

AI in Engineering to bring back statistics



16/11/2023 – Phimeca Day

François Deheeger – Senior Fellow AI & Data





Michelin ? A mobility company that also builds tires !

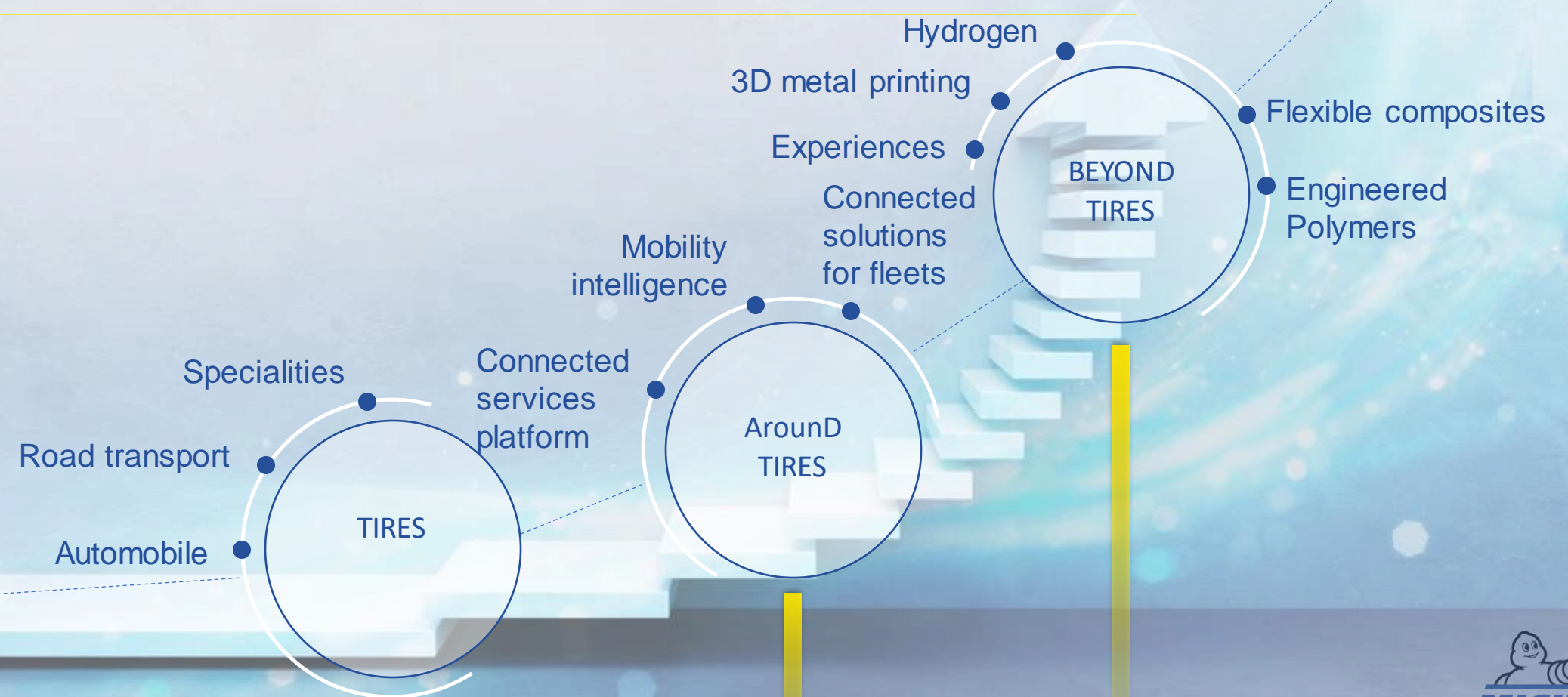


**TIRES WHICH ARE TAILORED
TO OUR CUSTOMERS' NEEDS**



