

Challenges and opportunities for evaluating and using the genetic potential of dairy cattle in the new era of sensor data from automation

Nicolas Gengler
nicolas.gengler@uliege.be



Outline of my presentation today

- New era of sensor data from automation
 - Challenges
 - Opportunities

- Genetic potential of dairy cattle
 - Evaluation
 - Use

Different focus

Sensor data from automation

- ❑ Precision dairy tools → automatic collection of data
- ❑ Not so new
 - Milk meters, automatic feeding stations around for some time



ATL



Lely

Sensor data from automation

- ❑ Precision dairy tools → automatic collection of data
- ❑ Not so new
 - Milk meters, automatic feeding stations around for some time
- ❑ Many traits (more or less in a chronological order)
 - Milk yield and milk flow
 - Concentrate intake
 - Milk components and milk conductivity → SCC
 - Daily body weight
 - More recent, many others:
 - ❖ Rumen pH, progesterone, behavioral patterns of feeding, rumination and activity, positioning, body condition scoring,

Buzzword: Big Data

Sensor data → Big Data

□ Four V

- Volume: many highly repeated records
- Variety: many different sensors
- Velocity: fast data acquisition ⇨ fast advice (?)
- Veracity: data integrity ⇔ quality of “sensors”

Many challenges, New opportunities

Many challenges, New opportunities

- ❑ Many challenges
- ❑ Not to be forgotten → first one:

Cost-benefits to farmers have to be clear

- ❑ Obviously new opportunities
- ❑ In this talk focus a little different

Evaluating and using genetic potential of dairy cattle

Many challenges, New opportunities

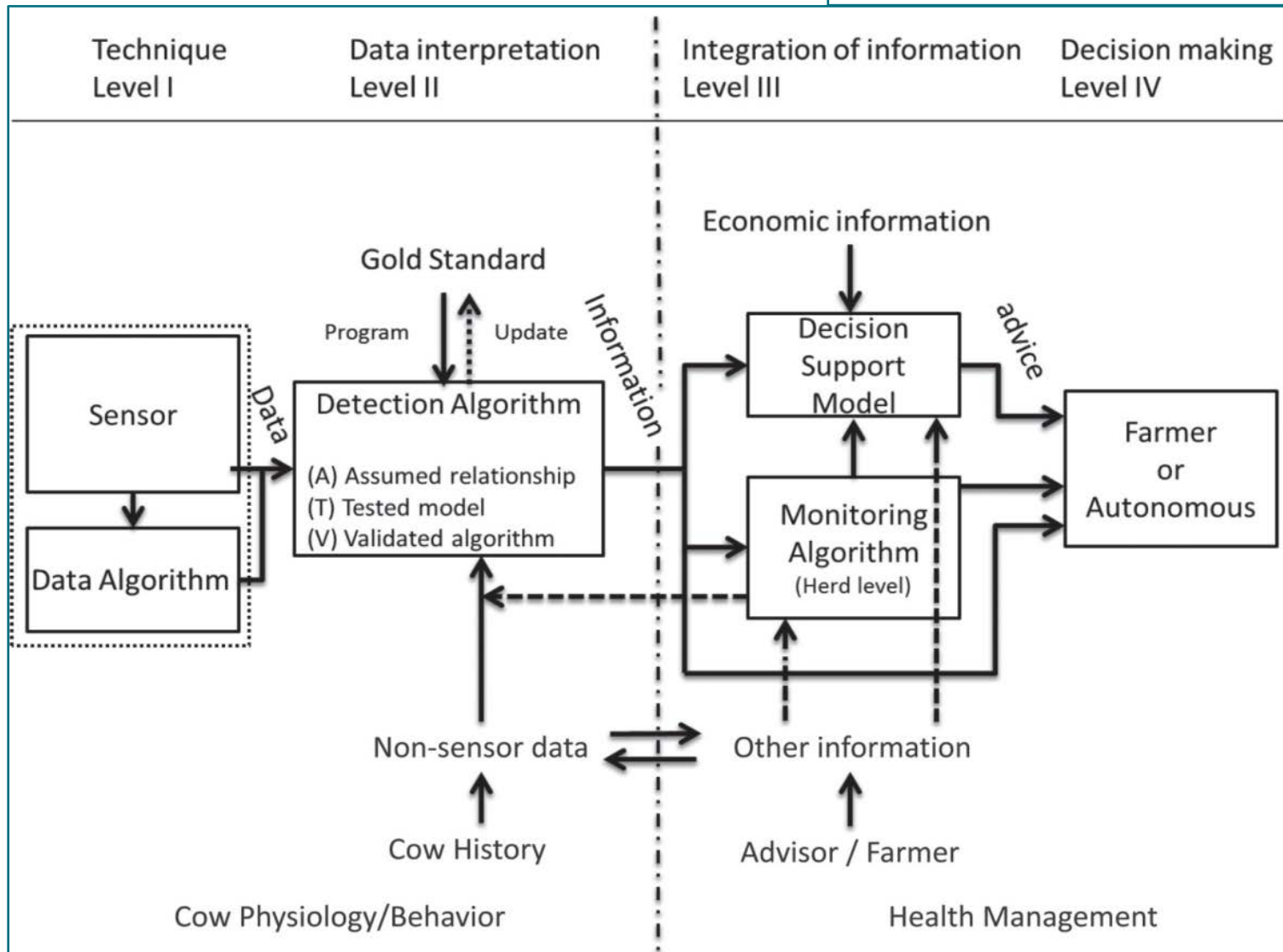
**Generating opportunities from
genetics and genomics**



