Smart Farming, Learning and PDE

Emmanuel Frénod[1]

December 14th, 2018

Work in collaboration with Hélène Flourent, PhD candidate of the LMBA and working at Neovia

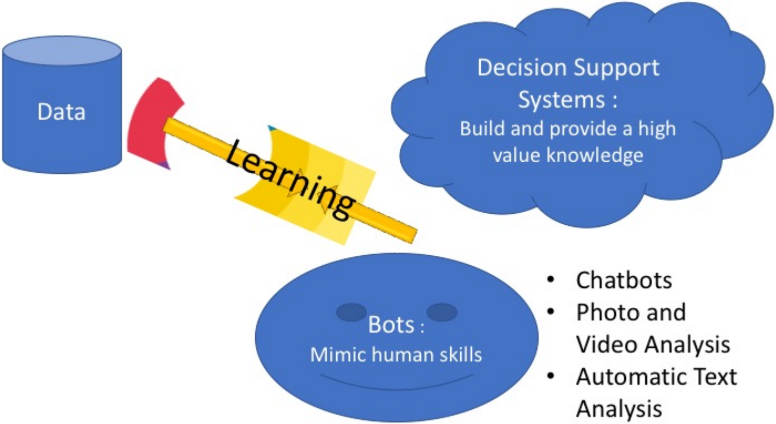
[1]LMBA (UMR 6205), Université de Bretagne-Sud, F-56017, Vannes, France.
emmanuel.frenod@univ-ubs.fr
http://web.univ-ubs.fr/lmam/frenod/index.html

AI, Machine Learning and Data Assimilation

AI - When?