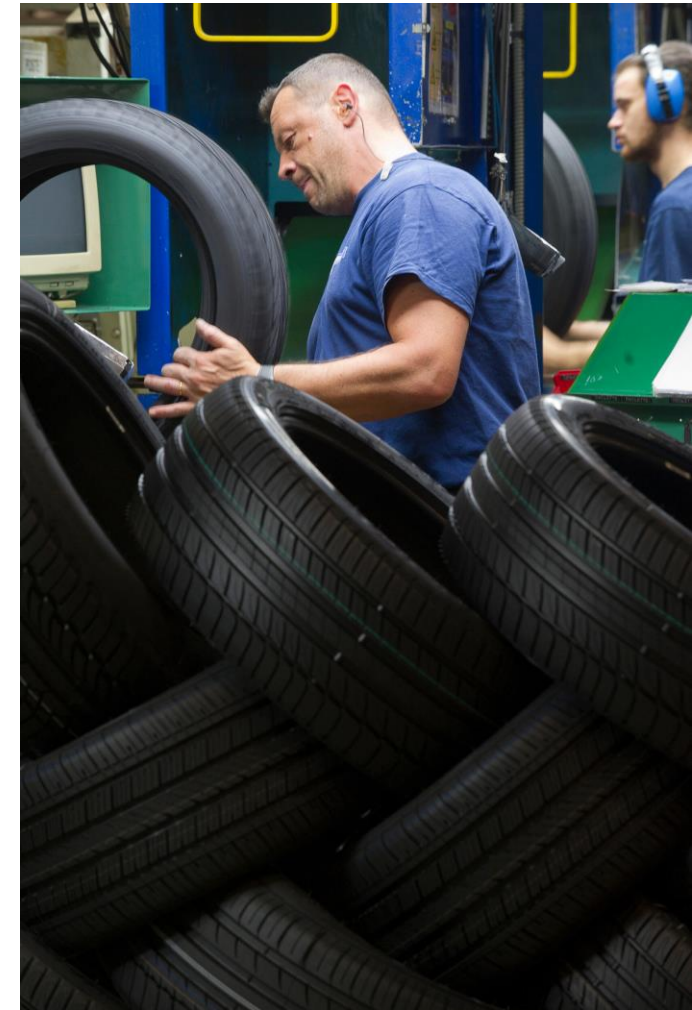
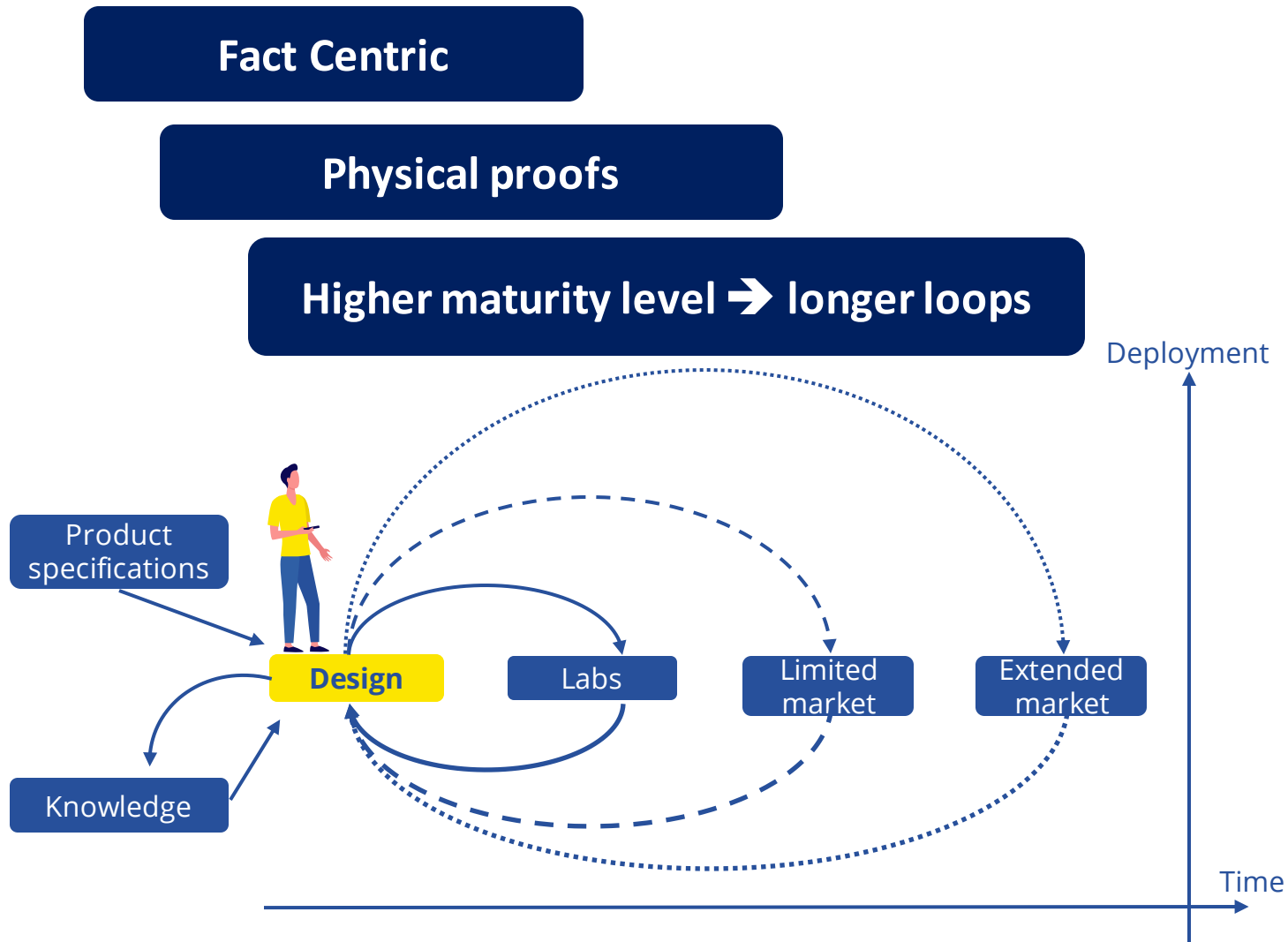


Three domains, for a sustainable growth





Our usual approach to ensure quality products





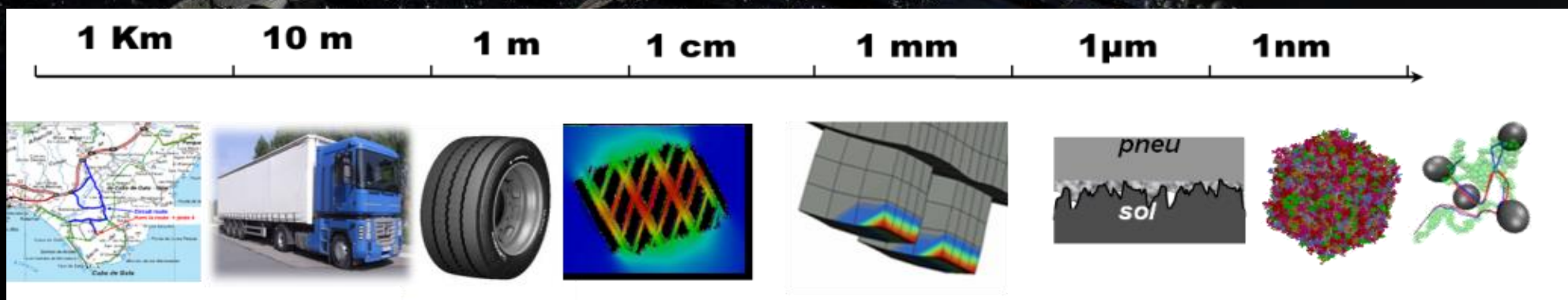
We are doing simulations from molecule to vehicle

