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Artificial Intelligence and Livestock. New data, new approaches

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Artificial Intelligence and Livestock

New data, new approaches

Denis Laloë


*(with the help of P Boudinot, L Canario, F Jaffrézic, A de Paula-Reis, A Trubuil, ENVT /
INRA)*

DATAIA – IA et Agriculture
4 décembre 2019



Precision livestock farming

(Berkwans, 2017; Morota et al, 2018;)



Increase of worldwide demand of 25-70% by 2050

- Much bigger herds / farmer
- Monitoring of animal health and welfare
- Environmental impact
- Productivity of the process

Precision livestock farming

Use of technology

- Biosensors
- Bioimaging

Continuous real-time monitoring of

- Management
- Sustainability
- Health & welfare
- Production / reproduction
- Environmental impact

Behaviour

Liakos et al, 2018

Devices	Observed features	Functionality	Models/Algorithm
Sensor Collars 3-axes accelerometer	Grazing, ruminating, resting, walking	Classification of cattle behaviour	Ensemble Learning /bagging Tree learner
Optical FBG Sensors	Chewing signals, rumination, idleness (Calves)	Classification of chewing patterns (calves)	Decision Trees
Depth cameras	3D-motion data	Behaviour annotation and changes; Welfare, Health monitoring (Pigs)	Gaussian mixture models

Development and validation of an embedded tool to measure postural activity of lactating sows

L Canario et al, 2018

Journées de la Recherche Porcine, 2018

Longitudinal study of Sow postural activity

Time spent in different positions LR, LL, LV, SI, ST

Change in **time budget**

↔ Welfare and Health issues

- Farrowing difficulties -> lying (LV, LL, LR)
- Unwillingness to nurse -> lying ventrally (LV)
- Post-farrowing restlessness -> sitting (SI) + standing (ST) crushing of piglets
- Lameness -> latency to lie down

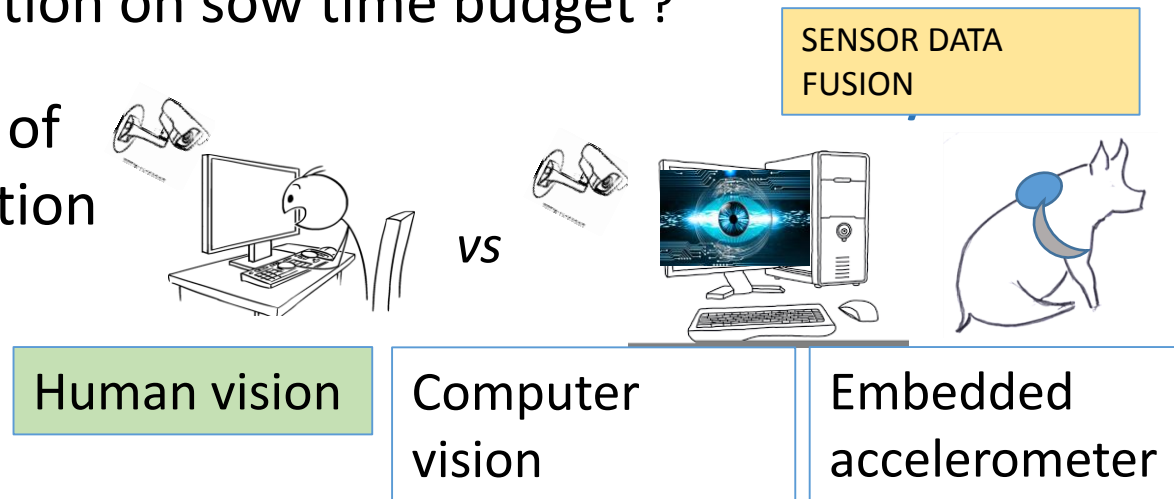
Objective

powerful tool to measure automatically sow postural activity

Question

Can a (combination of) sensor(s) provide accurate information on sow time budget ?