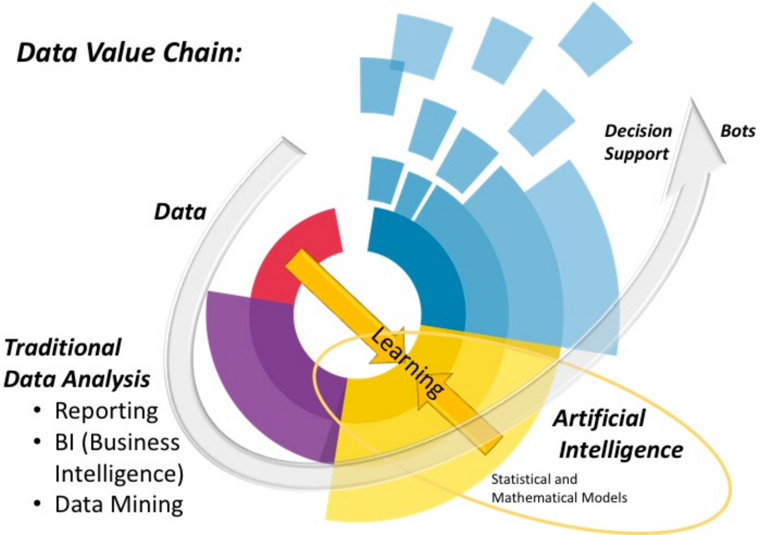
- Forecasts
- Optimization
- Pricing

- Enterprise Driving
- Smart Farming
- Predictive Maintenance

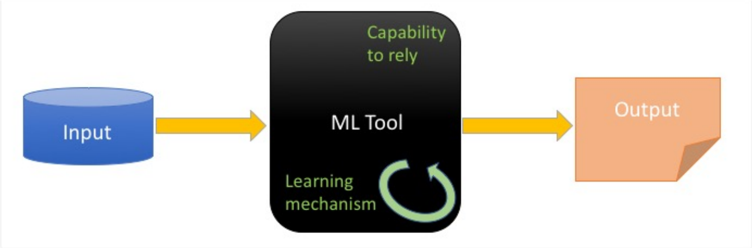


- Chatbots
- Photo and Video Analysis
- Automatic Text Analysis

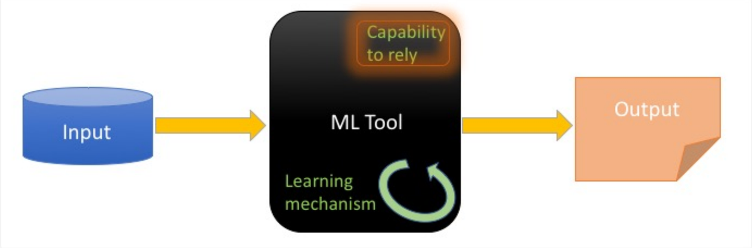
AI - Beyond Data Analysis



Learning and PDE (or ODE)



Learning and PDE (or ODE)

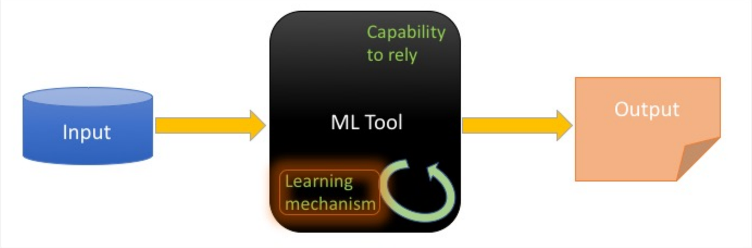


$$\frac{\partial u}{\partial t} - c\Delta u = 0,$$

$$u_{t=0} = u_0,$$

$$u_{t=1}.$$

Learning and PDE (or ODE)

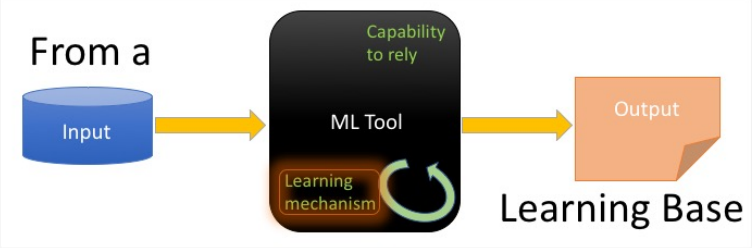


$$\frac{\partial u}{\partial t} - c\Delta u = 0,$$

$$u_{t=0} = u_0,$$

$$u_{t=1}.$$

Learning and PDE (or ODE)



$$\frac{\partial u}{\partial t} - c\Delta u = 0,$$
$$u_{t=0} = u_0,$$
$$u_{t=1}.$$

Learning and PDE (or ODE)

$$\frac{\partial u}{\partial t} - c\Delta u = 0,$$

$$u_{t=0} = u_0,$$

$$u_{t=1}.$$

Advantages of this "Model Data Coupling" Approach

- Embeds scientific and/or business knowledge
- Allows AI in a Small Data context
- Allows AI in a Big Data context as well
- Allows AI in a Heterogeneous Data context
- Can accompany transition from Small to Big Data

Drawbacks of this "Model Data Coupling" Approach

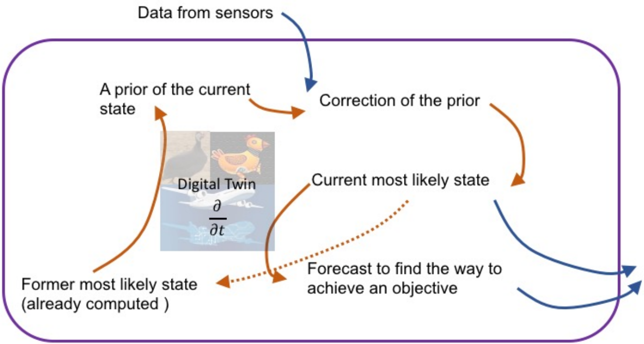
Demands working a bit more than just integrating existing API or functions

