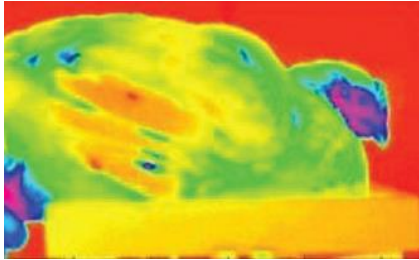


# The use of novel phenotyping technologies in animal breeding

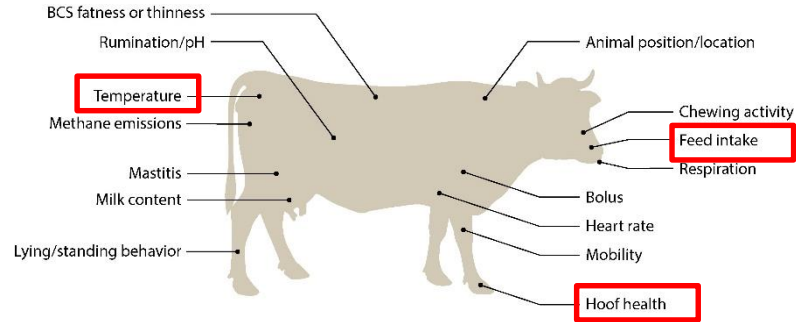
Henk Bovenhuis, ABG, Wageningen University & Research



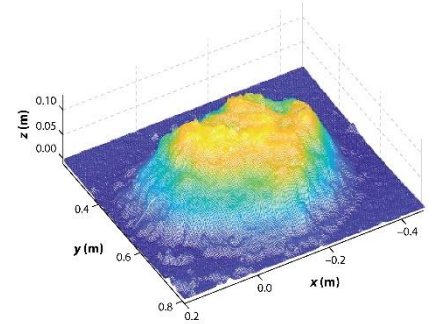
# Novel phenotyping technologies - sensors



Temperature



Halachmi I, et al. 2019.  
*Annu. Rev. Anim. Biosci.* 7:403–25

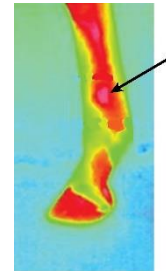


Halachmi I, et al. 2019.  
*Annu. Rev. Anim. Biosci.* 7:403–25

individual feed intake

## Sensors:

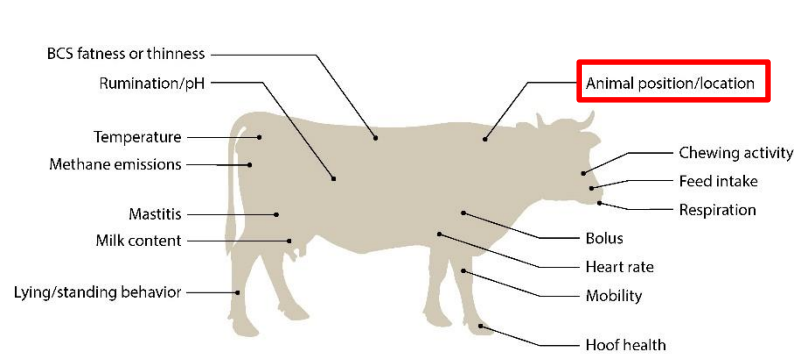
- **Machine vision (cameras)**
- Sound
- Accelerometers
- Electronic nose
- GPS
- ....



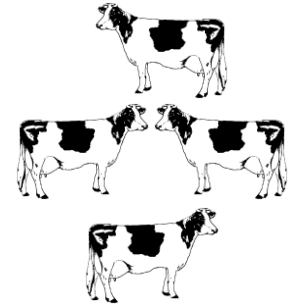
Halachmi I, et al. 2019.  
*Annu. Rev. Anim. Biosci.* 7:403–25

