Hybrid Twin

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The context: Industry4.0 & IoT

Component or system

Virtual Twin

Model, Calibration & TF-Based Control

Engineering

Manufacturing

In service

Digital & Hybrid Twin

+ Data for real-time decision making

Augmented Engineering

Manufact4.0

IoT

Data

Parametric model

Calibration

AI-based decision making

Data-Driven Enriched Model

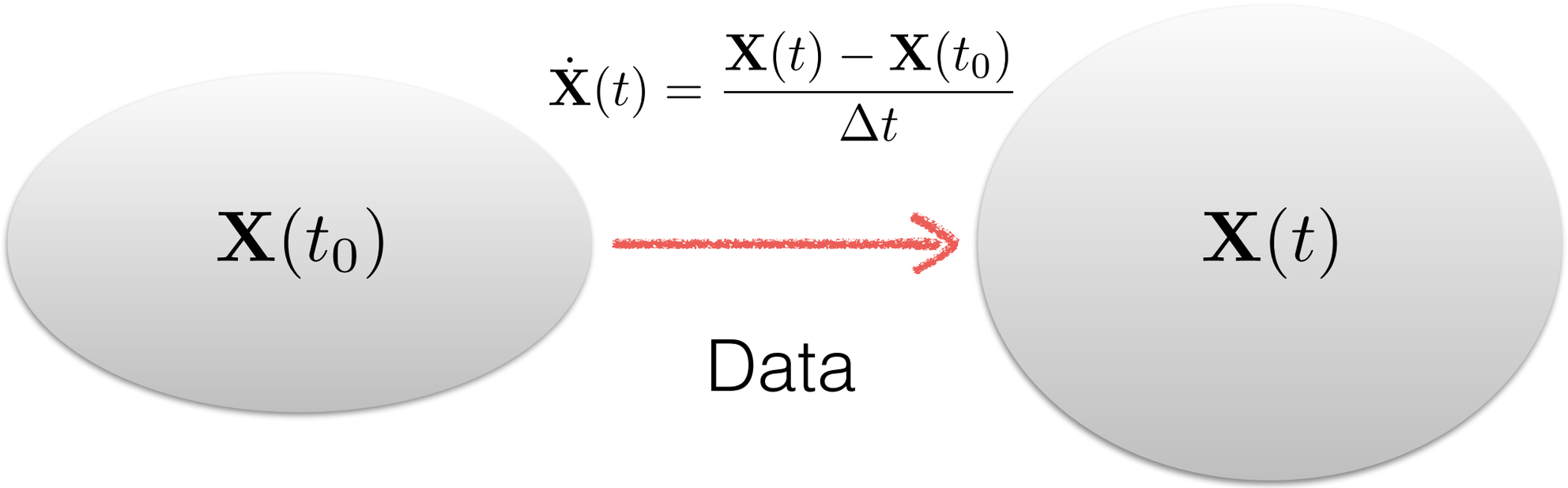
Virtual

Digital

Hybrid

Hybrid Twin

$$\dot{\mathbf{X}}(t) = \frac{\mathbf{X}(t) - \mathbf{X}(t_0)}{\Delta t}$$



Hybrid Model

Parametric model $\dot{\mathbf{X}}^{model}(t)$

Ignorance $\dot{\mathbf{X}}(t) - \dot{\mathbf{X}}^{model}(t)$

Data-Based
Divergence Model

What is needed?

- Real-time simulation
- Real-time calibration
- Real-time data-assimilation
- Real-time data-completion
- Real-time data-analytics
- Real-time data-driven modeling
- Real-time decision making

Real-time simulation via MOR

FEM

$$u(x,t) \approx \sum_{i=1}^{\mathtt{N}} U_i(t) N_i(x)$$

$$\mathbf{KU} = \mathbf{F}$$

POD

learning $\longrightarrow$ $\phi_i(x),\ i = 1, \cdots, \mathtt{R}$

$$u(x,t) \approx \sum_{i=1}^{\mathtt{R}} u_i(t) \phi_i(x)$$

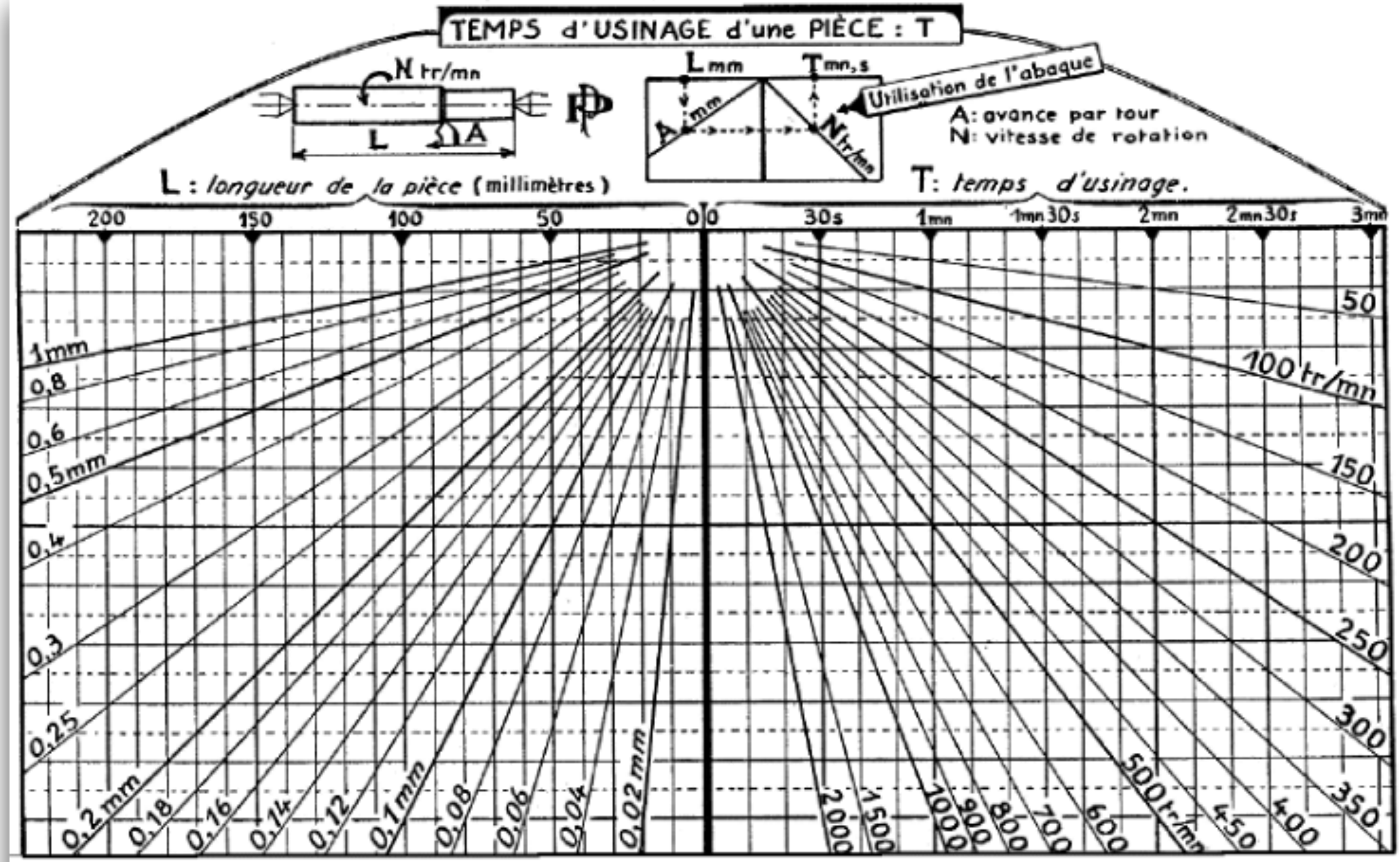
$$\mathbf{ku} = \mathbf{f}$$

PGD

$$u(x,t) \approx \sum_{i=1}^{\mathtt{M}} T_i(t) X_i(x)$$

Vademecum $u(x,t,p) \approx \sum_{i=1}^{\mathtt{M}} T_i(t) X_i(x) P_i(p)$

Machining vademecum



Parametric solutions in action

$$u(x,t,p) \approx \sum_{i=1}^{\mathtt{M}} T_i(t) X_i(x) P_i(p)$$

Almost

- Real-time simulation
- Real-time optimization
- Real-time inverse analysis
- Real-time uncertainty propagation
- Real-time control