Improving cost-benefit ratios

Classically: Management perspective

Rutten et al., 2013



Challenges: Data quality and validation

- ❑ On-farm sensor by design → stand-alone
- ❑ Need to be able to auto-adjust itself
- ❑ Example of advanced milk-meters
 - Milk quiet reliable (rather simple measures)
 - NIR* based spectrometers for components less evident
→ here reference from DHI possible (MIR* based)
- ❑ Even less evident for “novel” types (e.g., pH boluses)
 - **How to validate the results ?**
- ❑ High implications for management and breeding uses

*NIR = Near-Infrared and MIR = Mid-Infrared

Challenges: Data accessibility

- ❑ Sensors designed to be used in given (eco-)system
 - Specific algorithms, decision support systems,
- ❑ Many consequences
 - Data stays on a farm
(or goes in a system specific “cloud”)
 - Raw data from sensor not available → “information”
 - No exchanges across different systems
 - Very limited exchanges with DHI, even for milk and standard milk components not optimal

➤ **Important for flow of data to genetic evaluations!**

Challenges: Data consolidation

- ❑ Raw data not available → Management traits
- ❑ “Consolidated” data
- ❑ Advantage:
 - Limit the challenge of extreme high data volumes generated by sensors
- ❑ Disadvantage:
 - But management traits also adapted to breeding?
 - Step performed often without considering breeding

Challenge: Management and breeding

- Therefore additional challenge
 - Sensors nearly always in context of (herd) management
 - In breeding perspective changing
 - ❖ Precise values less important
 - ❖ However excellent ranking of animals matters

- Different consequences on different levels

Challenge: Data ownership

- ❑ Now clearly emerging as a major issue
- ❑ Many aspects including latest legal developments
- ❑ **One of major blocking issues**
- ❑ Makes it difficult to
 - Exchange
 - Combine
 - Consolidate
 -
- ❑ Data outside of farm, “sensor”, manufacturer,....

After challenges → opportunities

Opportunities: Evaluating animals

- Two ways to see this:

- Classically: “sensor” → phenotypes
 - Access to relevant (novel) phenotypes
 - Crucial for every genetic / genomic evaluation system