inflammation in the leg

# Novel phenotyping technologies - sensors



Halachmi I, et al. 2019.  
*Annu. Rev. Anim. Biosci.* 7:403–25

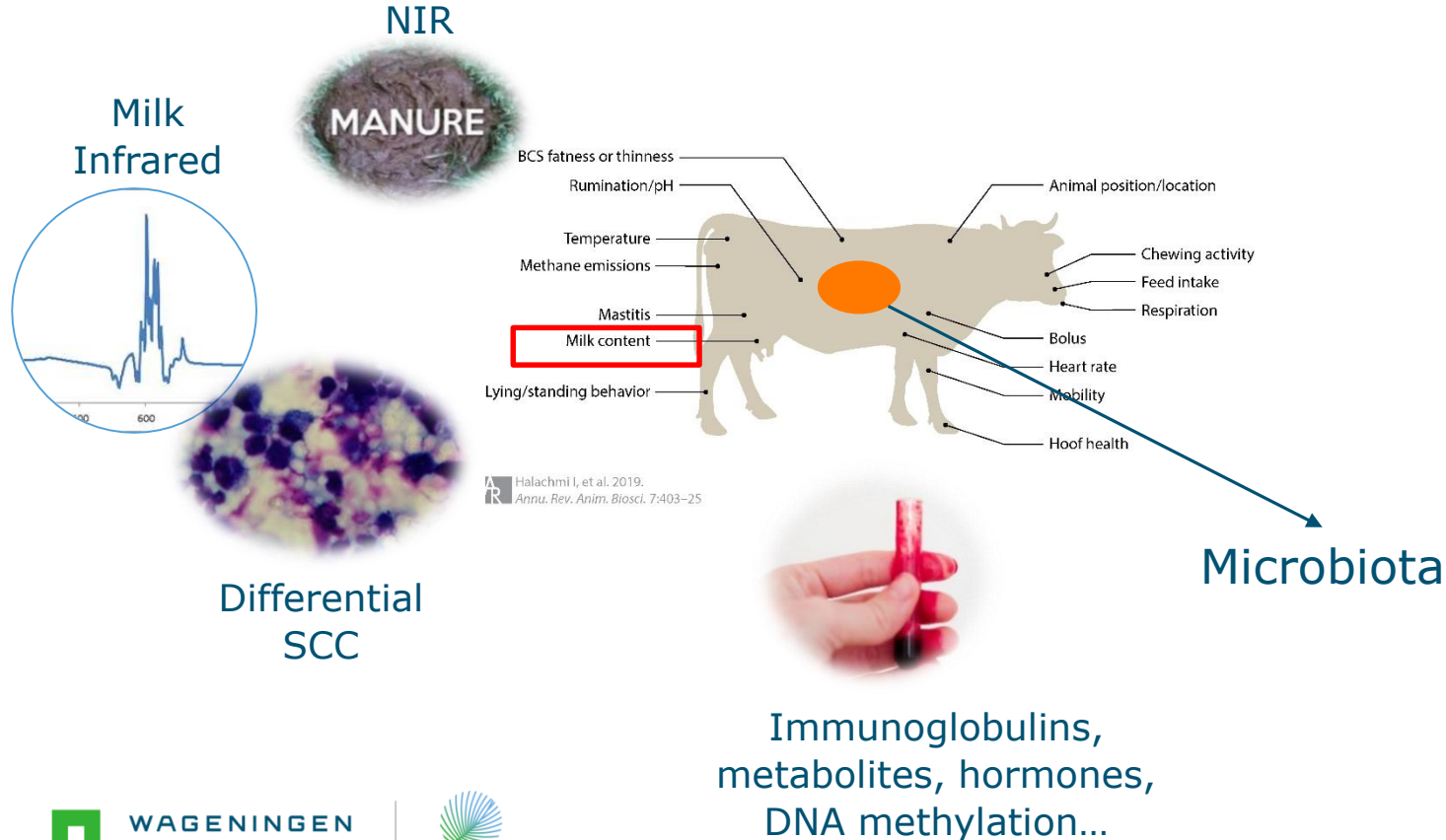


Behaviour: social interactions  
Disease: Transmission  
Infection

## Sensors:

- Machine vision (cameras)
- Sound
- Accelerometers
- Electronic nose
- **GPS**
- ....

# Novel phenotyping technologies – “omics”



# Novel phenotyping technologies – organoids

From Clevers  
(2016)

© 2017. Published by The Company of Biologists Ltd | Development (2017) 144, 938-941 doi:10.1242/dev.150201