Non-Intrusive PGD-based meta-modeling

Commercial software

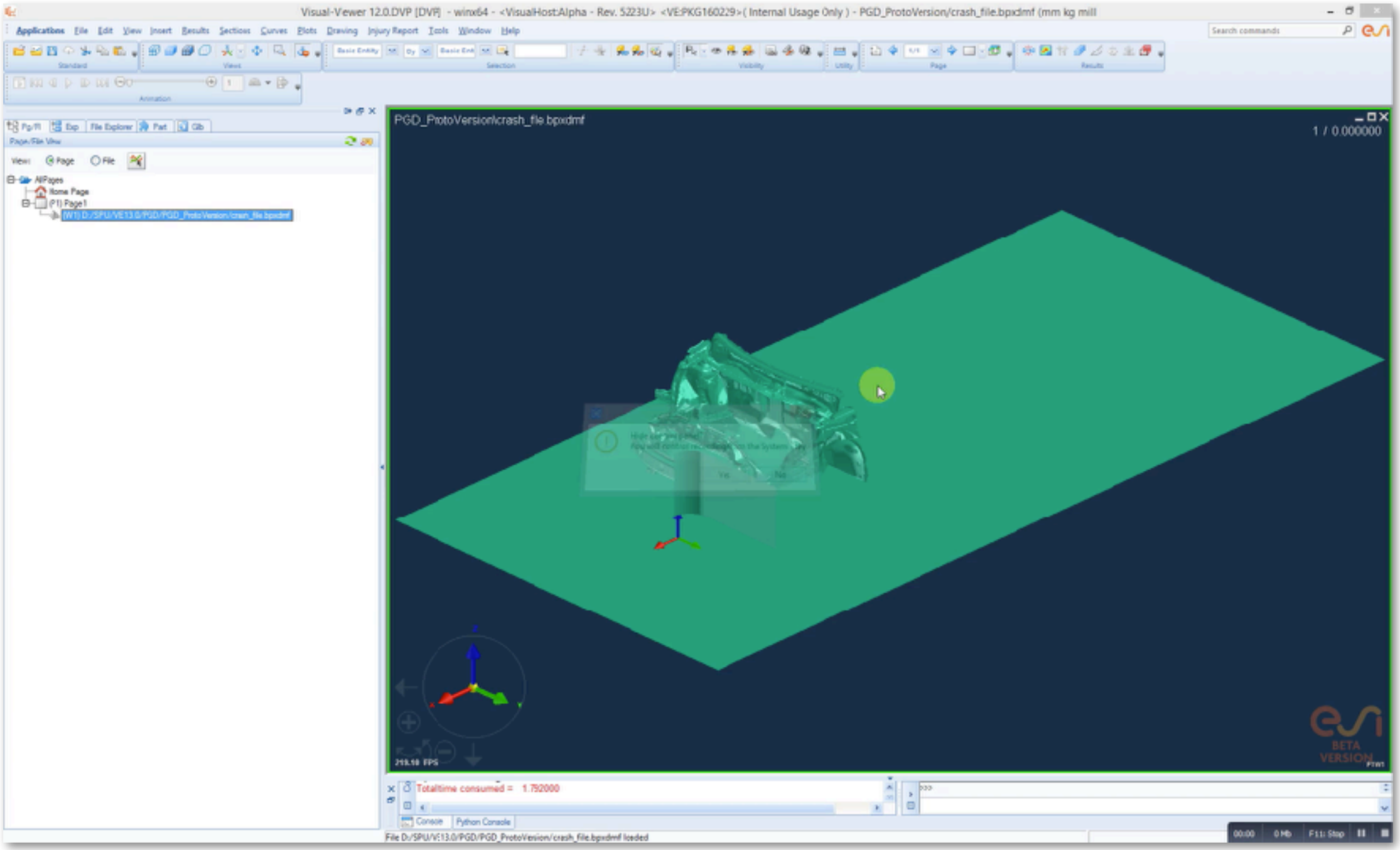
SSL, sPGD, NI-PGD, IPGD, …

Parametric solutions

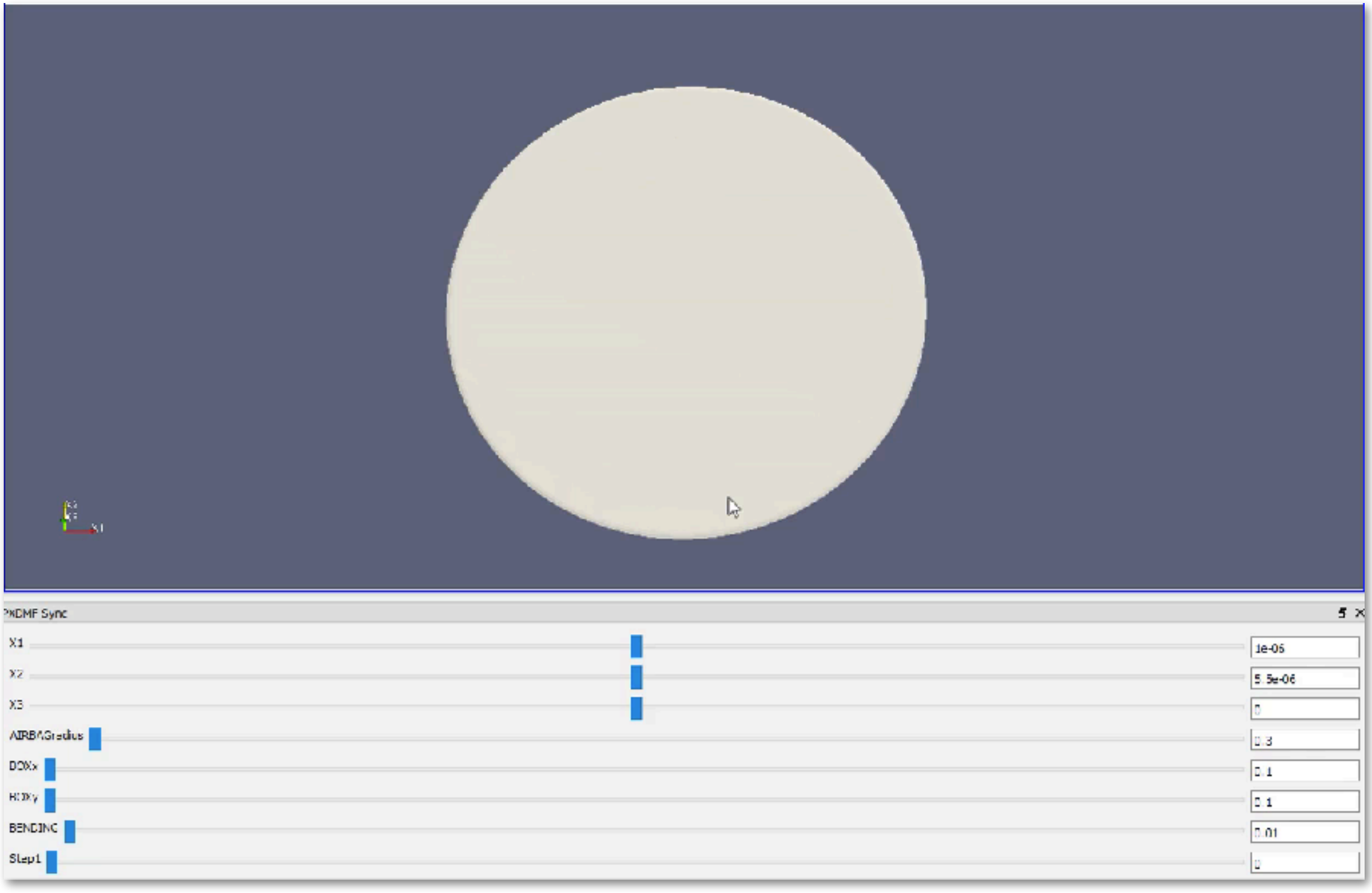
$$u(x,t,p) \approx \sum_{i=1}^{\mathtt{M}} T_i(t) X_i(x) P_i(p)$$