Product performance

- virtual tire as a product
- virtual vehicle & tire co-design

Material conception levers

- optimize material recipe
- virtual material for simulation



Services & usage

- predictive maintenance
- real time condition assessment

Tire conception levers

- real-time performance prediction
- early integration of industry constraints



AI models: a key factor to accelerate ... and more

Fact Centric

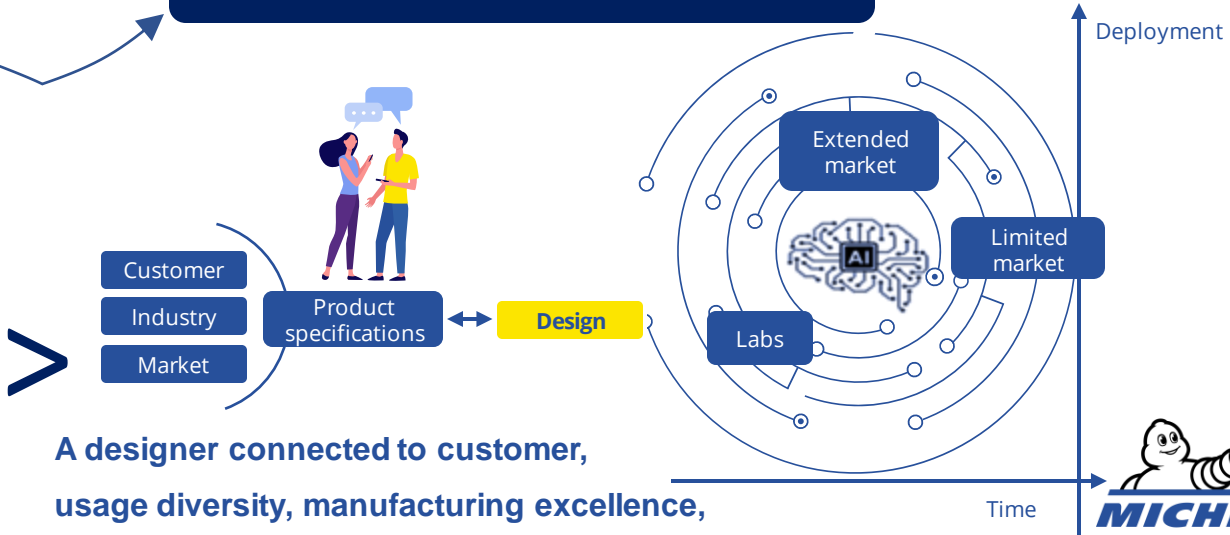
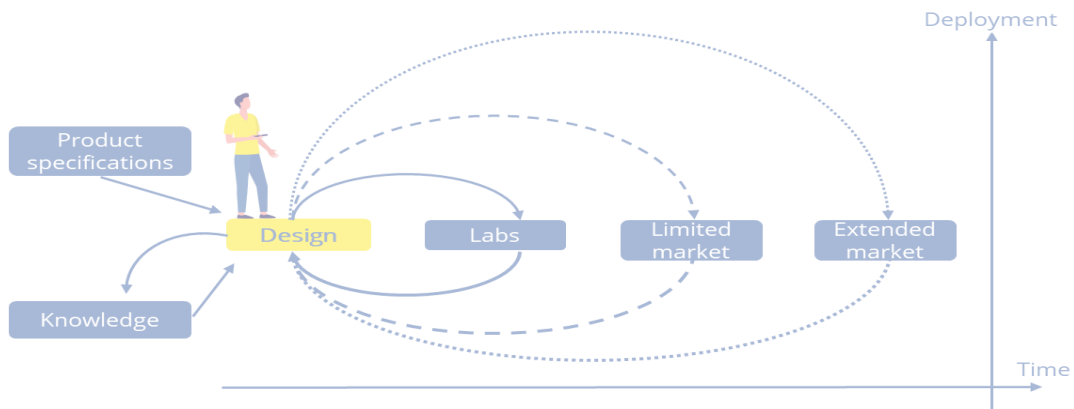
Physical proofs

Higher maturity level → longer loops

Multi factorial

Data Insights

Real Time



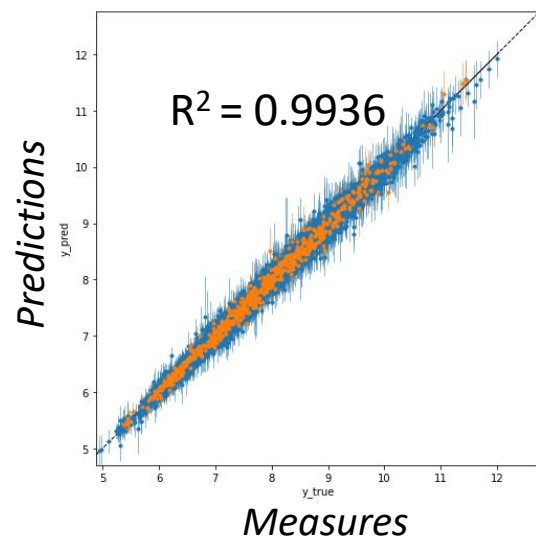
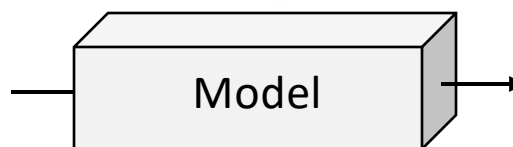
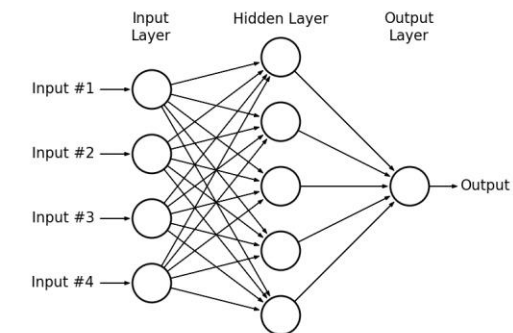
A designer connected to customer, usage diversity, manufacturing excellence, end-to-end



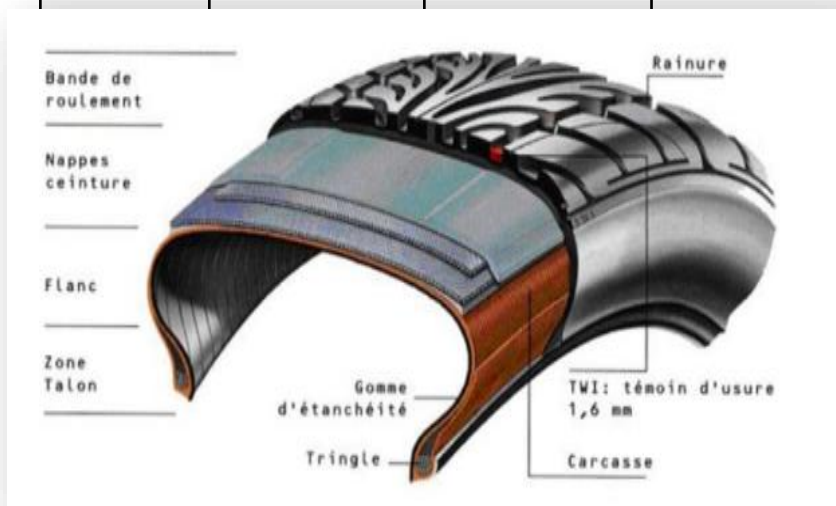


Machine learning applied to product data

ID	Material Id	Geometry	Tread Depth	Sre
1	KM1	0.87	2.7	Sre1
2	KM3	1.4	3.4	Sre3
3	KM1	5.2	5.1	Sre1