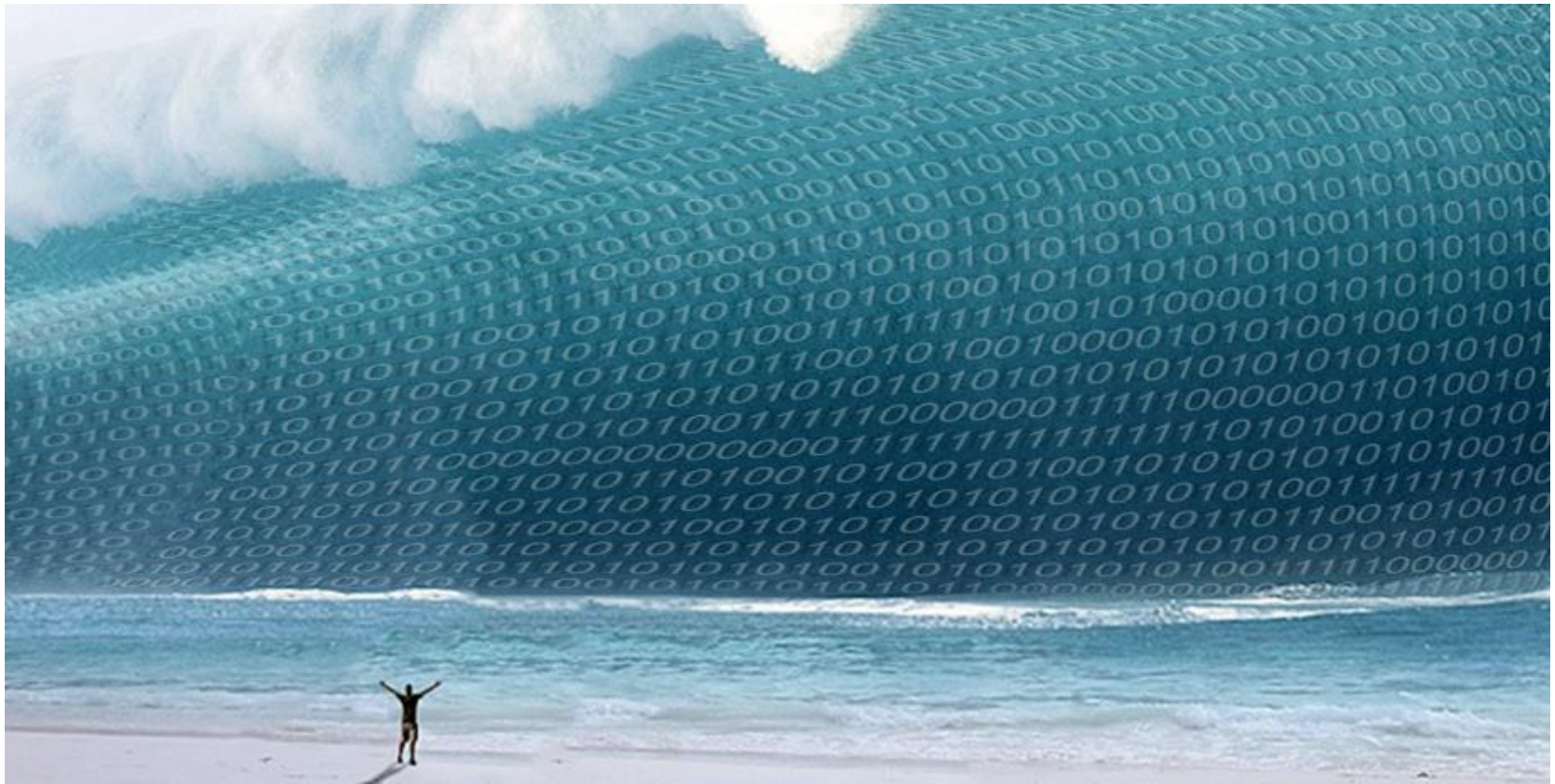
The Company of Biologists

**SPOTLIGHT**

## The hope and the hype of organoid research

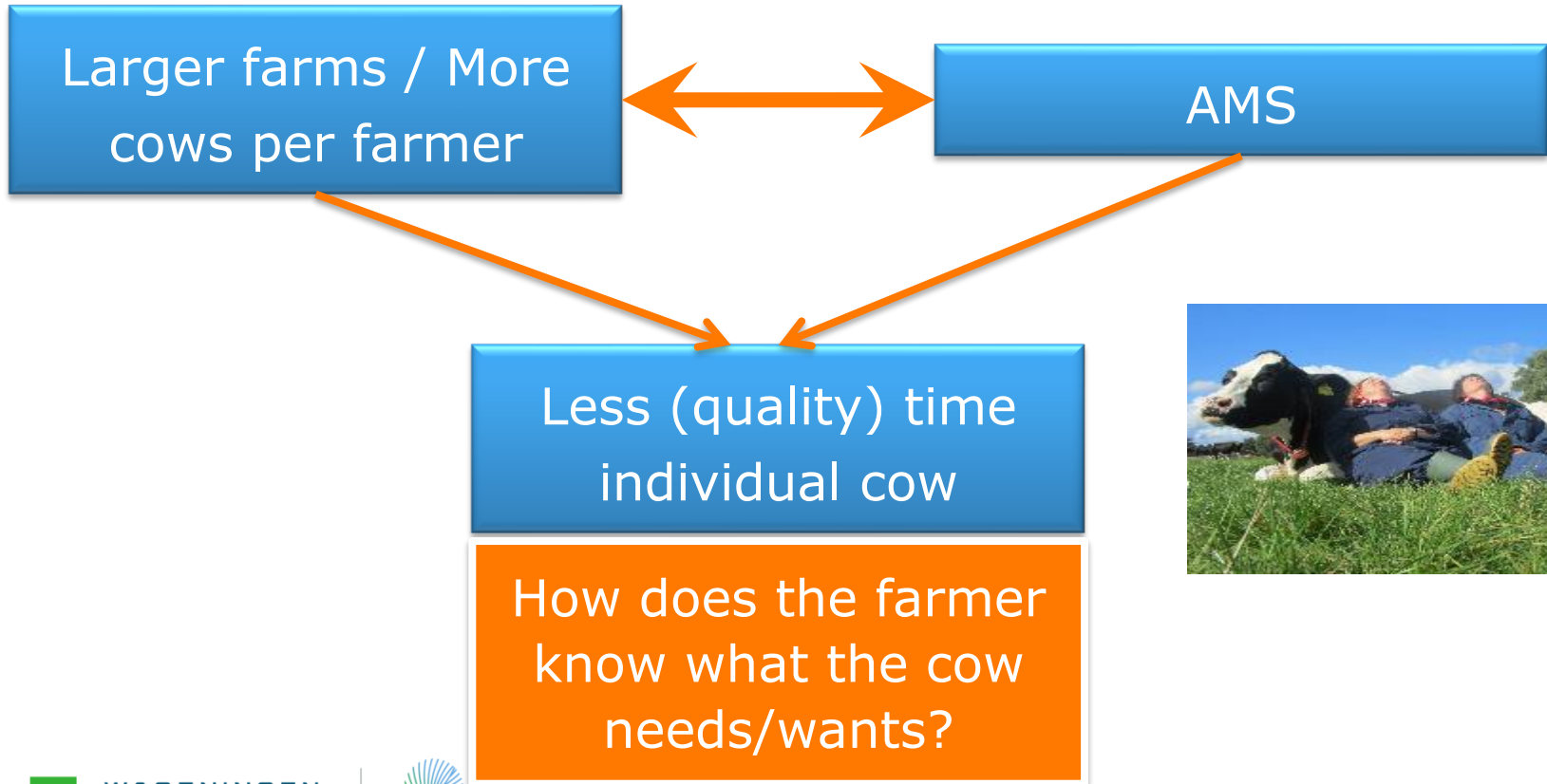
Meritxell Huch<sup>1,2,3,\*,\$</sup>, Juergen A. Knoblich<sup>4,\*,\$</sup>, Matthias P. Lutolf<sup>5,6,†,\$</sup> and Alfonso Martinez-Arias<sup>7,†,\$</sup>

Feed efficiency?      NEB?      Stress?