Yet, even more: Data Assimilation

When

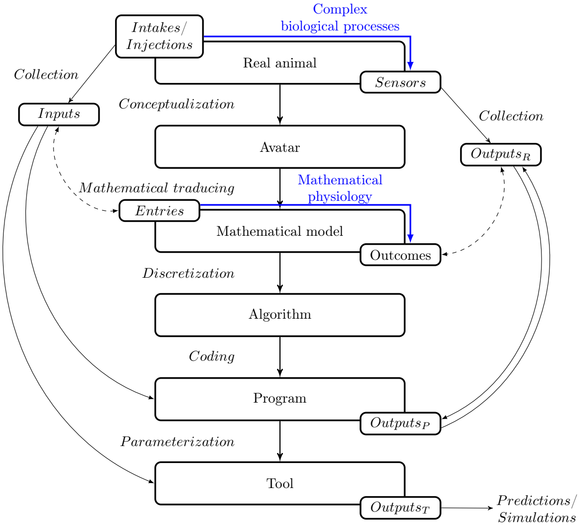
$$\frac{\partial}{\partial t}$$

Numerical Twin for Data Assimilation:



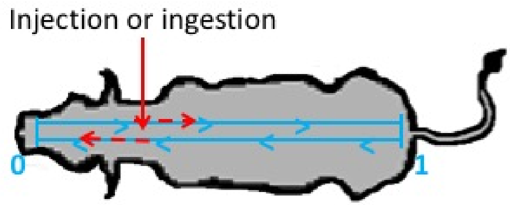
Real Animal, Avatar & Involved PDE

Avatar


Complex biological processes
Intakes/ Injections
Real animal
Sensors
Collection
Inputs
Conceptualization
Collection
Avatar
Outputs$_R$
Mathematical traducing
Mathematical physiology
Entries
Mathematical model
Outcomes
Discretization
Algorithm
Coding
Program
Outputs$_P$
Parameterization
Tool
Outputs$_T$
Predictions/ Simulations