Sources of information

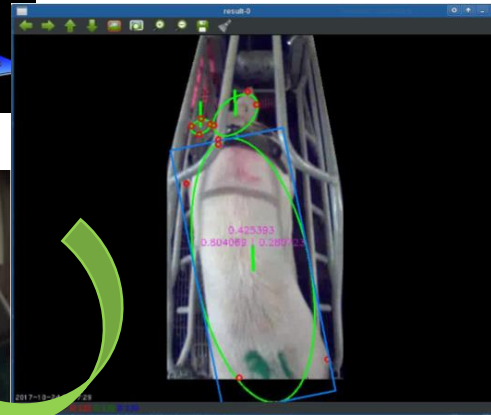


Methodology 1 – visual assessment

1. Human video analyses : gold standard
LR, LL, LV, SI, ST
2. Automatic video image analysis

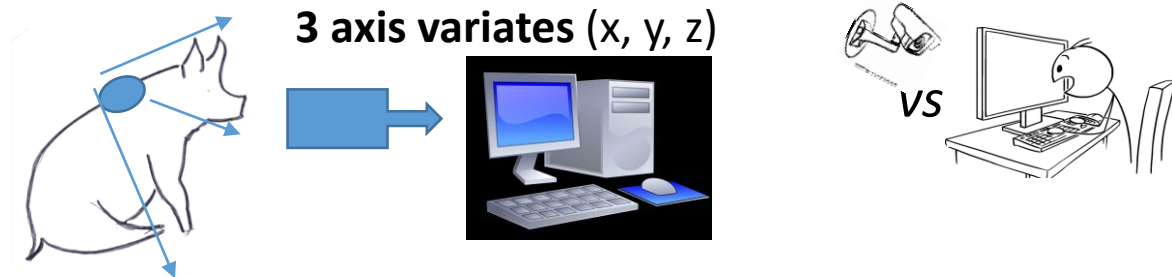


14 variates



13 images / sec

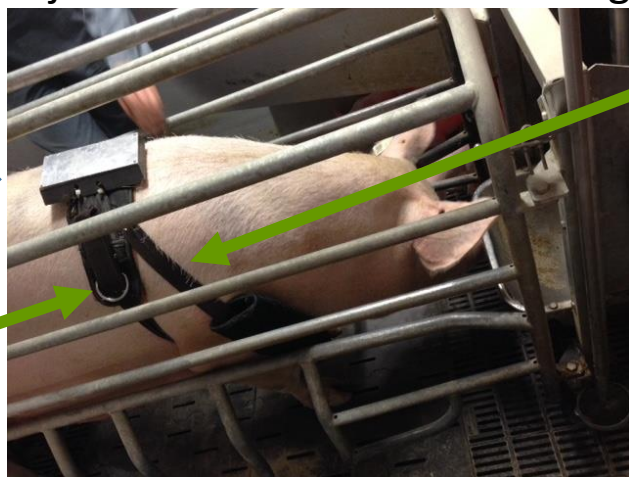
Methodology 2 – embedded accelerometer



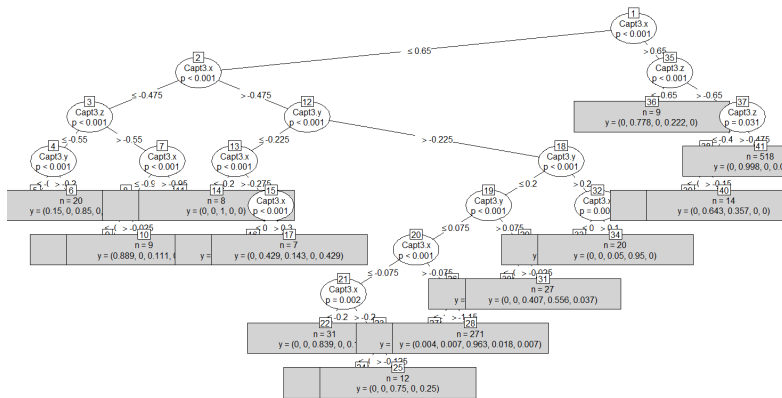
Custom-built belt: adjusted to avoid friction in long term => girthes

