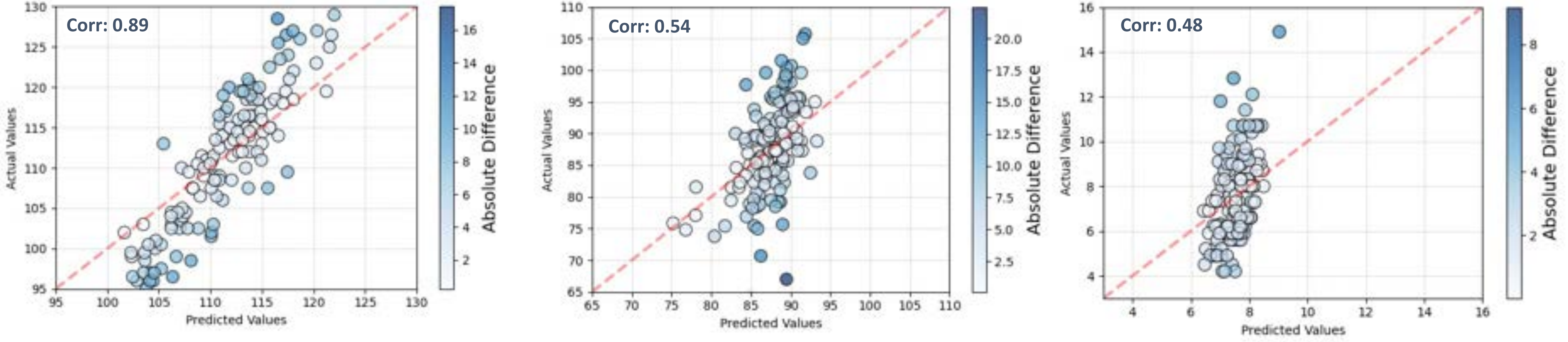


Predicted average backfat





Actual vs. predicted phenotype



Predicted average body weight   Predicted average loin depth   Predicted average backfat

- Low correlation for LD and BFT
    - 3D cameras
- High correlation for BW
    - Correlation < 1: how to model this noise in genomic prediction models?
    - Which phenotype is more accurate?

Take home message

- Capturing, cleaning, and processing digital phenotypes is challenging
  - Large videos and many data points
- Machine learning techniques changed the game
  - If a human can see it, machine learning techniques can detect it
- Opportunities for more precise phenotyping
  - Higher heritabilities: categorical vs. continuous scale
- Opportunities for hard to record phenotypes
  - Behavior traits for future selection
- Precision will increase with time: new methods and proper devices
  - If there is uncertainty, how to model it in genomic evaluations

Acknowledgments





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