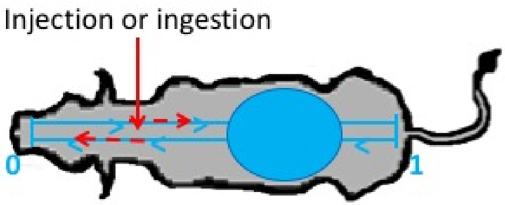
Avatar

$t \in [0, \infty)$, $\mathbf{x} \in (0, 1)$



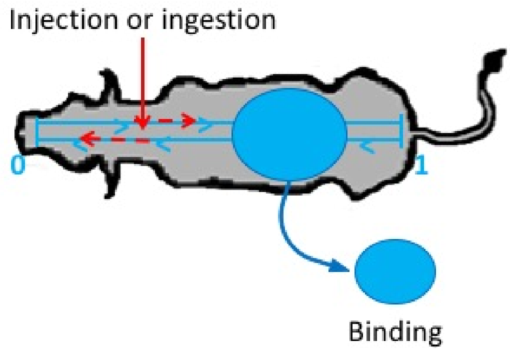
Avatar

$t \in [0, \infty)$, $\mathbf{x} \in (0, 1)$



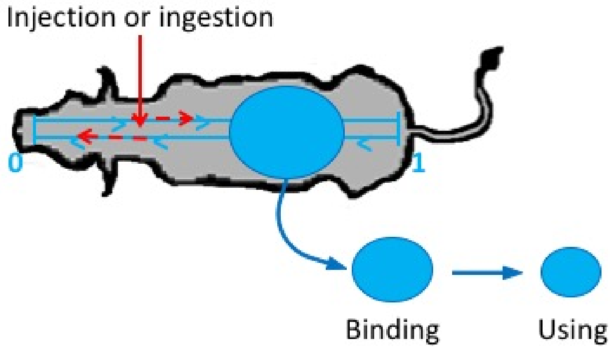
Avatar

$t \in [0, \infty)$, $\mathbf{x} \in (0, 1)$



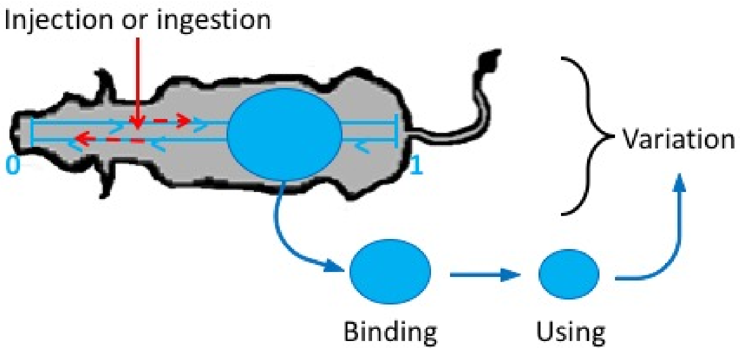
Avatar

$t \in [0, \infty)$, $\mathbf{x} \in (0, 1)$



Avatar

$t \in [0, \infty)$, $\mathbf{x} \in (0, 1)$



Involved PDE - 1

$$\frac{\partial\{\Phi_f(\mathrm{d})\}}{\partial t}(t,\mathbf{x})+\omega_{\mathrm{d}}\frac{\partial\{\Phi_f(\mathrm{d})\}}{\partial \mathbf{x}}(t,\mathbf{x})-\frac{\partial\left[c_{\mathrm{d}}\chi\frac{\partial\left[\{\Phi_f(\mathrm{d})\}+\{\Phi_b(\mathrm{d})\}\right]}{\partial \mathbf{x}}\right]}{\partial \mathbf{x}}(t,\mathbf{x})$$
$$=\frac{1}{2}\{Q(\mathrm{d})\}(t,\mathbf{x})-f_{\mathrm{d}}\{F(\mathrm{d})\}(\mathbf{x})\{\Phi_f(\mathrm{d})\}(t,\mathbf{x})-r_{\mathrm{d}}\{\Phi_f(\mathrm{d})\}(t,\mathbf{x}), \quad (1)$$

$$\frac{\partial\{\Phi_b(\mathrm{d})\}}{\partial t}(t,\mathbf{x})-\omega_{\mathrm{d}}\frac{\partial\{\Phi_b(\mathrm{d})\}}{\partial \mathbf{x}}(t,\mathbf{x})-\frac{\partial\left[c_{\mathrm{d}}\chi\frac{\partial\left[\{\Phi_f(\mathrm{d})\}+\{\Phi_b(\mathrm{d})\}\right]}{\partial \mathbf{x}}\right]}{\partial \mathbf{x}}(t,\mathbf{x})$$
$$=\frac{1}{2}\{Q(\mathrm{d})\}(t,\mathbf{x})-f_{\mathrm{d}}\{F(\mathrm{d})\}(\mathbf{x})\{\Phi_b(\mathrm{d})\}(t,\mathbf{x})+r_{\mathrm{d}}\{\Phi_f(\mathrm{d})\}(t,\mathbf{x}) \quad (2)$$

$$\frac{\partial\{\Psi(\mathrm{d})\}}{\partial t}(t,\mathbf{x})=f_{\mathrm{d}}\{F(\mathrm{d})\}(\mathbf{x})\left[\{\Phi_f(\mathrm{d})\}+\{\Phi_b(\mathrm{d})\}\right](t,\mathbf{x})$$
$$-u_{\mathrm{d}}\{\Psi(\mathrm{d})\}(t,\mathbf{x}). \quad (3)$$

Involved PDE - 2

$$\frac{\partial\{\Xi(\mathrm{d})\}}{\partial t}(t,\mathbf{x}) = u_{\mathrm{d}}\{\Psi(\mathrm{d})\}(t,\mathbf{x}), \tag{4}$$

or

$$\frac{\partial\{\Xi(\mathrm{d})\}}{\partial t}(t,\mathbf{x}) = u_{\mathrm{d}}\{\Psi(\mathrm{d})\}(t,\mathbf{x})\left(\frac{L_{\mathrm{d}} - \{s(\mathrm{d})\}(t)}{L_{\mathrm{d}}}\right), \tag{5}$$

$$\{s(\mathrm{d})\}(t) = \int_{\Omega(\mathrm{d})} \{\Xi(\mathrm{d})\}(t,\mathbf{x})\, d\mathbf{x}. \tag{6}$$