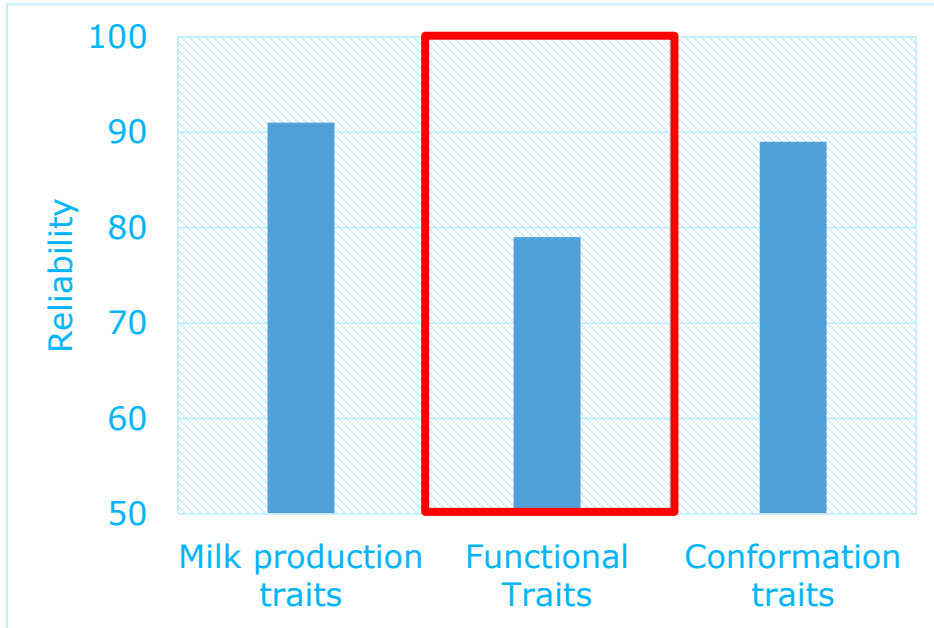


# Management indicators





# Do breeders need additional phenotypes??



Average reliability published EBV Dutch HF bulls (n=950, 12-2018)

$$H = v_1A_1 + v_2A_2 + \dots$$

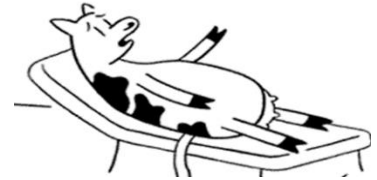
Additional breeding goal traits??

# Do breeders need additional phenotypes??

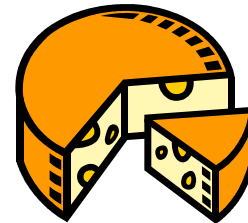
- Environmental impact  
Feed efficiency, Methane emission,  
Phosphorus efficiency, Nitrogen efficiency....



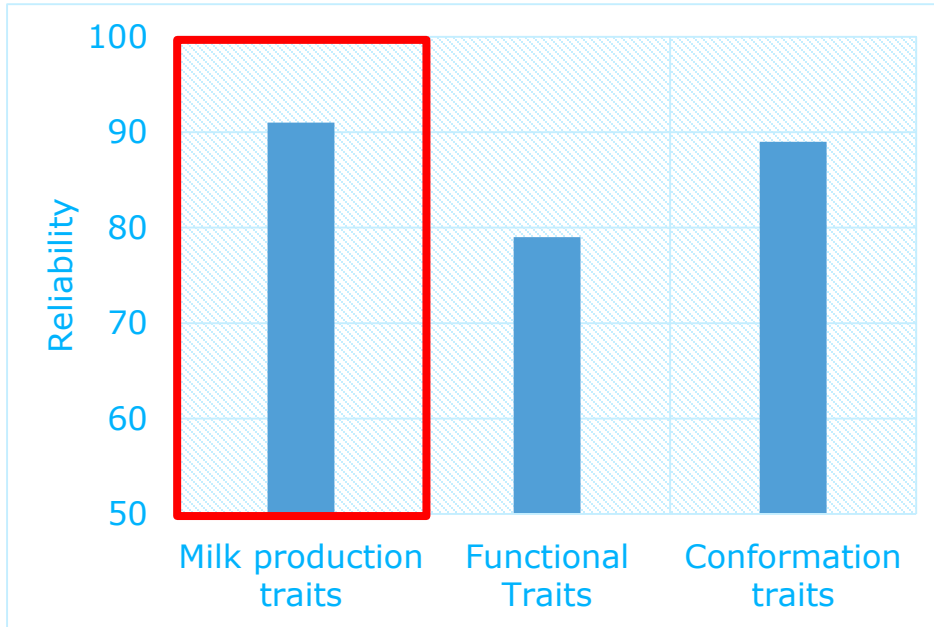
- Cow Health  
Disease resistance, longevity....



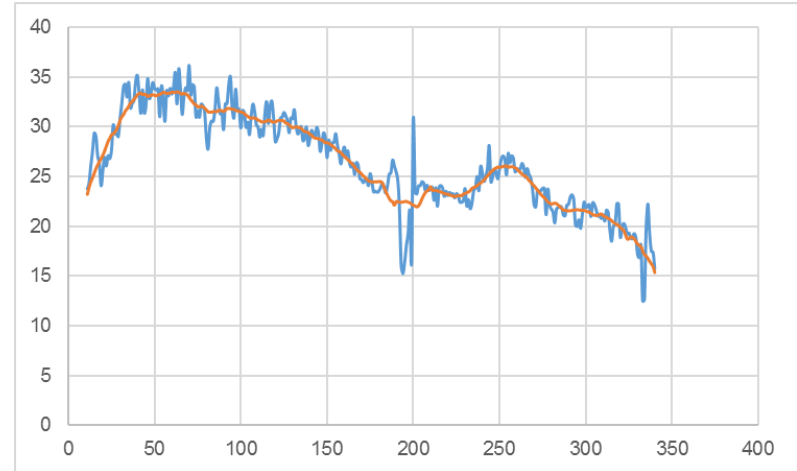
- Product quality  
Manufacturing, Nutritious value



# Do breeders need additional phenotypes??



Average reliability published EBV Dutch HF bulls (n=950, 12-2018)



Fluctuations in milk yield as resilience indicator – Han Mulder.