Metal box
holding 1 to 3
accelerometers

Bilateral
fasteners



Statistical Process



Machine learning
Random forest

Calculations

For each position

- Sensitivity
- Specificity

Global prediction error rate

R software, Random Forest Package

Conclusions and perspectives

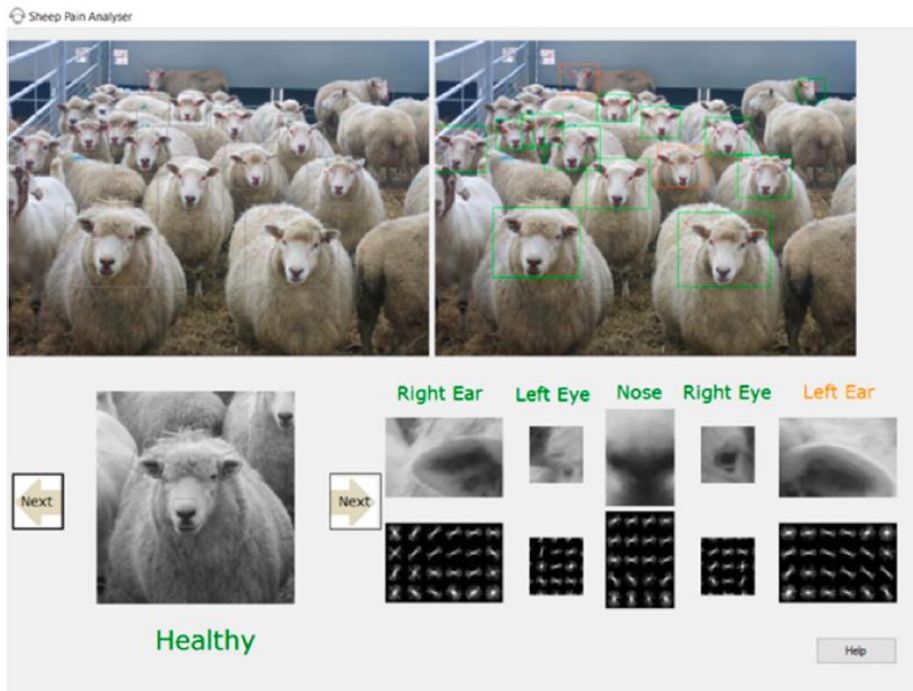
Sensor data fusion highly promising

Perspectives

- Validation of sensor data fusion on longer records
- other phenotypes
- multi-sensor approaches : larger number of behaviours

Face recognition

K Mc Lennan & M Mahmoud, 2019. *Development of an automated pain facial expression detection system for sheep (Ovis Aries)*, Animals 9,196



Sheep Pain Facial Expression Scale

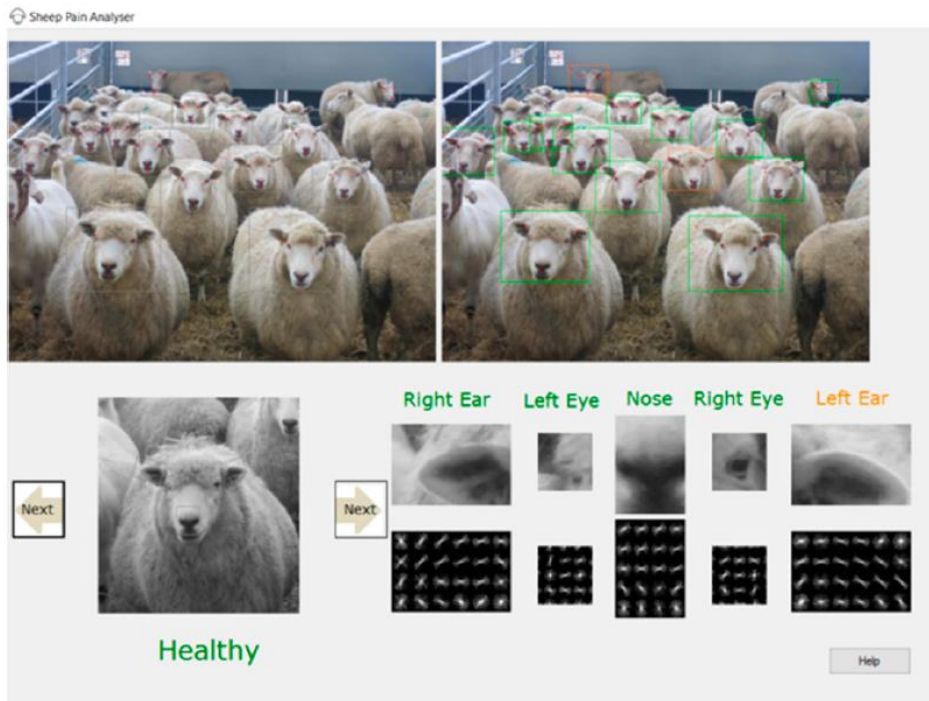
- Honest signal of the intensity of the pain
- Temporal nature of the pain