Opportunities: Evaluating animals

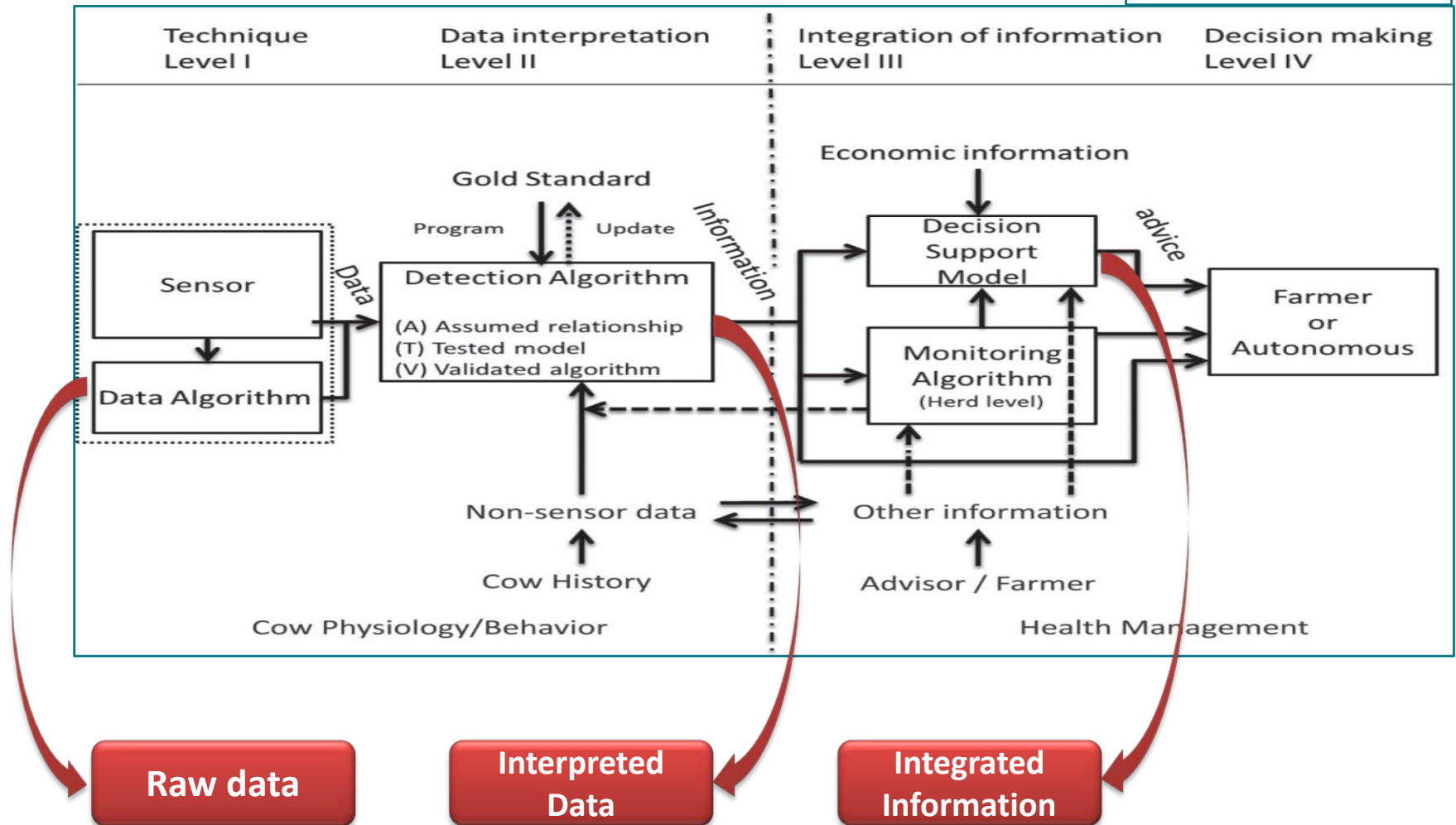
- ❑ Two ways to see this:

- ❑ Classically: “sensor” → phenotypes
 - Access to relevant (novel) phenotypes
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- ❑ More innovative:
 - **Exploiting the specific (multi-layer) architecture**

“Sensor” ⇒ Data ⇒ Genetic evaluations

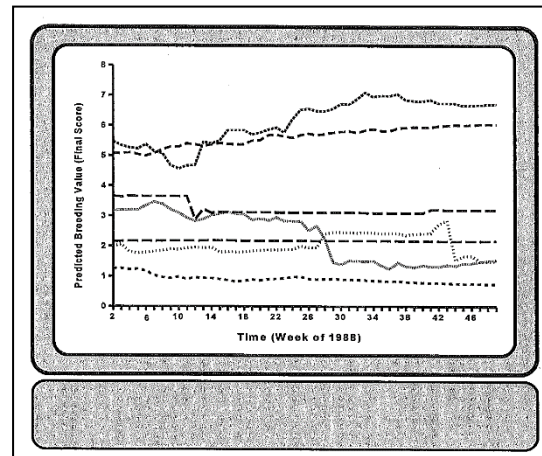
Rutten et al., 2013



“Sensor system” ↔ Genetic evaluations

PROCEEDINGS OF THE SYMPOSIUM ON CONTINUOUS EVALUATION IN DAIRY CATTLE

College Park, MD
June 13, 1993



SYMPOSIUM ORGANIZATIONAL COMMITTEE

I. Misztal, Committee Chair
Department of Animal Sciences
University of Illinois
Urbana, IL 61801

T. J. Lawlor
Holstein Association of America
Brattleboro, VT 05301

R. D. Shanks
Department of Animal Sciences
University of Illinois
Urbana, IL 61801

G. R. Wiggans
Animal Improvement Programs Laboratory
USDA-ARS
Beltsville, MD 20705

Wiggans and VanRaden, 1993

FUTURE OPTIONS

To make genetic information more easily available and up to date, some calculations could be made on the farm. Milk recording systems might provide local updates of cow evaluations by combining new data with existing genetic estimates. Alternatively, new data could be automatically transmitted to and from a central site where national evaluations are computed essentially continuously with dedicated equipment.