Vademecum

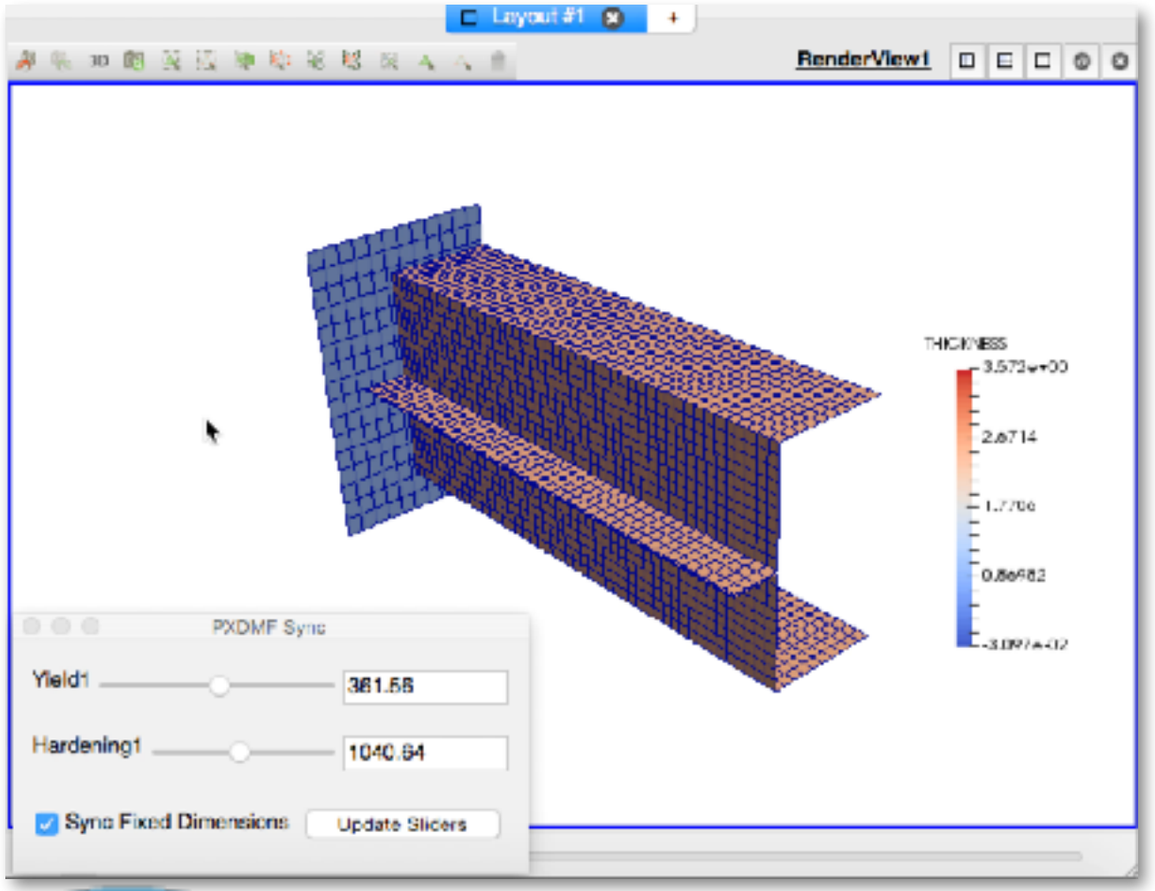
PAM-CRASH-based vademecum

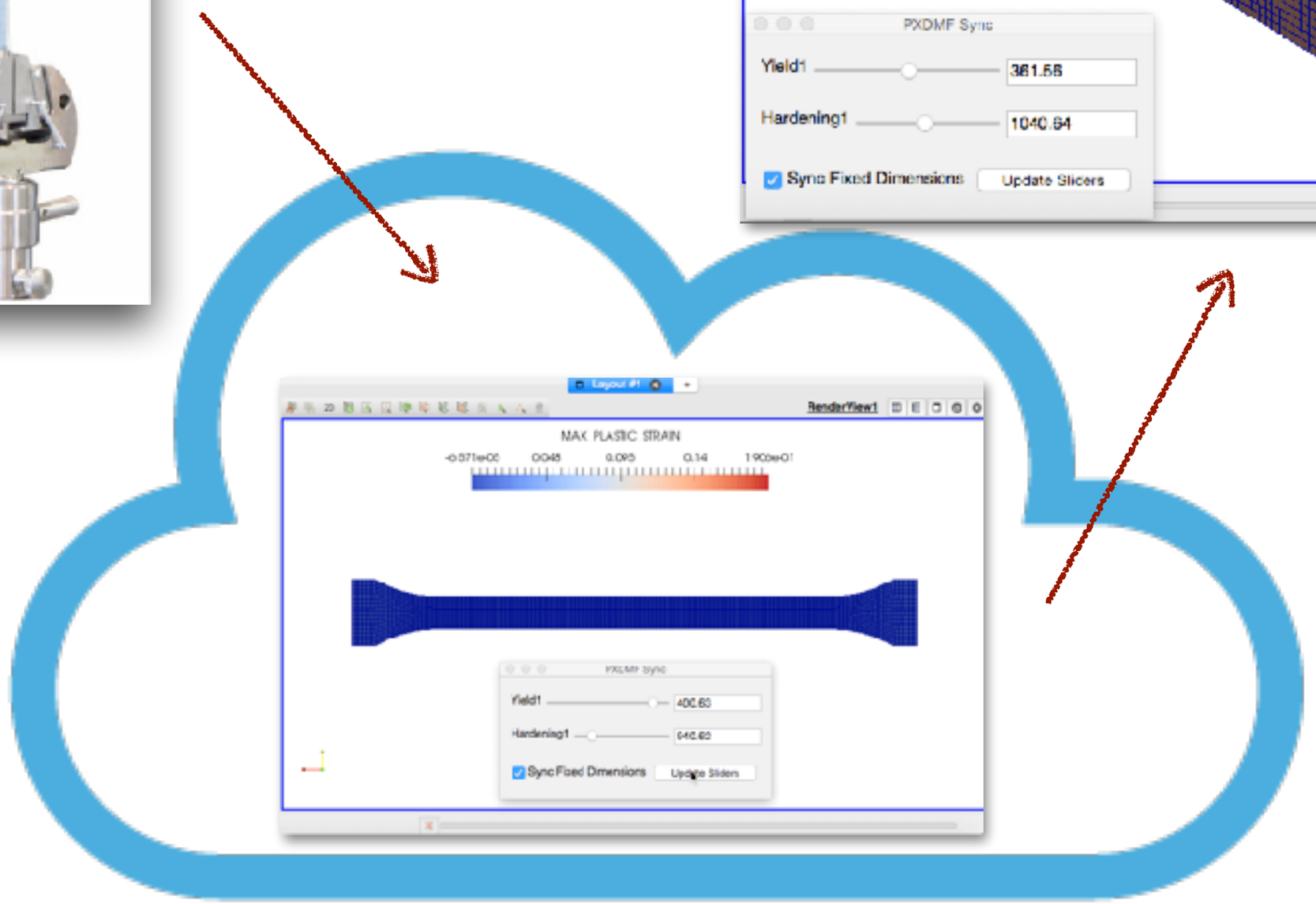


AIRBAG-based vademecum



Real-Time Calibration





Real-Time Data-Based Model Learners

What is a model?

the relation between inputs and outputs

$$\begin{pmatrix} K_{11} & K_{12} & \cdots & K_{1N} \\ K_{21} & K_{22} & \cdots & K_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ K_{N1} & K_{N2} & \cdots & K_{NN} \end{pmatrix} \begin{pmatrix} U_1 \\ U_2 \\ \vdots \\ U_N \end{pmatrix} = \begin{pmatrix} F_1 \\ F_2 \\ \vdots \\ F_N \end{pmatrix}$$