ID	RR
1	6.87
2	8.4
3	5.2
4	9.1
5	7.2
6	6.0
7	5.2



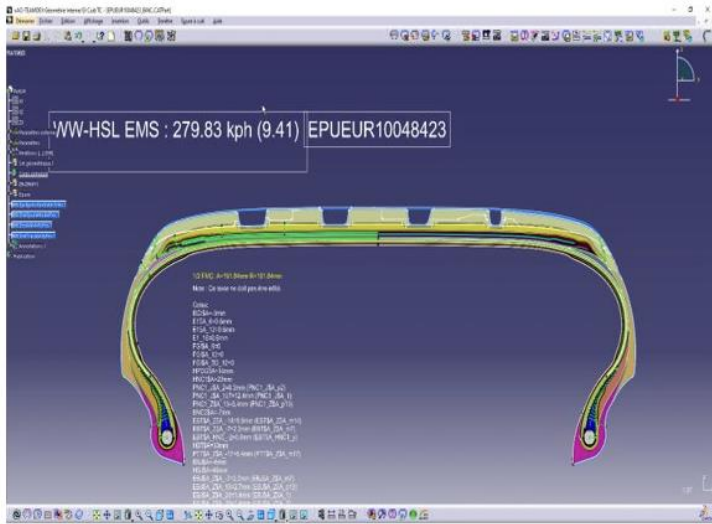
Sre2
Sre6
Sre3
Sre1



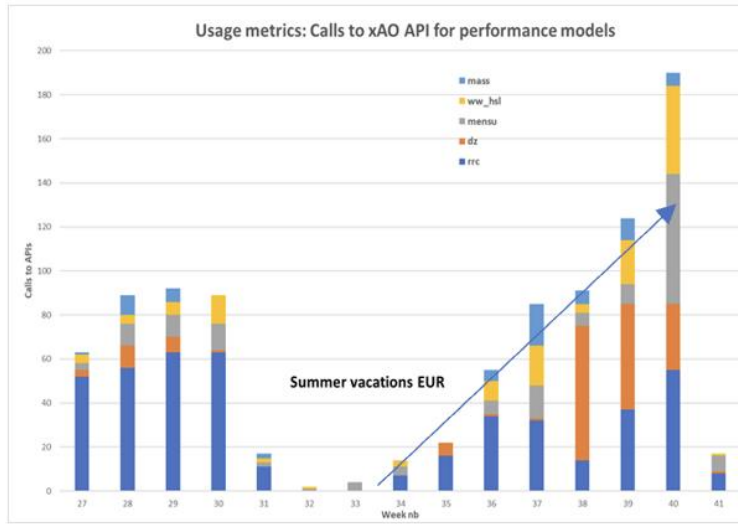


5 AI Models delivered to 250+ B2C Tyre Designers (Dz, RR, HSL, SW/OD, Mass)

Models delivered to CATIA



Weekly Usage growing!



2021

Use-cases consolidation



LOUIS CAPON: “The AI told me that the margin was sufficient in RR and VLI. Without these models, I would have asked for more letters in the factory.”



PATRICK PALLOT: “The AI model is the most accurate model I've had to use”





Great !

***Is that the end
of the story ?***





A systemic technology development

WE NEED to make sure they are good

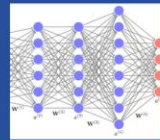
Well, give me a solution

2

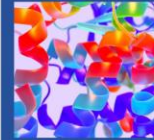
Enable trust-worthy AI solutions for engineers
Through prediction uncertainty and
Exploitation domain assessment

Quantmetry

école _____
normale _____
supérieure _____
paris-saclay _____



CERTIFICATION
EXPLAINABILITY



OPTIMIZATION
GENERATIVE

3

A need to quickly assess the best trade-off
inside a defined perimeter *exploitation*
or beyond *exploration*

école _____
normale _____
supérieure _____
paris-saclay _____

AI for engineering

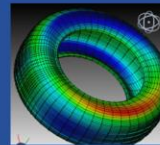
1

Use physics knowledge in AI
Toward hybrid simulation for
accuracy and acceleration

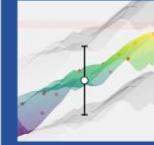


école _____
normale _____
supérieure _____
paris-saclay _____

PRIOR & PHYSICS
KNOWLEDGE



UNCERTAINTY
QUANTIFICATION



Assess solutions robustness with respect
to real use uncertainty: manufacturing, usage,
to predict real life performance. Toward digital twin.



4

Is-this True ?

WE NEED BETTER MODELS





***Let's have a look
at two examples***





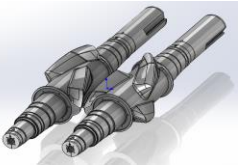
MIMO: a simulation-based decision making assistant for mixing line process



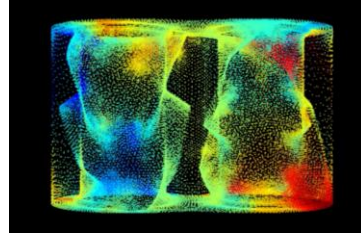
Choose a factory ; Define process parameters ; Analyse mix. properties