- Some ideas already developed in 1993
 - “... genetic information ... up to date ...”
 - “... some calculations could be made on farm ...”
 - “... new data could be automatically transmitted to and from ...”
- However in practice we are often still far away from these “old” ideas

“... genetic information ... up to date ...”

- Very relevant in the genomic area because
 - Genomic predictions available with SNP effects updated on a very regular bases
 - Sensors provide on-farm phenotypes

→ Next step: putting these together

- Allowing updated GEBV on a female side
- GEBV → Genomic Predicted Producing Abilities (GPPA)
- Large interest for culling decision

“... some calculations ... on farm ...”

- ❑ Most farm PC clearly under-used
- ❑ As shown before potential to integrate information
- ❑ But one can go several steps further....

Federated learning: collaborative machine learning without centralized training data

Straight from Google AI



The latest news from Google AI

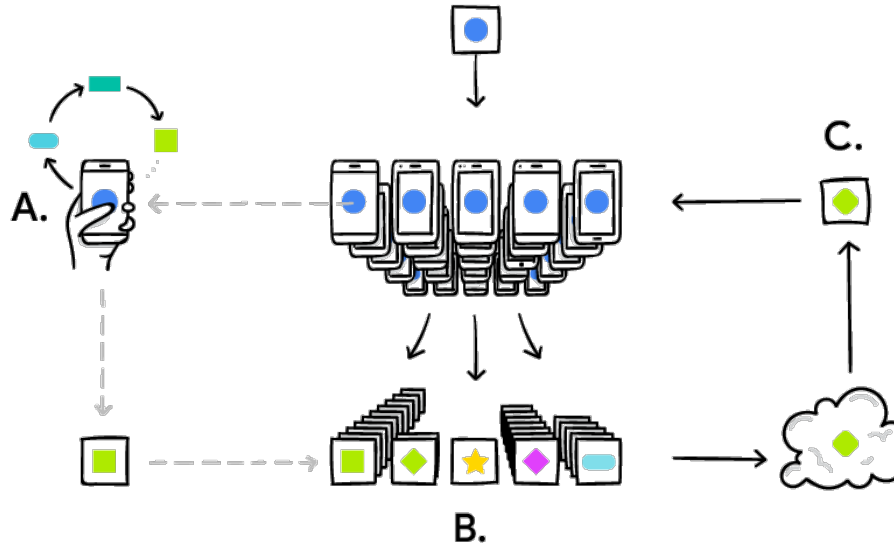
Federated Learning: Collaborative Machine Learning without Centralized Training Data

Thursday, April 6, 2017

Posted by Brendan McMahan and Daniel Ramage, Research Scientists

<https://ai.googleblog.com/2017/04/federated-learning-collaborative.html>

Federated learning



- A. Your phone personalizes model locally, based on usage
- B. Many users' updates are aggregated
- C. Forming consensus change to shared model, after which the procedure is repeated.

Opportunities: Evaluating animals

- ❑ Now in our world
 - ➔ “Sensor” generation of “reference” data
 - Opportunity to get access to novel, precise, continuously updated and relevant data
- ❑ “Reference” can here mean many different things
 - From data to update “sensor” algorithms
to data going straight into genomic prediction models
- ❑ Associated to the use of Federated “Deep” Learning

Novel opportunities for evaluating animals

... automatically transmitted to and from ...

- ❑ Even today bi-directional data transfer between farms and external databases not easy
 - E.g., fast Internet in rural areas!
- ❑ This was before data ownership started to block....
- ❑ Again innovative approaches needed to avoid issues

Avoiding exchange of data but updating models (coefficients)

Creating added value? ← Using genomics

- ❑ Many novel traits (e.g. disease related) low(er) h^2
- ❑ In these situations the “holy grail” is

Accurate genome-guided decision making

- ❑ Human medicine leading the way
- ❑ Dairy cattle genome-guided management

Creating added value? ← Using genomics


- ❑ Many novel traits (e.g. disease related) low(er) h^2
- ❑ In these situations the “holy grail” is

Dairy cattle genome-guided management


- ❑ Few examples emerging

Journal of
Animal Breeding and Genetics



ORIGINAL ARTICLE |  Free Access

Prediction of whole-genome risk for selection and management of hyperketonemia in Holstein dairy cattle

K.A. Weigel , R. S. Pralle, H. Adams, K. Cho, C. Do, H.M. White

First published: 15 May 2017 | <https://doi.org/10.1111/jbg.12259> | Cited by: 2

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Thank you!

Any questions?

nicolas.gengler@uliege.be