Model Output Input

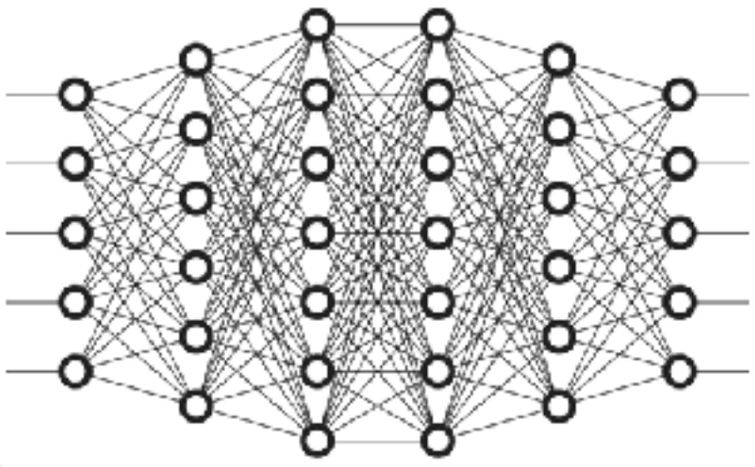
When the model is known

Given **U** compute **F:** $\mathbf{KU} = \mathbf{F}$

Given **F** compute **U:** $\mathbf{U} = \mathbf{K}^{-1}\mathbf{F}$

Usual model-based simulation tools

When model is unknown:
Deep learning

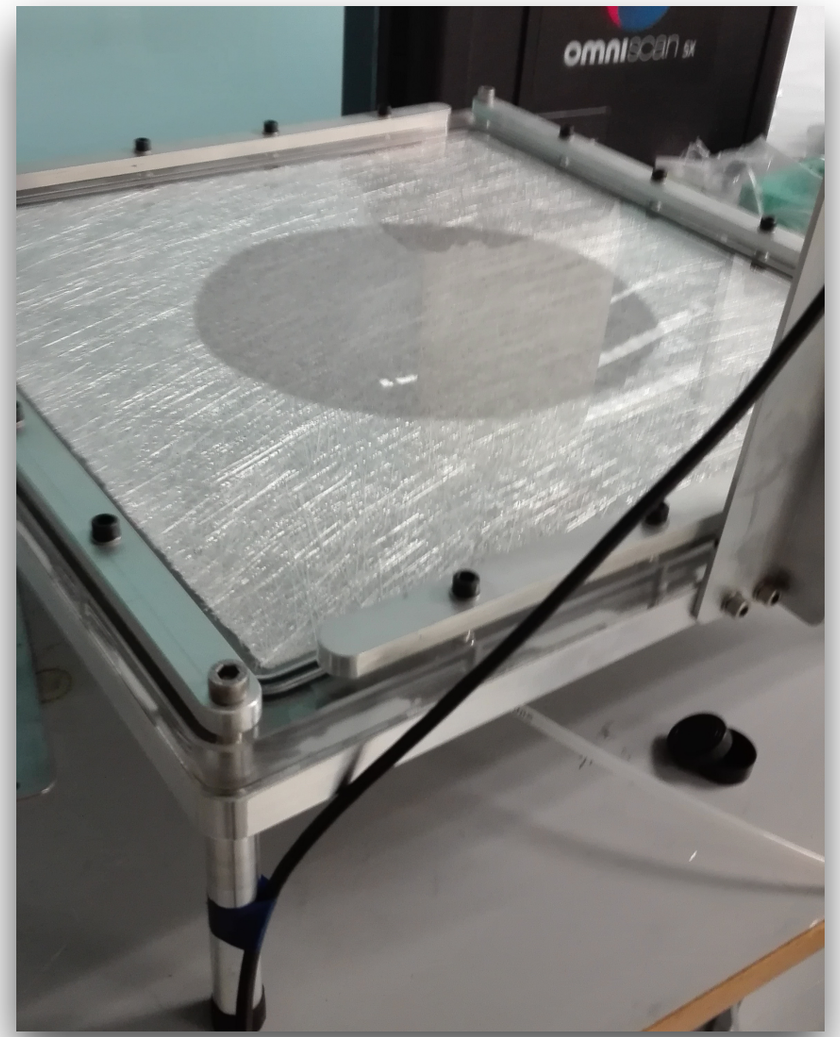