# Novel phenotyping technologies

## Requirements ??

- Accuracy and bias
- Price
- High-throughput
- Non-destructive
- .....

# Novel phenotyping technologies

Use??

- Research
- Management
- Breeding value estimation
- Payment
- .....

# Novel phenotyping technologies

## Use??

- Research
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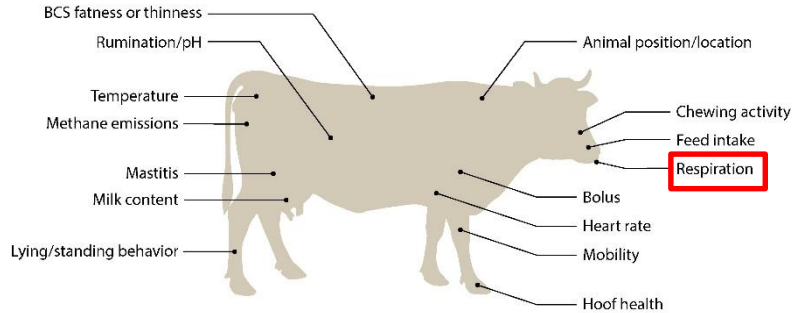
# Novel phenotyping technologies

## Use??

- Research
- Management
- **Breeding value estimation**
- Payment
- .....

## Requirements ??

- **Accuracy and bias**
- Price
- High-throughput
- Non-destructive
- .....



Halachmi I, et al. 2019.  
*Annu. Rev. Anim. Biosci.* 7:403–25

## Sensors:

- Machine vision (cameras)
- Sound
- Accelerometers
- **Electronic nose**
- GPS
- ....

## Breath sensor CH<sub>4</sub> "sniffer"



## Sniffer CH<sub>4</sub>

- $h^2 \approx 0.10$
- $r \approx 0.25$
- herd  $\approx 0.60$





J. Dairy Sci. 101:9619–9620  
<https://doi.org/10.3168/jds.2018-14704>  
© American Dairy Science Association®, 2018.

## ***Letter to the Editor: Challenging one sensor method for screening dairy cows for reduced methane emissions***

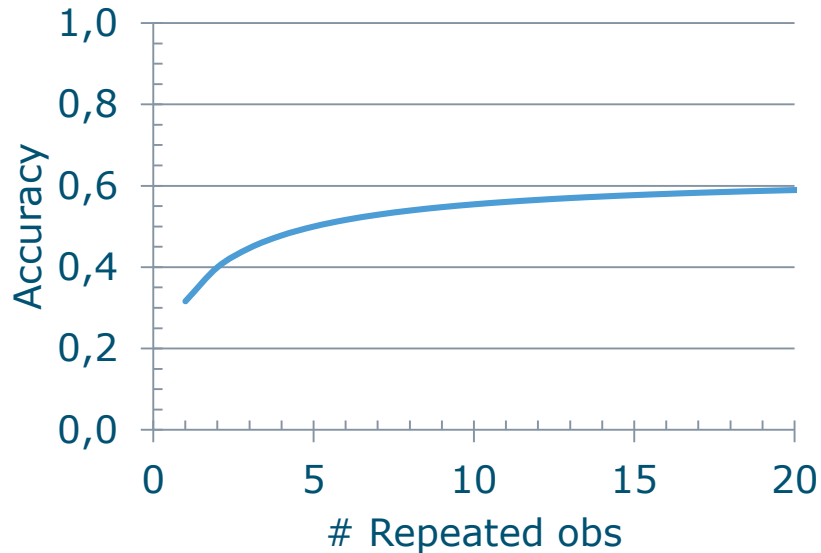
**P. Huhtanen\*<sup>1</sup> and A. N. Hristov†**

\*Department of Agricultural Science, Swedish University of Agricultural Sciences, S-90183 Umeå, Sweden

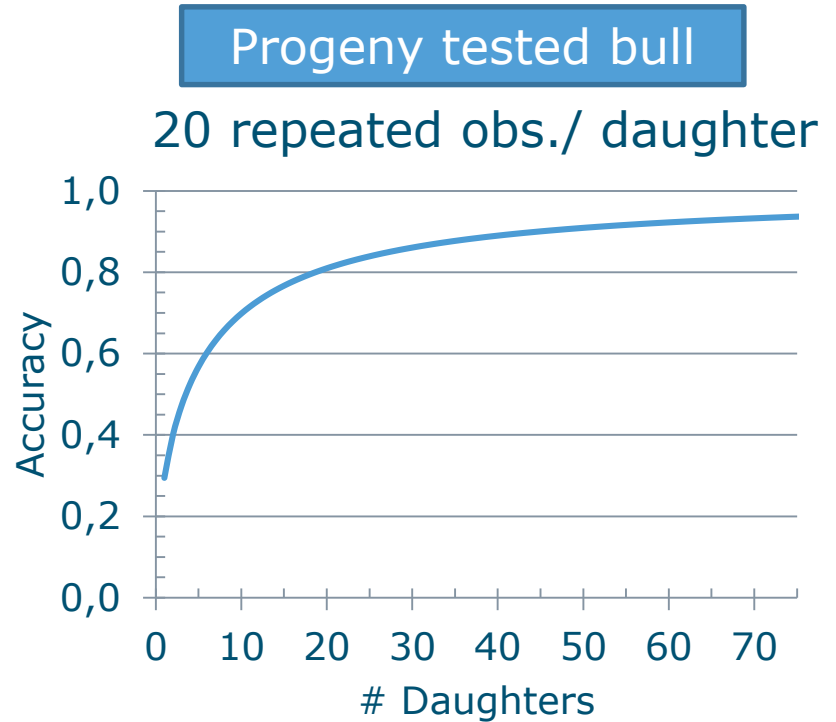
†Department of Animal Science, The Pennsylvania State University, University Park 16802

“... the need for high throughput methodology, e.g. for screening large numbers of animals for genomic studies, **does not in itself justify the use of methods that are inaccurate, imprecise, or biased**” (Hammond et al., 2016).