-> Frequency, duration

-> Better pain-management strategy

Face recognition

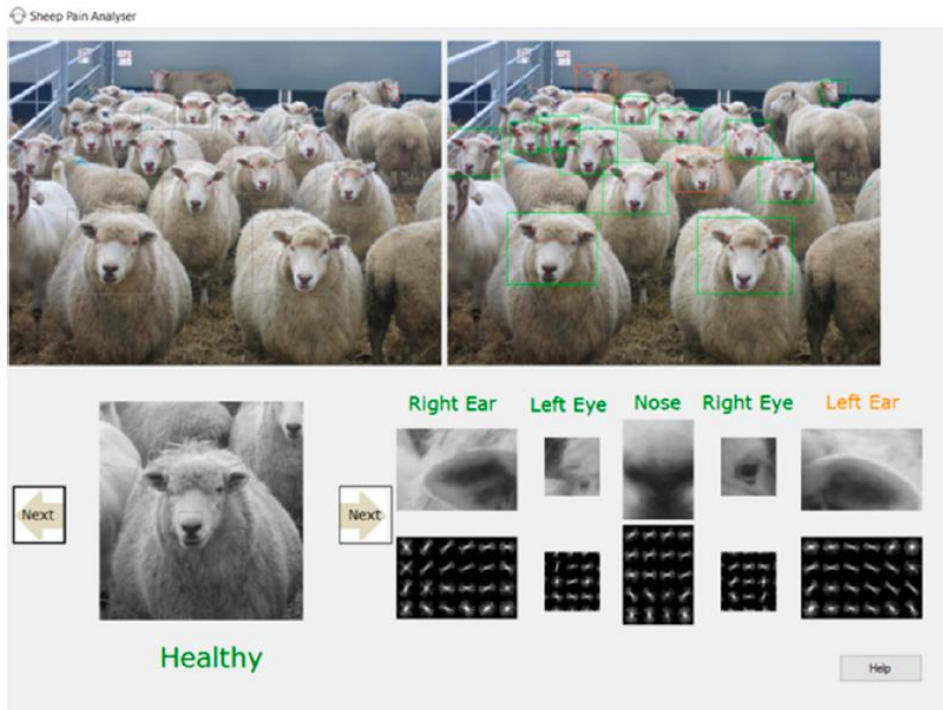
K Mc Lennan & M Mahmoud, 2019. *Development of an automated pain facial expression detection system for sheep (Ovis Aries)*, *Animals* 9,196



1. Detecting the face of the sheep
2. Localizing/marketing important facial points (eyes, nostrils, mouth),
3. Machine learning models to learn changes in the facial features (Deep Learning model -> 25 facial landmarks) that indicate signs of pain based on the SPFES scale
4. Automatically assessing the pain score

Face recognition

K Mc Lennan & M Mahmoud, 2019. *Development of an automated pain facial expression detection system for sheep (Ovis Aries)*, *Animals* 9,196



Top left. Flock of sheep, sheep faces automatically marked with boxes

Top right. Expressions analyzed with machine learning;