$(\Omega(\mathrm{d}) = (0,1))$

Involved PDE - 3

Input : $\{Q(\mathtt{d})\}$ Output : $\{s(\mathtt{d})\}$

Boundary conditions :

- Diffusion is made evanescent near 0 and 1 via χ.
- $\{\Phi_f(\mathtt{d})\} = \{\Phi_b(\mathtt{d})\}$ in 0 and $\{\Phi_b(\mathtt{d})\} = \{\Phi_f(\mathtt{d})\}$ in 1.
- Not needed for $\{\Psi(\mathtt{d})\}$, $\{\Xi(\mathtt{d})\}$ and $\{s(\mathtt{d})\}$

Initial conditions :

- Everything at 0
- Or at the right value when the process is in progress

Application : Predict the weight of a farm animal at the end of a fattening period

Data

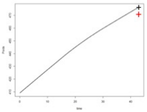
- First Farm
  - 7 animals
  - Weight at
    - Beginning
    - After 29 days
    - After 64 days
    - After 105 days
  - Feed consumption
- Second Farm
  - 8 animals
  - Weight at
    - Beginning
    - After 42 days
  - Feed consumption

Small Data context
Then :

- Reduce the number of parameters : $f_{\mathtt{d}}$, $u_{\mathtt{d}}$ and $L_{\mathtt{d}}$
- Implementation of a "sampling" or "bootstrap" method

First use case - Setting

- Ajusted parameters : f_{d}, u_{d} and L_{d}
- "Sampling" or "bootstrap" method: 7 adjustments on 6 animals of the First Farm
- Fitting function for the Learning : Weights after 29 days, 64 days and 105 days
- Test on the 8 animals of the Second Farm : Weight after 42 days



First use case - Results

Parameter Adjustment

	-5588	-5595	-6097	-7672	-9852	-6100	-7664
f_d	5,5	5,4	6,1	5,6	5,5	5,7	5,6
L_d	800	800	782	800	772	781	780
u_d	1	0,98	1	1	0,57	0,61	0,72

Variance relative	moyenne
0,01	5,63
0,18	787,86
0,05	0,84

Test :

id	J0	J42	Pred42	Erreur	Erreur relative
5461	414,5	515,5	502,2	-13,3	0,026
7976	427,5	503,5	505,5	2,0	0,004
8987	425,5	505,0	518,5	13,5	0,027
428	411,5	513,5	503,4	-10,1	0,020
3282	419,5	493,0	494,0	1,0	0,002
3719	434,5	507,5	518,7	11,2	0,022
3720	402,5	465,5	479,5	14,0	0,030
5455	392,0	470,0	482,1	12,1	0,026

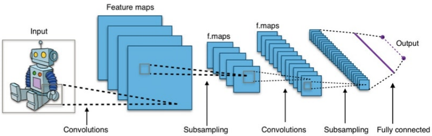
Erreur relative moyenne
1,95%

Second use case

- Ajusted parameters : f_{d}, u_{d} and L_{d}
- Learning on 10 animals (5 from the First Farm, 5 from the Second Farm)
- Fitting function for the Learning :
  - Weights after 64 days of the First Farm
  - Weights after 42 days for animals of the Second Farm
- Test on the 2 animals of the First Farm : Weights after 29 days, 64 days and 105 days
- Accuracy
  - at 29 days: 97%
  - at 64 days: 97%
  - at 105 days: 96%

Mutually Benefiting Interactions PDE - AI

- PDE based Artificial Intelligences (explained in this talk)
- Contribute understanding Deep Learning



- Analyse robustness of software tools via classical Machine Learning