≈ 100 mix designers & industrializers users WW



Modelling of rubber internal mixer is **inaccurate** but **fast (minutes)**

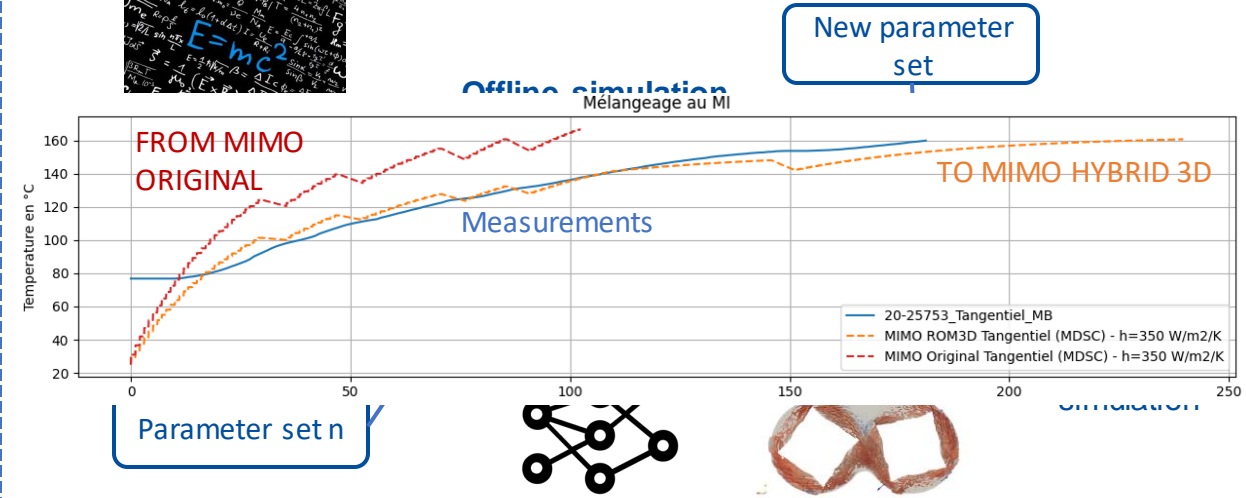
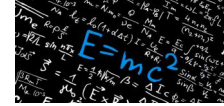


3D physics-based simulations are **accurate** but **slow (days)**

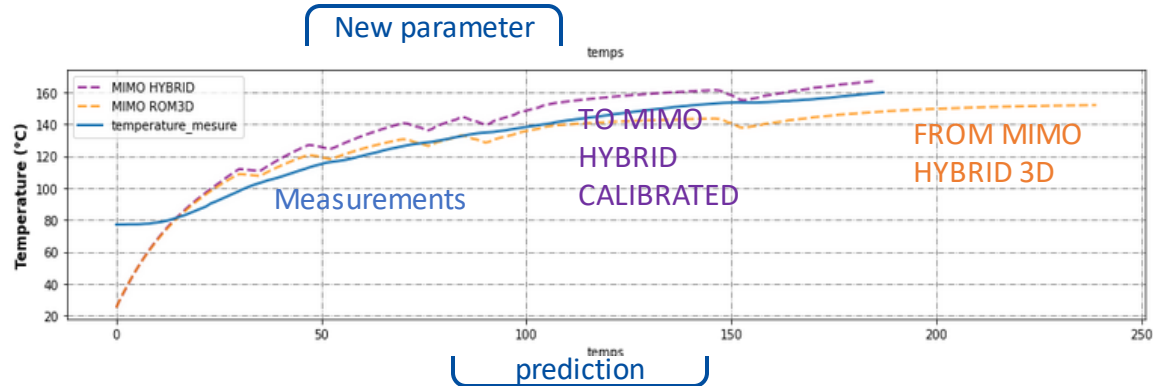
Lead by P. Tremblay

Reduce cost and industrialization delays with augmented simulation

Modelling trade-off: use 3D simulation as a data generator for machine learning



Still possible to improve modelling using process measurements



Advanced research (3 last years) opens the way to MIMOV2

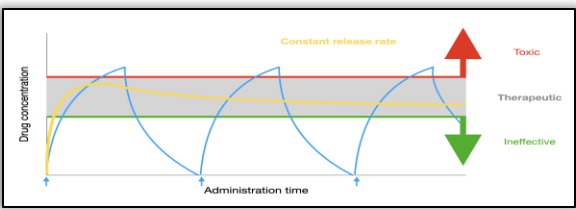


- K. Hayes (DORD/MAT) & P. Tremblay (PM/MAT): “3D hybrid models will allow us to assess the **impact of rotor geometry** and define accurate **mixing criteria**”
- **Prediction time compatible** with the needs of MIMO’s user community





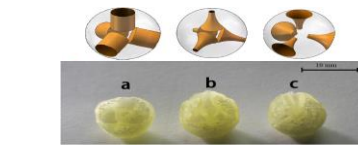
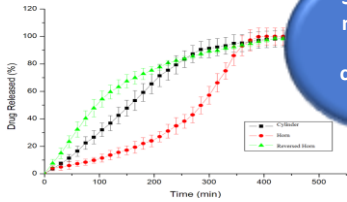
Controlled Release of Active Pharmaceutical Ingredients



SOLESIS

Poly-(Glycerol Sebacate) based implant

Shape as a new lever for controlled release

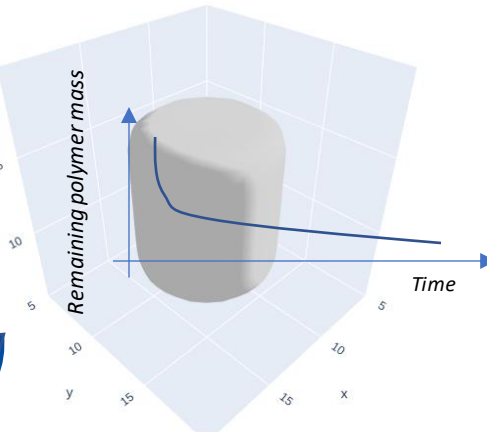
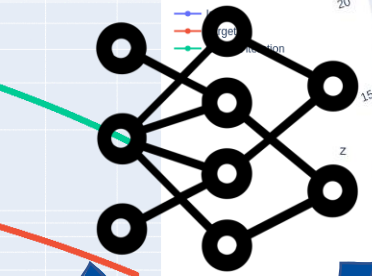
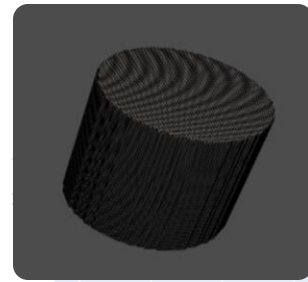


implant shape drive the release kinetics

Xu, X., Zhao, J., Wang, M., Wang, L., & Yang, J. (2019). 3D printed polyvinyl alcohol tablets with multiple release profiles. Scientific reports, 9(1), 1-8.