- orange : pained ($P(\text{pain}) > .5$)
- green : healthy

Bottom : Analyses of facial features

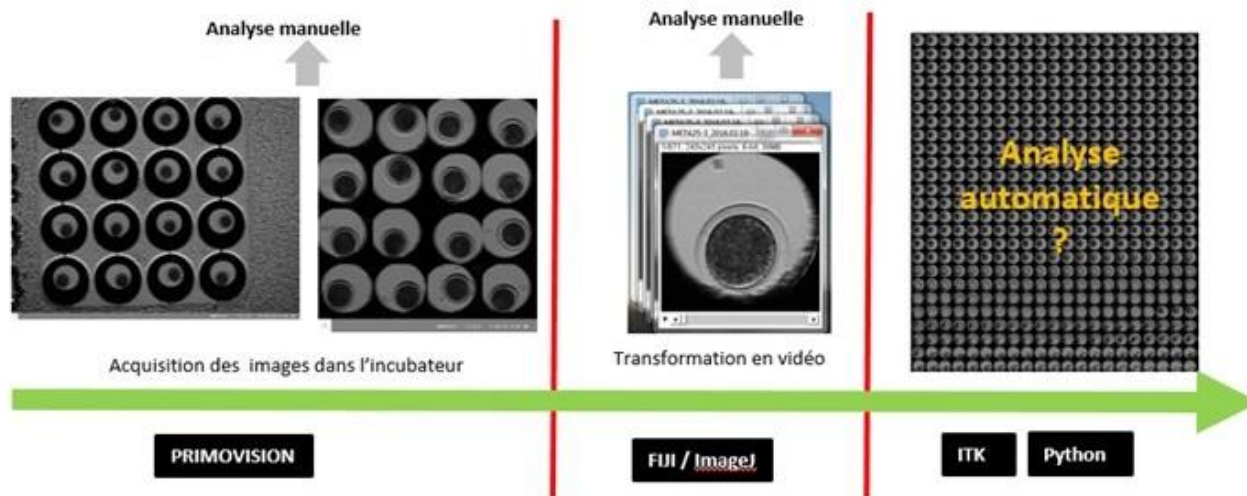
SPFES

Introduction

AUTOMATISATION DE L'ANALYSE MORPHOCINETIQUE

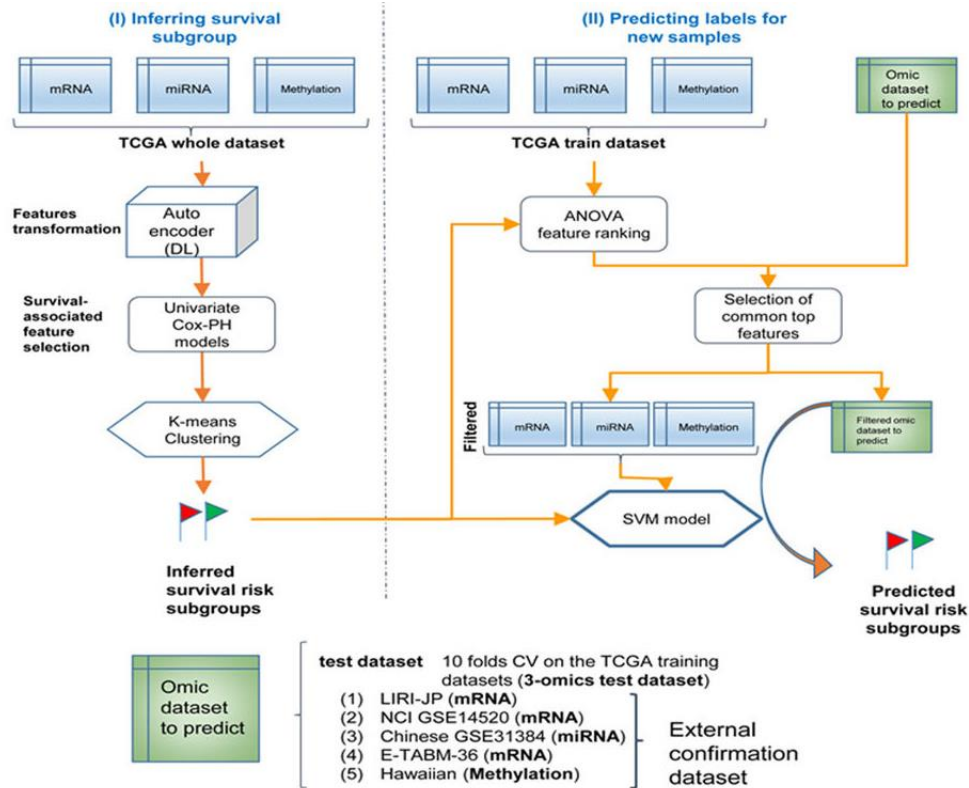
INRA BosexDIM, P.Adenot (BDR MIMA2)

HYPOTHESE: Détecter des différences durant les premiers cycles cellulaires des embryons en relation avec leur aptitude au développement



1. To identify through an automatic process the morphokinetic profile of embryos.
2. To study the impact of these profiles on the embryo development and the success of embryo transfer.

Data integration



P Bellot et al, 2018, Genetics 210, 809-819.

Can deep learning improve genomic prediction of complex human traits ?