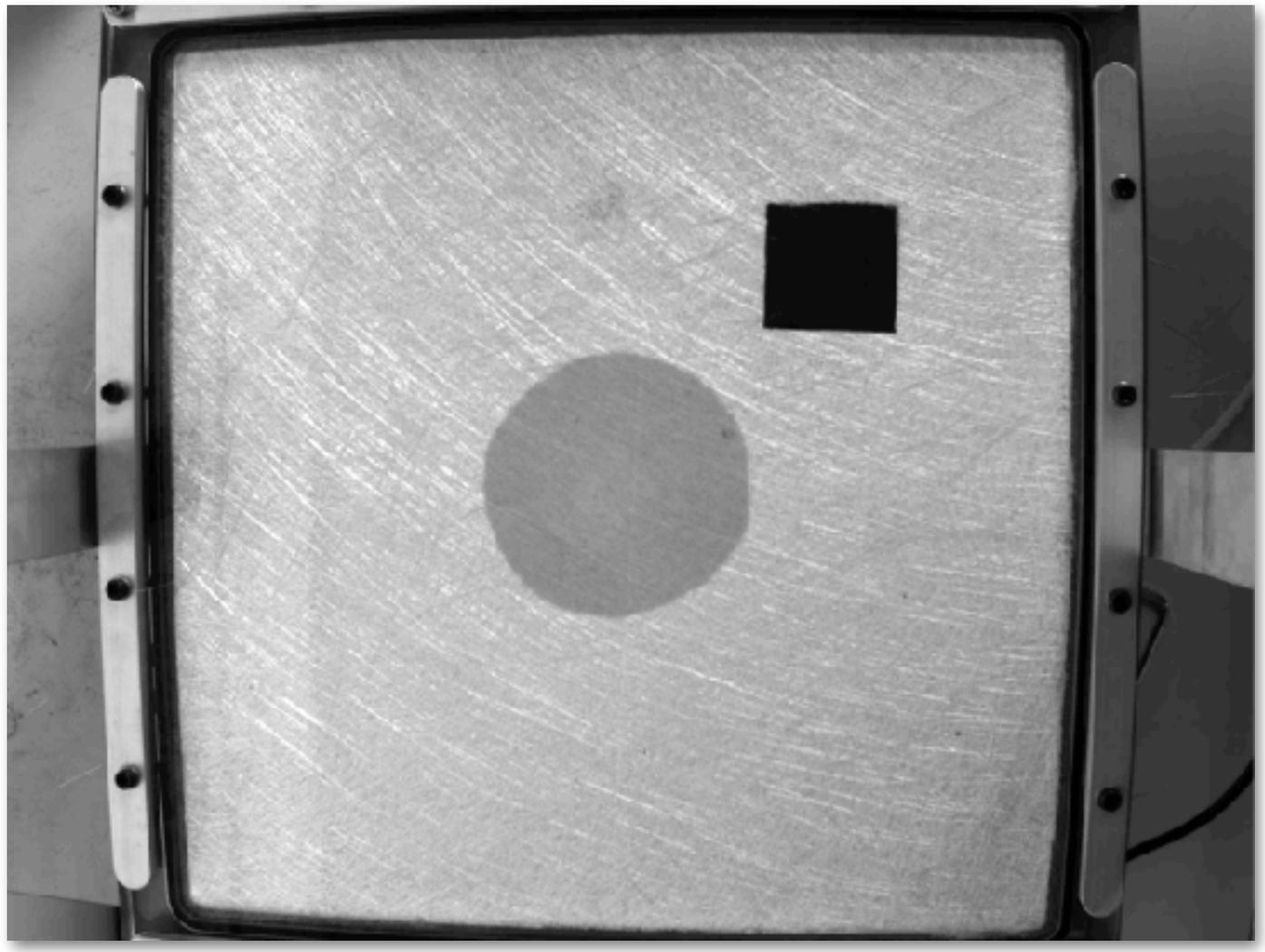
Pro: it provides in general very good predictions

Con: Physical foundations

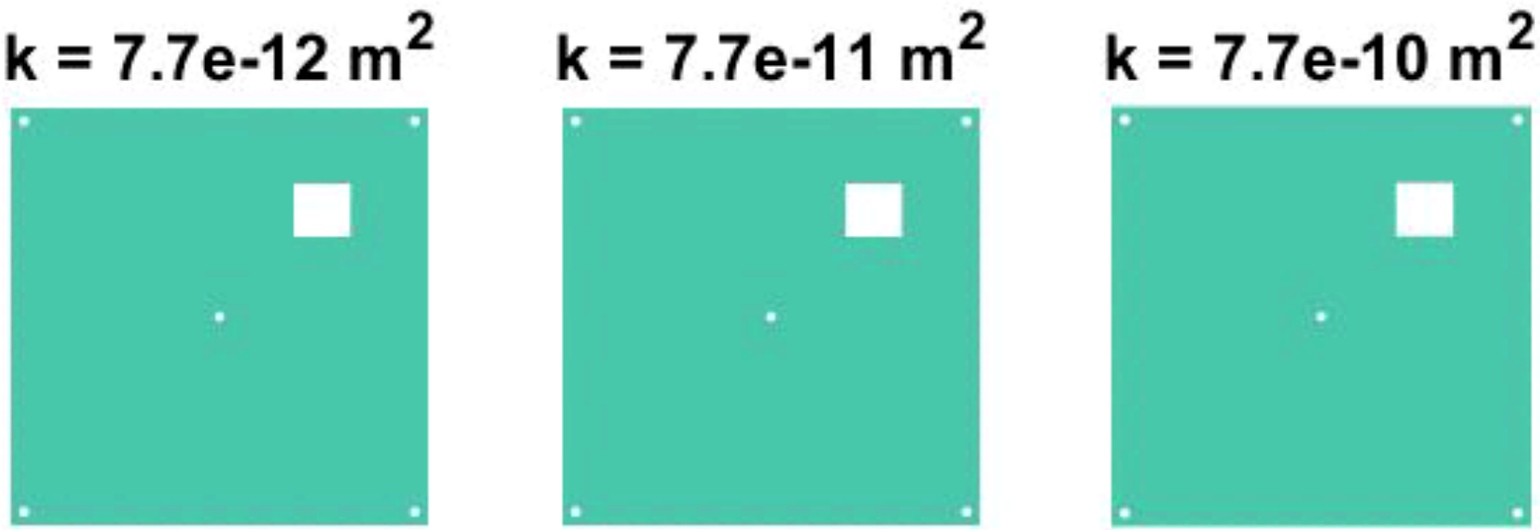
Resin Transfer Moulding

$$\dot{\mathbf{X}} = \mathbf{A}(\mathbf{X}, t, \boldsymbol{\mu}) + \mathbf{B}(\mathbf{X}, t) + \mathbf{C}(\mathbf{X})$$