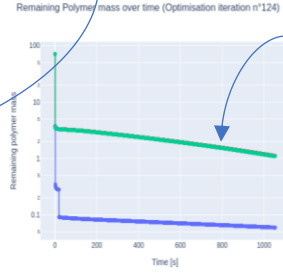
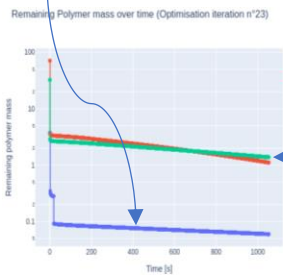
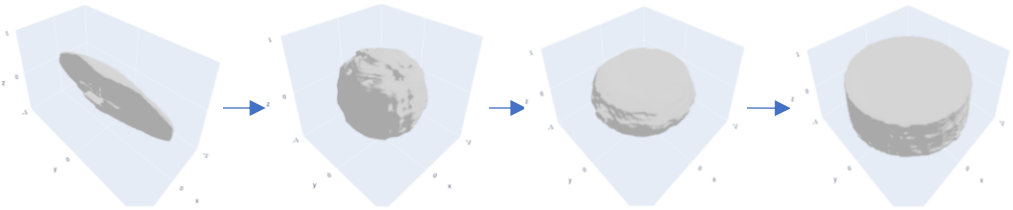
Generative design, an example

Remaining Polymer mass over time (Optimisation iteration n°1)



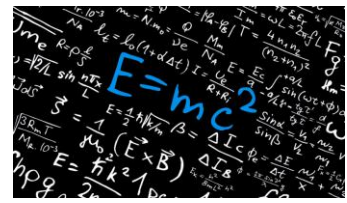
SOLESIS: discovering medical implants optimal shape

Navigate through different shapes



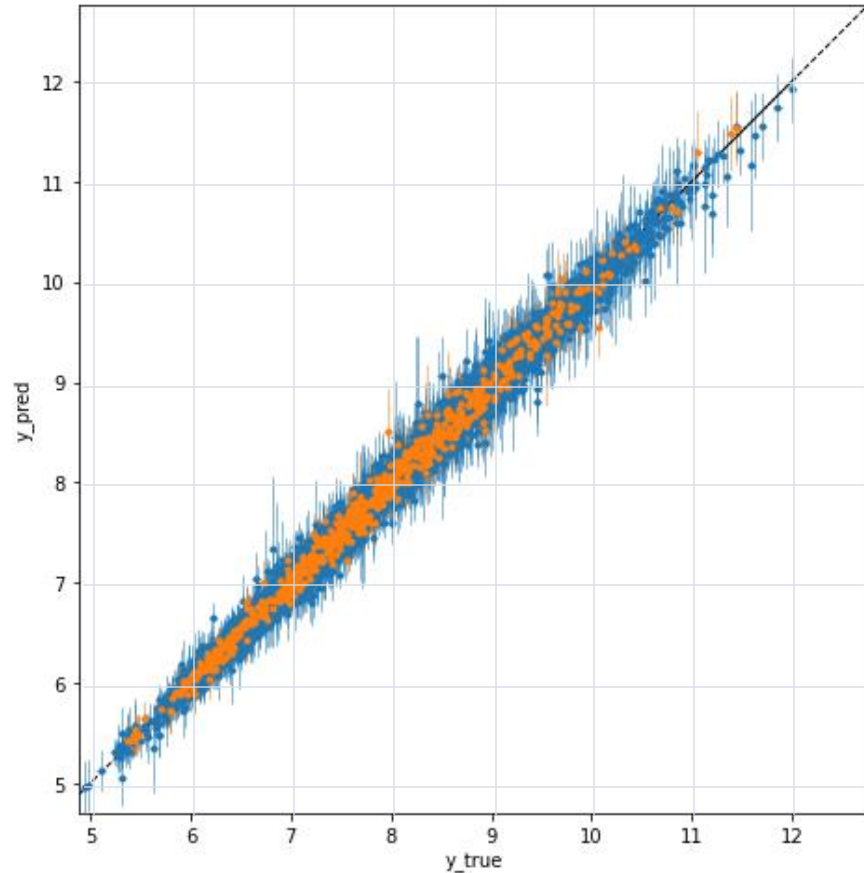
What's next ?

- ⊙ Fast shape optimization is one keyboard away
- ⊙ Can be used by anyone (especially non numerical experts)
- ⊙ Pluggable in physics-based solvers
- ⊙ Generative design to target other applications:
 - Tire design
 - Belts
 - Materials





«All models are wrong, but some are useful »



- ⊙ We all have ideas on how to compute the score of a model...
- ⊙ But for homologation of the model, what is the right population to estimate error ?
 - the historical data ?
 - balanced by market coverage ?
 - balanced by future sales ?

Quality with AI models requires to go beyond R^2

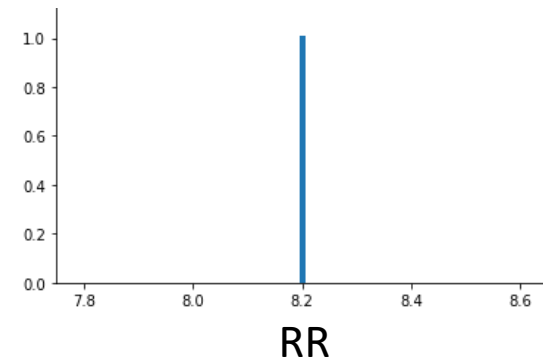
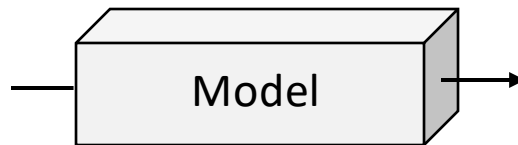