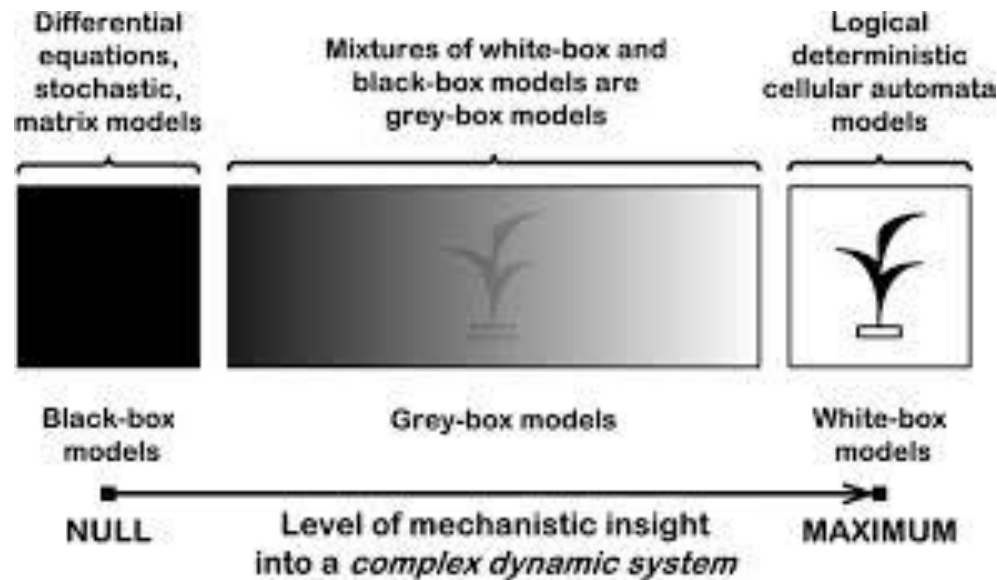
UK Biobank

- 100 000 humans
- 500 000 SNPs
- 5 traits, $h^2 \sim 0.20 - 0.70$

ABSTRACT: ...CNN [*Convolutional Neural Network*] performance was competitive to linear models, but we did not find any case where DL [*Deep Learning*] outperformed the linear model by a sizable margin.

Beyond the black box

The Grey Box



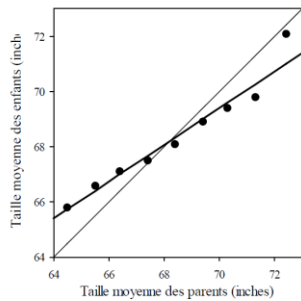
Kalmykov & Kalmykov, 2015

Mathematical models of complex systems are of three types: black-box (phenomenological), white-box (mechanistic, based on the first principles) and grey-box (mixtures of phenomenological and mechanistic models)....

The Grey Box

An example : Quantitative Genetics (eg, Laloë, 2011)

Black Box : Regression model



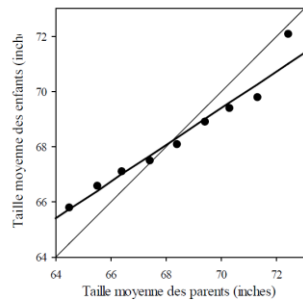
Prediction

- A prediction is not an explanation
The advantage of things that work
is that they work

The Grey Box

An example : Quantitative Genetics

Black Box : Regression model



Prediction

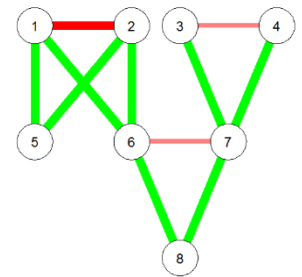
- A prediction is not an explanation
- The advantage of things that work is that they work

White box :

Phenotype = Genotype + Environment

$$individual = \frac{(sire + dam)}{2}$$

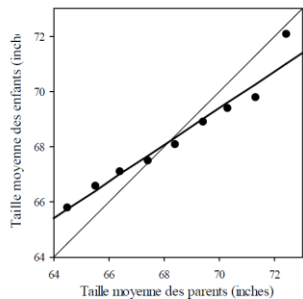
A priori dependencies among individuals



The Grey Box

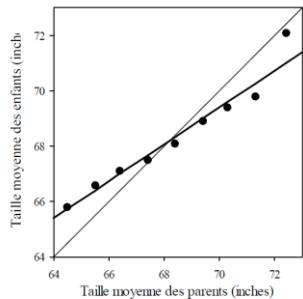
An example : Quantitative Genetics

Black Box : Regression model



Prediction

- A prediction is not an explanation
- The advantage of things that work is that they work



$$h^2 = b$$

$$\hat{A}_i = E(A_i | P_i) = h^2 (P_i - \mu)$$

$$\Delta G_H = \frac{i \times \rho_{HI} \times \sigma_H}{T}$$

White box :

Phenotype = Genotype + Environment

$$individual = \frac{(sire + dam)}{2}$$

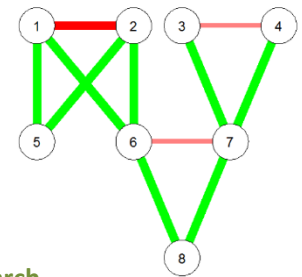
A priori dependencies among individuals

Grey Box

Quantitative Genetics
Heritability, genetic correlations
Genetic evaluation
Optimisation of breeding schemes

Statistical research

Fixed / Random effects
Mixed models
Variance components



New data (sensor data, images,...) : essential

« Old » data: to be considered

Moving to a « grey box »

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