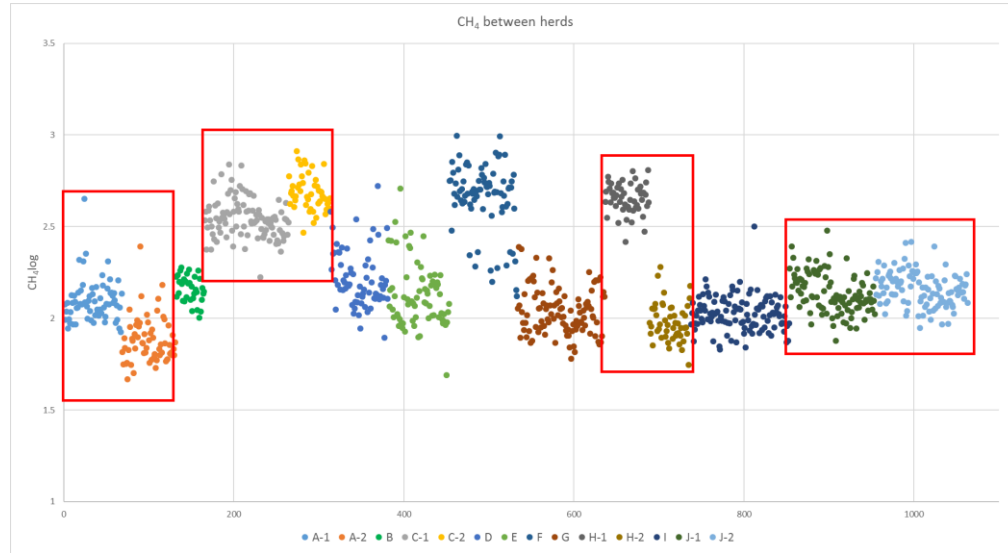
# Accuracy of EBV- $h^2=0.10$ , $r=0.25$



Cows



# Bias due to Herd effects



$$Y = \text{HTD} + \dots + \text{Anim} + \text{PE} + e$$

$$\text{anim} \sim N(0, A\sigma_a^2)$$

# Systematic "errors"



$$H = v_1A_1 + v_2A_2 + \dots + v_n \text{CH}_4$$



Genetic correlation

$$I = b_1X_1 + b_2X_2 + \dots + b_n \text{CH}_4\text{-sniffer}$$

Sniffer CH4 as **indicator** for "true" CH4.

# Sniffer CH<sub>4</sub>

Use??

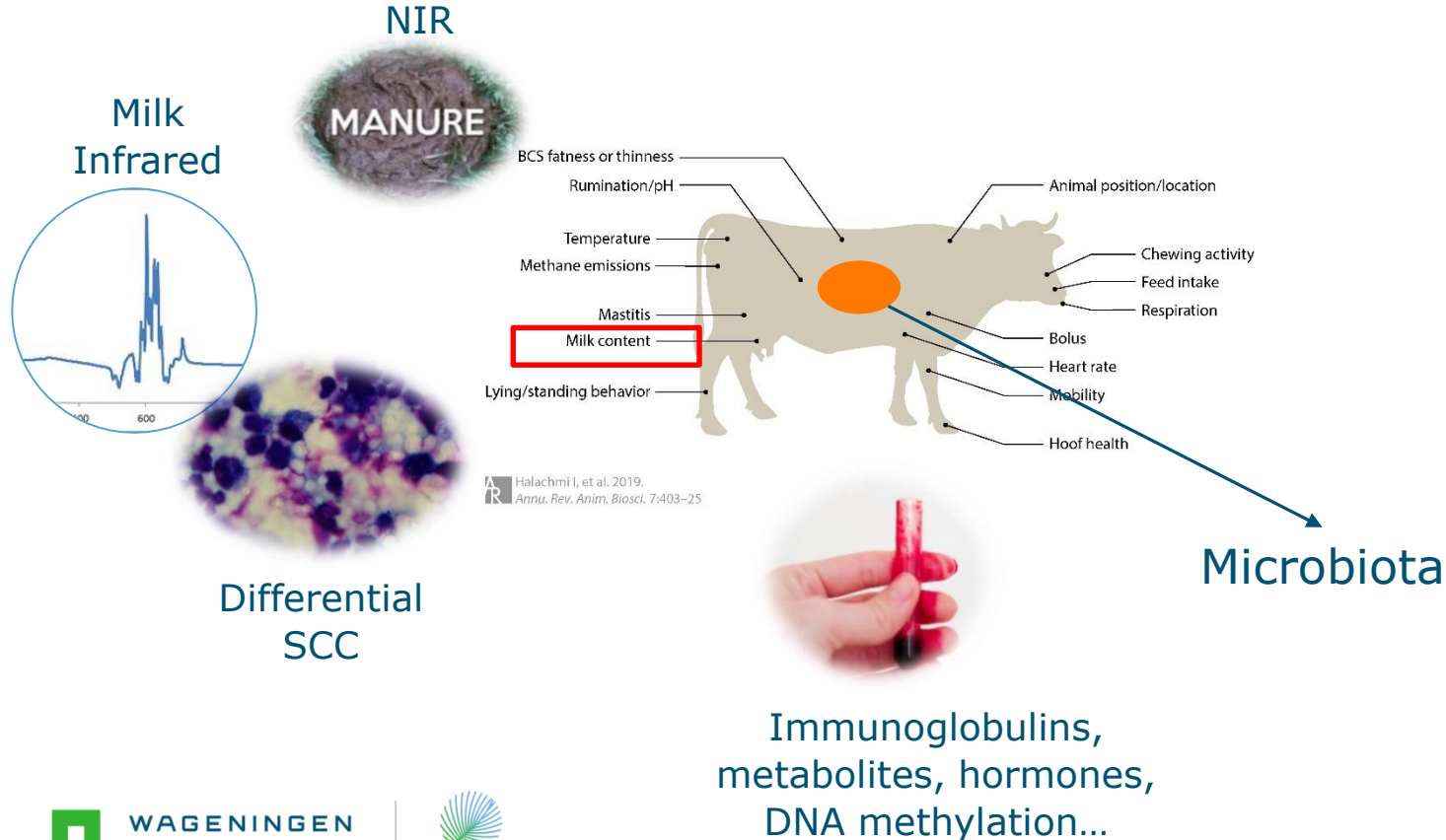
- Research 
- Management 
- Breeding value estimation 
- Payment 
- .....