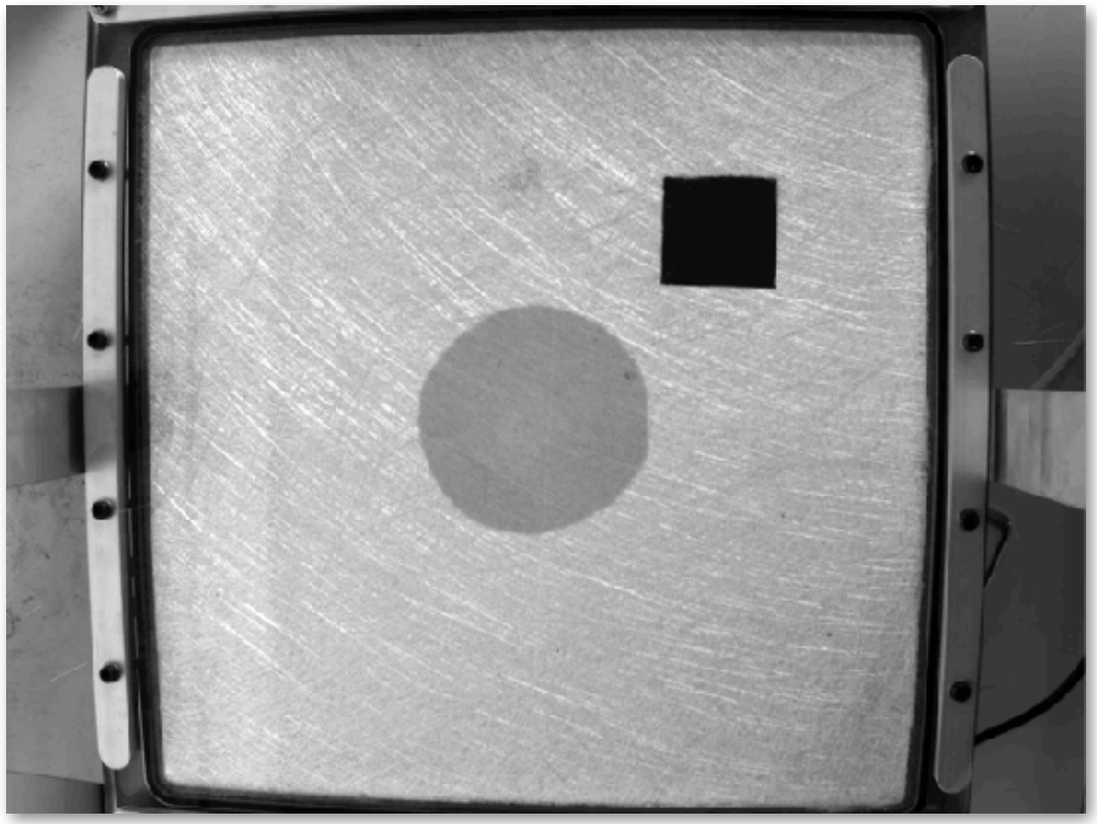


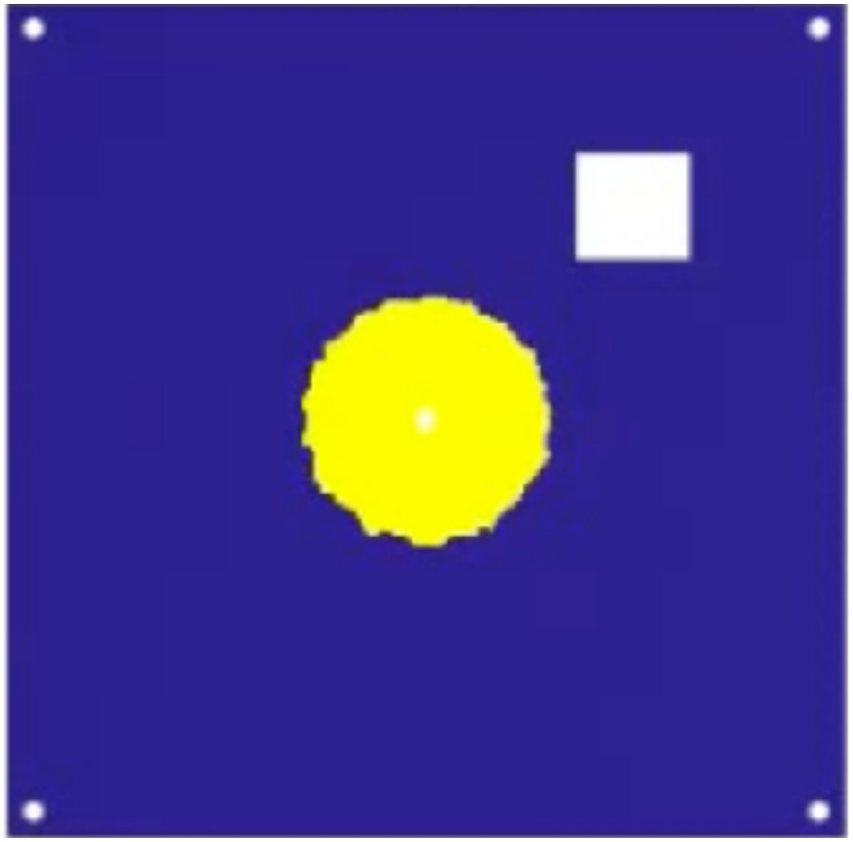


Parametric filling



Data assimilation & Online calibration





Data assimilation

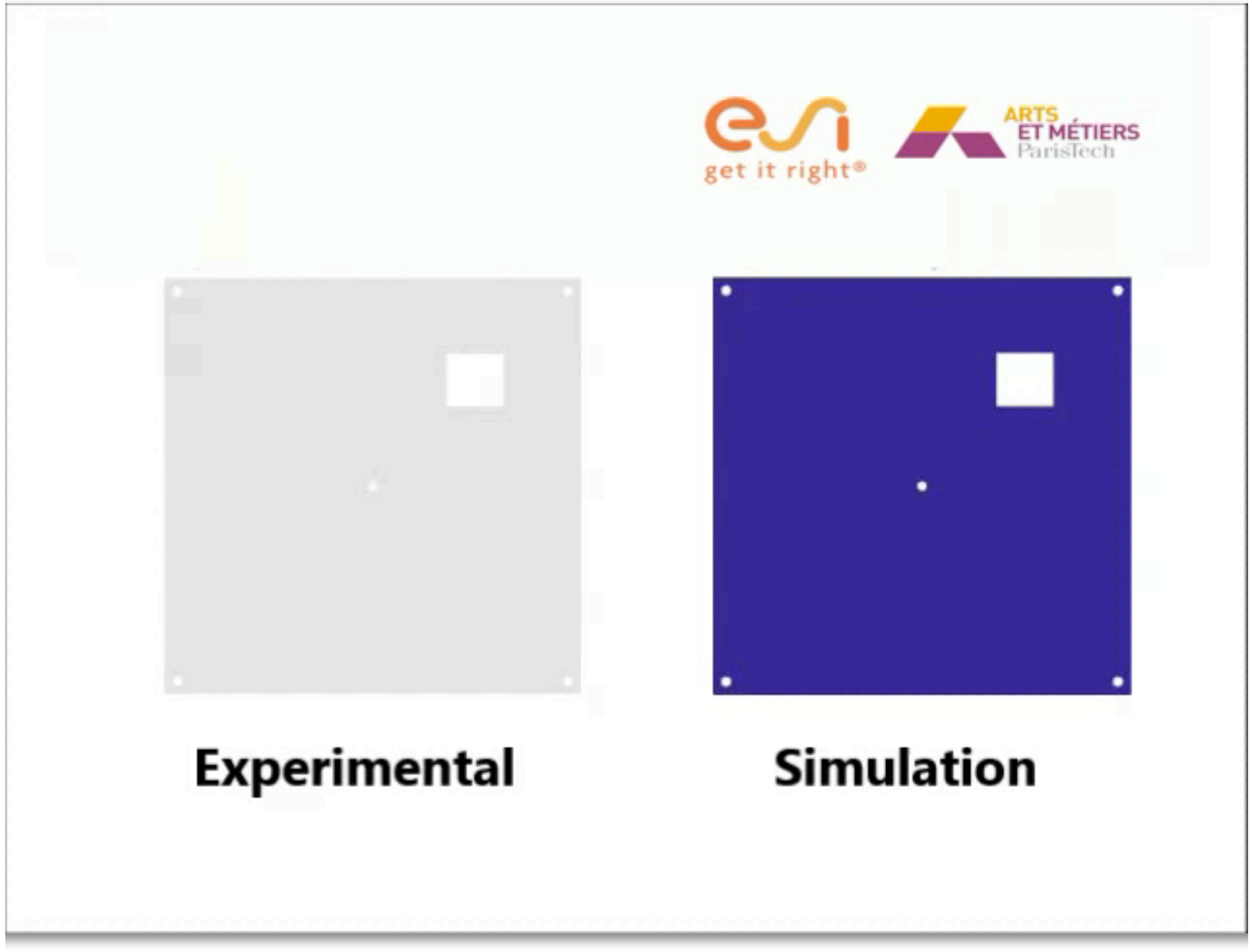
$$k^{ident} = \text{argmin} \left\{ \sum_{e=1}^{E} \sum_{j=1}^{P} \left(I^{num}(\Omega_e, t_j, k) - I^{exp}(\Omega_e, t_j) \right)^2 \right\}$$ & Levenberg-Marquardt