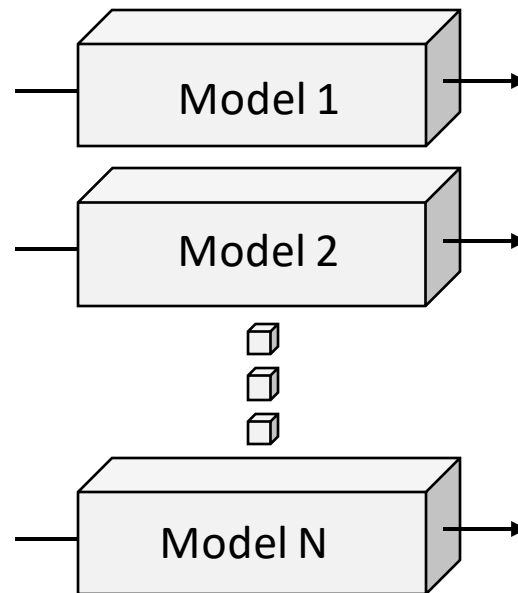
And... usually we build N AI models

ID	KM	Xao ...	Hsre	sre
1	KM1	0.87	2.7	Sre1

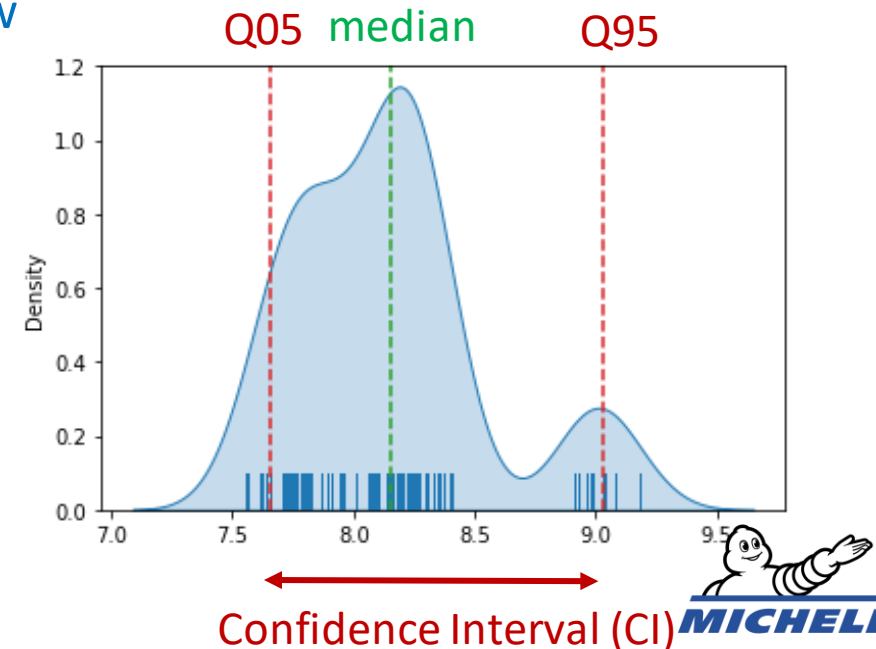
From Single point of view



To an ensemble point of view



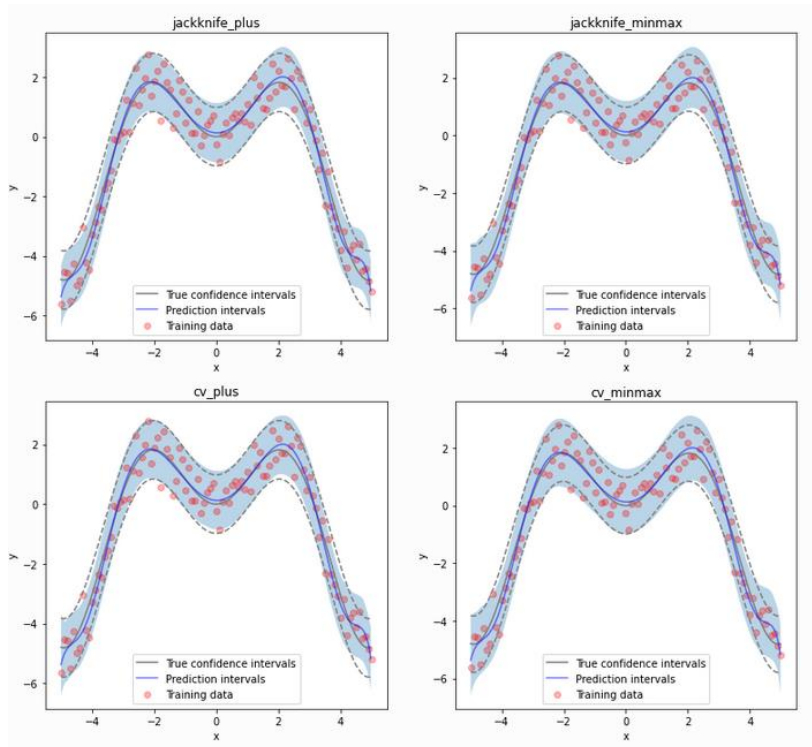
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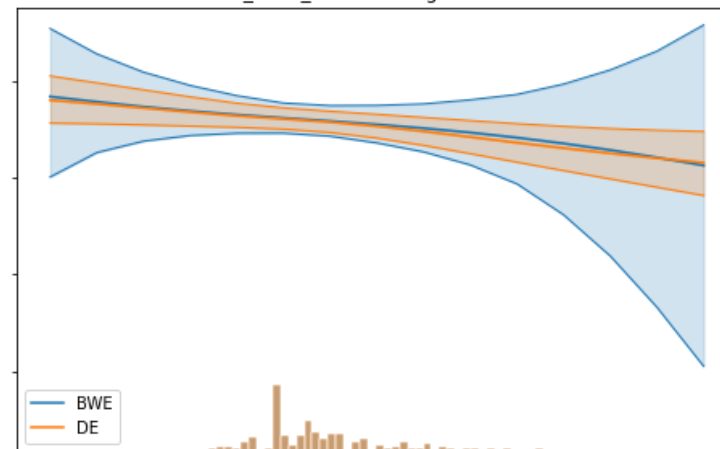
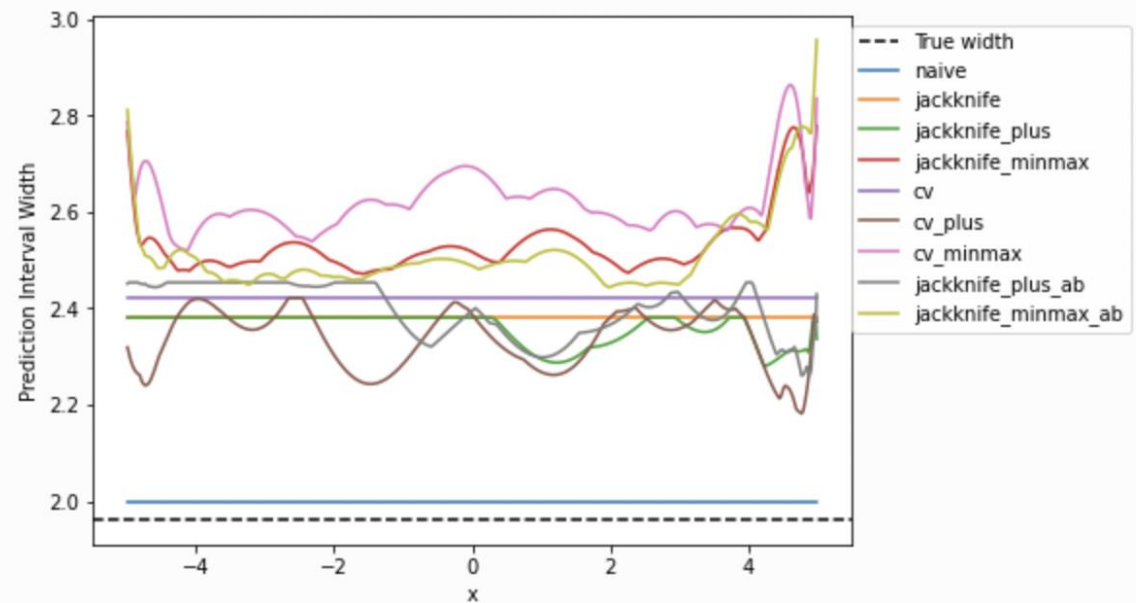