Inaccurate and biased sensor data can provide valuable information for selective breeding.

“Nice to have” vs “Need to have”



# Novel phenotyping technologies – “omics”





J. Dairy Sci. 102:6288–6295  
<https://doi.org/10.3168/jds.2018-15684>

© American Dairy Science Association®, 2019.

## Validation strategy can result in an overoptimistic view of the ability of milk infrared spectra to predict methane emission of dairy cattle

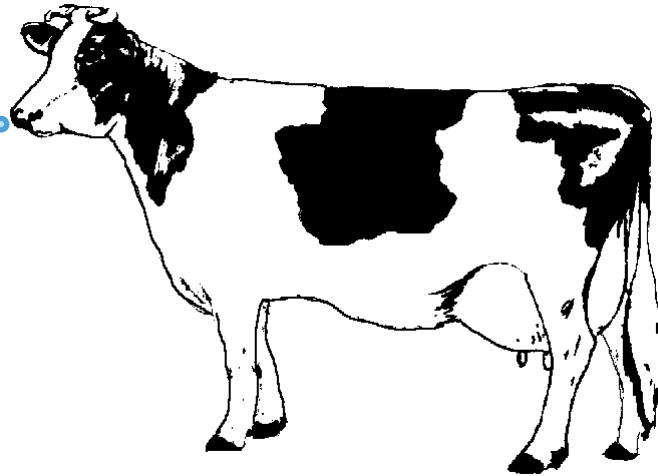
Qiuyu Wang and Henk Bovenhuis\*

Animal Breeding and Genomics Group, Wageningen University, PO Box 338, 6700AH, Wageningen, the Netherlands

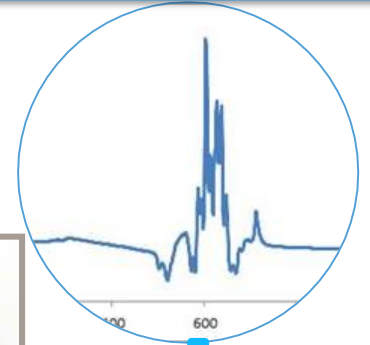




Breath sensor CH<sub>4</sub>  
"sniffer"



Milk IR spectra



Milk IR Prediction  
equation CH<sub>4</sub>

# Data

- CH<sub>4</sub>

  - Sniffer in AMS

  - Average over 5-day period: 2 days before, during and 2 days after milk recording

- IR spectra - Qlip

  - Selected set of 275 IR wavenumbers

- Animals

  - 801 cows on 10 commercial herds

# Methods

- Partial Least Squares Regression
- Validation Strategy - Random Cross-Validation

# Random cross validation

Calibration

n=640 (80%)

Validation

n=161 (20%)

# Results – validation $R^2$

Prediction	Random CV $R^2$
Infrared	0.49

$R_{cv}^2 = 0.49$  is within the range of published values (0.13-0.72)

## Random cross validation

Calibration  
n=640 (80%)

Validation  
n=161 (20%)

## Block cross validation

Calibration  
9 herds

Validation  
Herd 10

# Results – validation $R^2$

Prediction	Random CV $R^2$	Block CV $R^2$
Infrared	0.49	0.01

Cross validation strategy has a big impact on the results (and conclusions)!!

# “Negative control”

Selected 114 wavenumbers from the Water Absorption Regions:

- ✓ contain mainly “noise”
- ✓ not informative for predicting milk composition –  
Expected  $R^2 \approx 0$



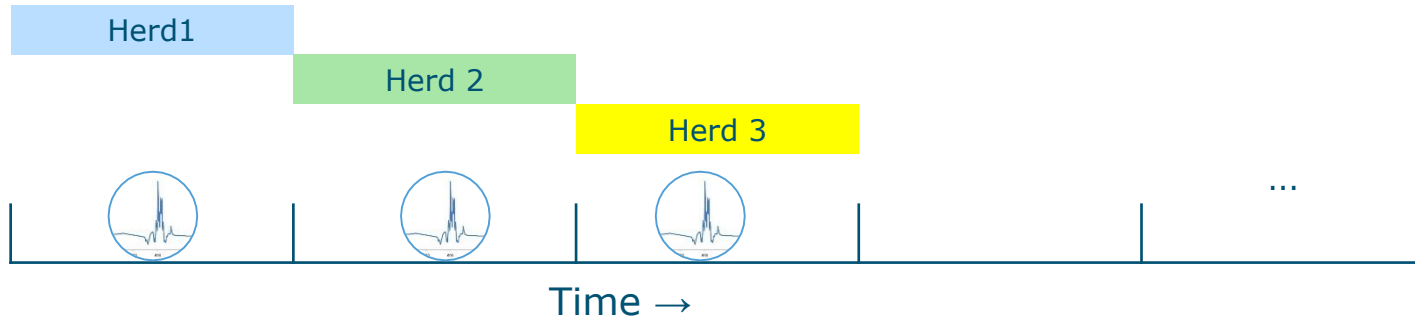
# “Negative control”