Addressing noise:

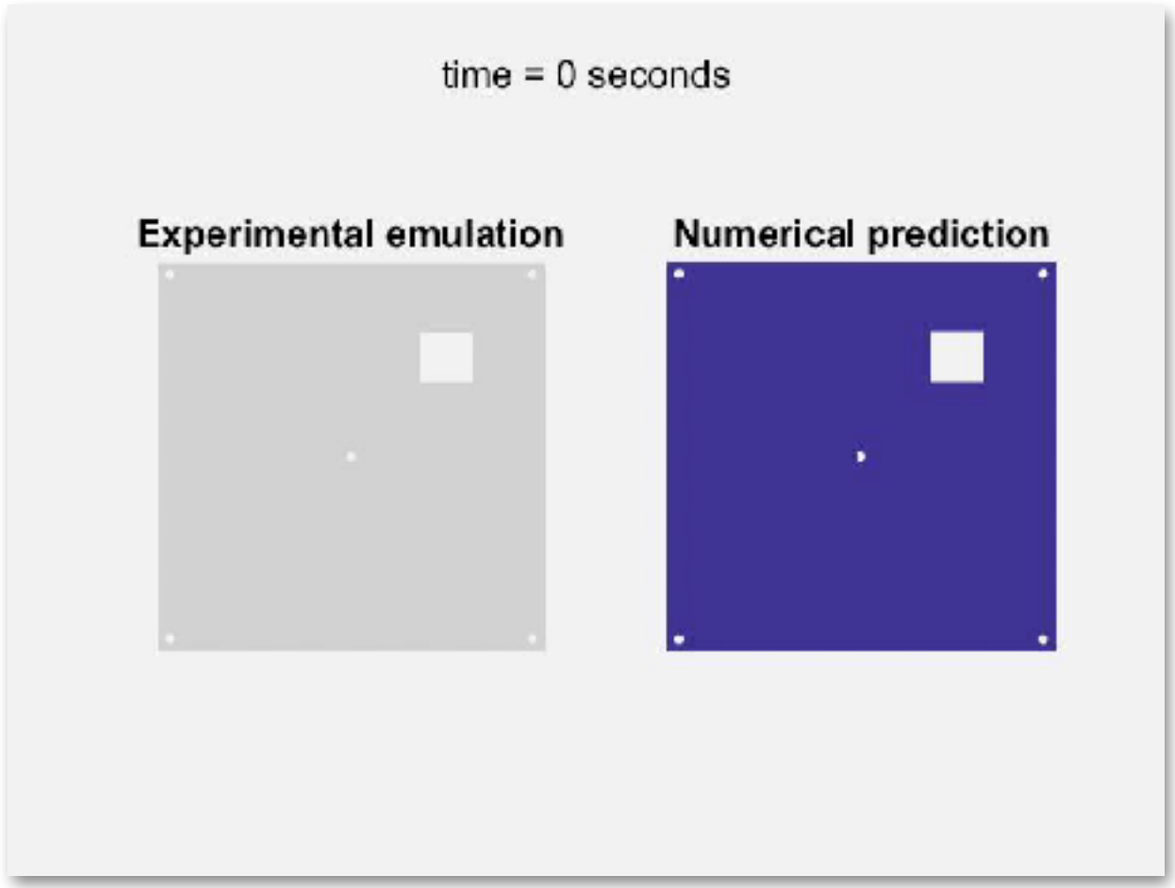
(i) Kalmann filters

(ii) Bayes within a probabilistic framework

Calibrated model

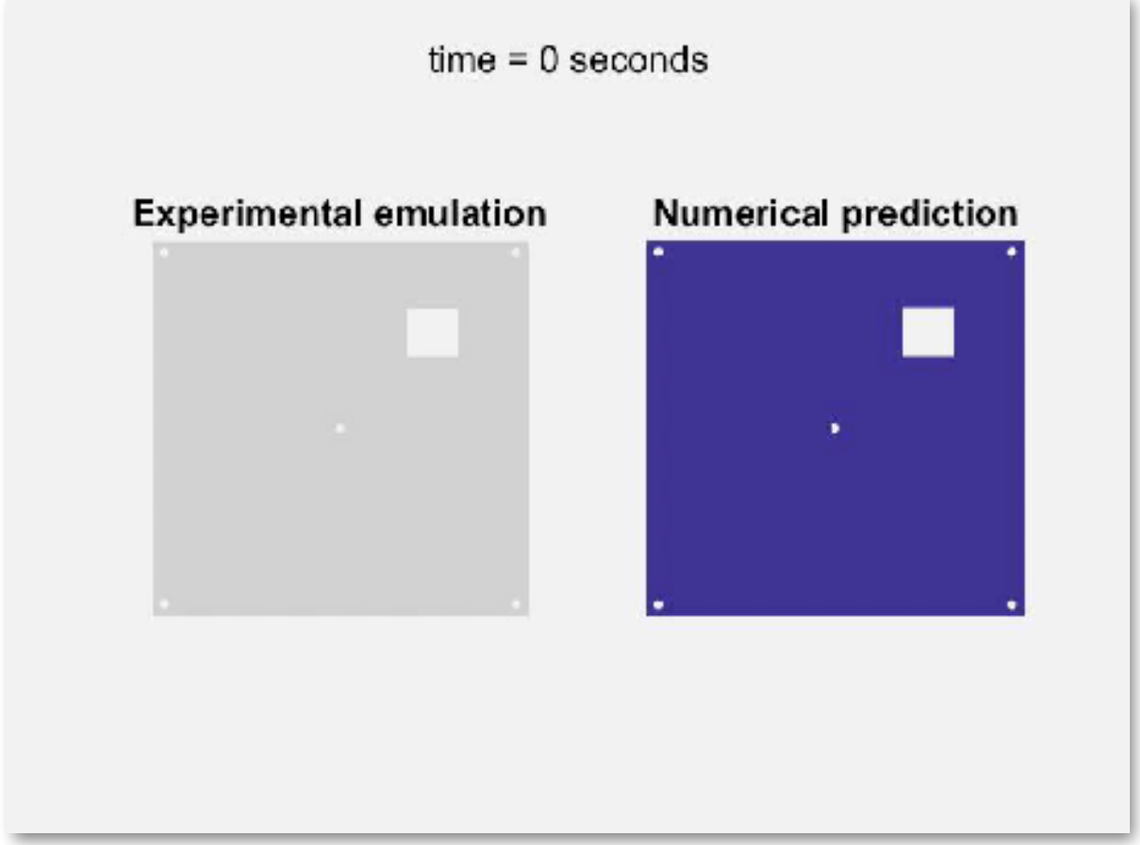


Modeling the ignorance

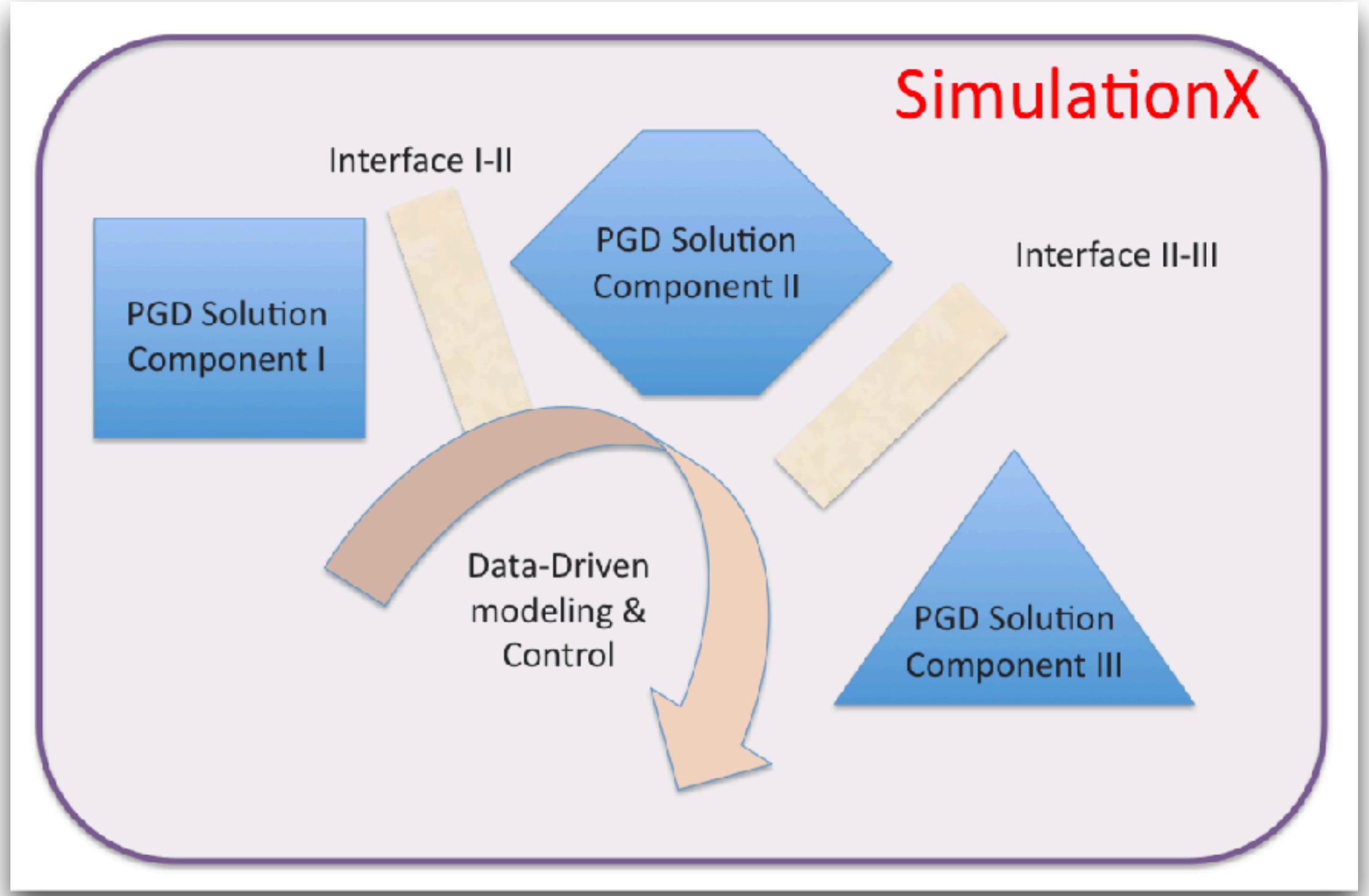


Without correction

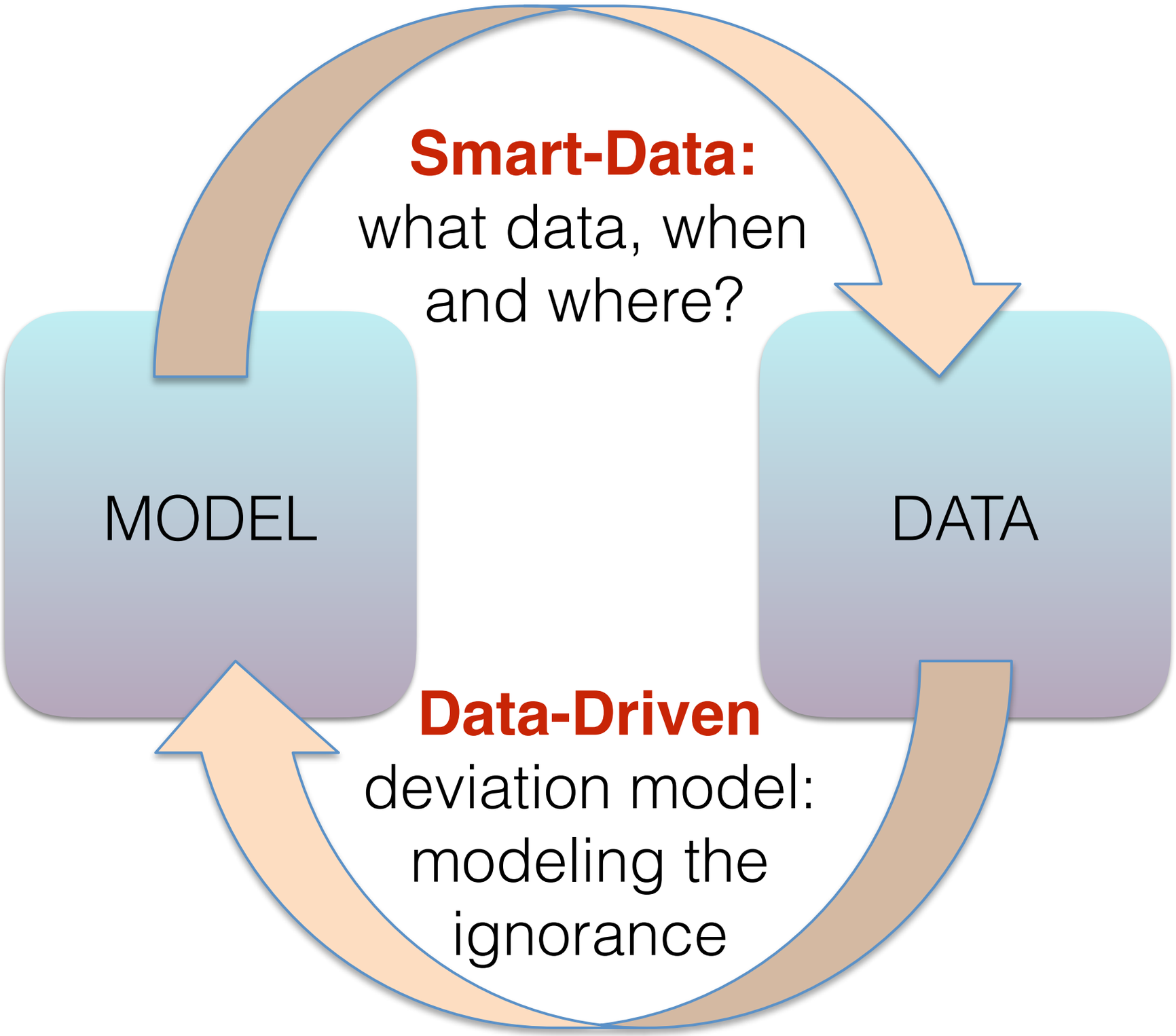
With divergence model



System Modelling



CONLUSIONS & PROSPECTS



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