Prediction	Random CV $R^2$	Block CV $R^2$
Infrared	0.49	0.01
<b>Negative control</b>	<b>0.25</b>	<b>0.03</b>

## Conclusion

- ✓ There is a problem with the random cross validation strategy.
- ✓ Negative control can identify these problems.

# Diagnosis



- Confounding of “herd” and “date of IR” analysis
- Random Cross Validation:  
errors associated with “date of IR” analysis explain between herd differences in CH<sub>4</sub>

# Is this a special case??

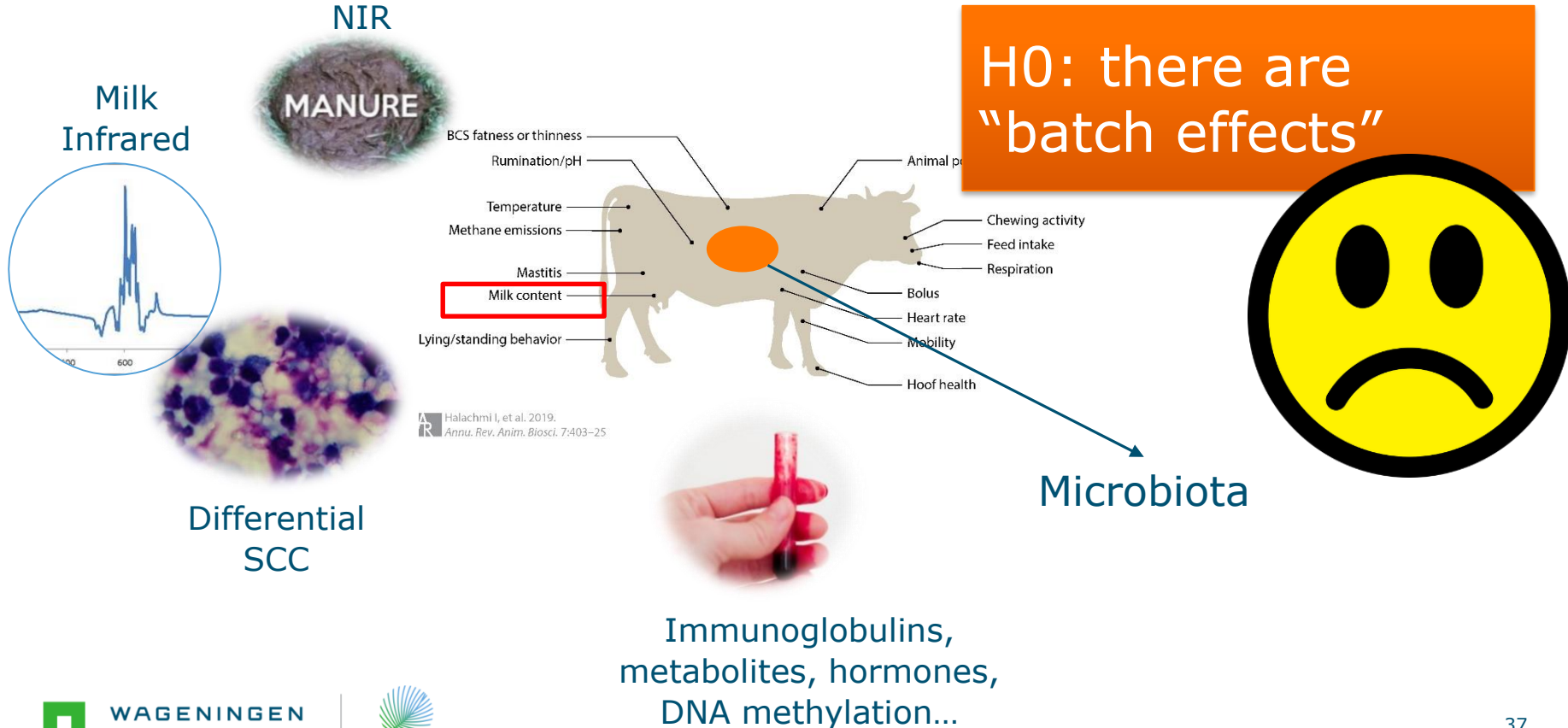
- Confounding “herd” and “date of IR” analysis
- Differences due to herds – 60% variation
- CH<sub>4</sub> respiration chambers???  
Ring test calibration of respiration chambers in the UK suggest substantial “batch effects” (Gardiner et al. 2015)

# Tackling the widespread and critical impact of batch effects in high-throughput data

*Jeffrey T. Leek, Robert B. Scharpf, Héctor Corrada Bravo, David Simcha, Benjamin Langmead, W. Evan Johnson, Donald Geman, Keith Baggerly and Rafael A. Irizarry*

“One often overlooked complication with such studies is **batch effects**, which occur because measurements are affected by laboratory conditions, reagent lots and personnel differences.

# Novel phenotyping technologies – “omics”



# Conclusions

- Inaccurate and biased sensor data can provide valuable information for selective breeding.
- Choose your validation strategy carefully.
- H0: high throughput data are affected by “batch effects”.