Assess quality from uncertainty approaches

Can we use local uncertainty ?



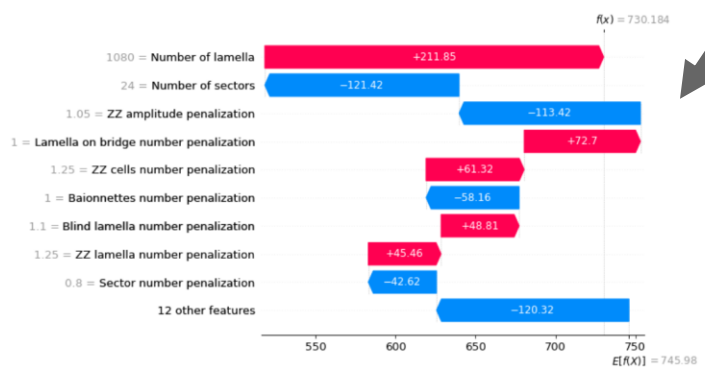
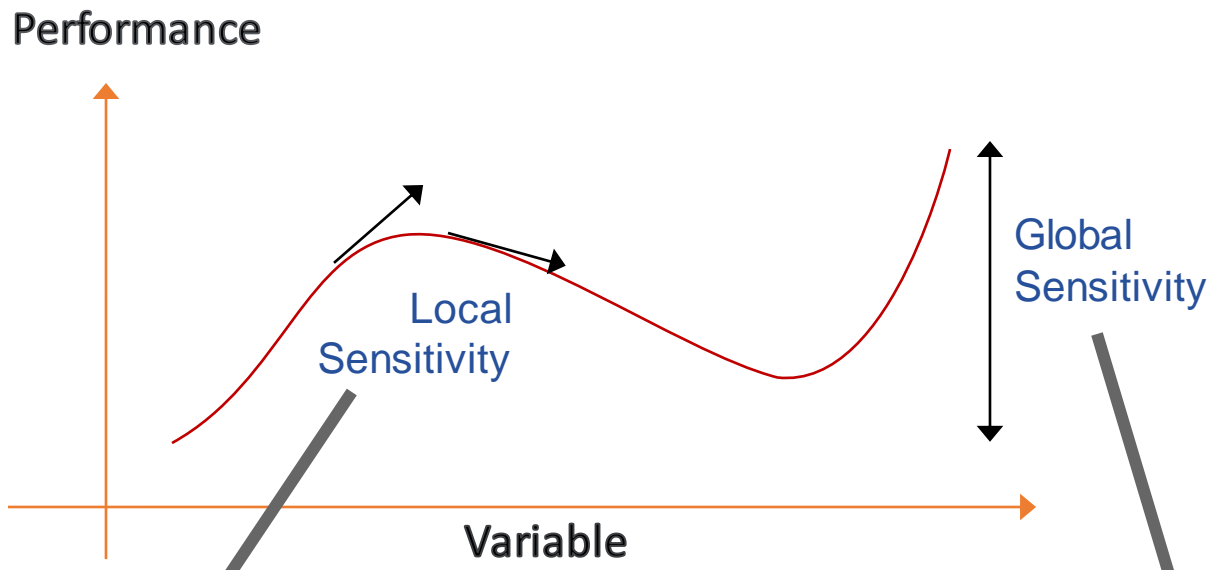
<https://github.com/simai-ml/MAPIE>



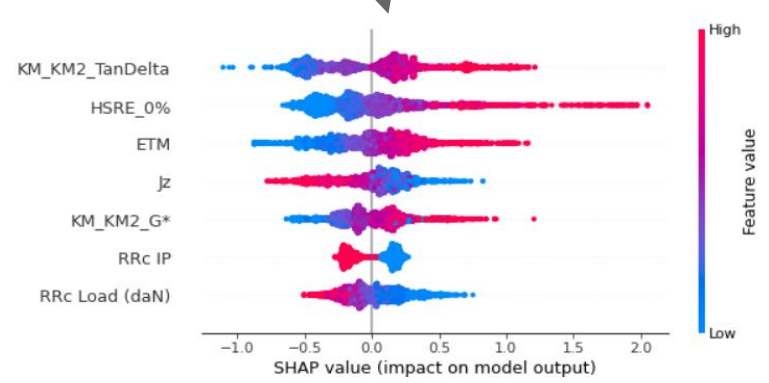


Physical validity – to be assessed with Subject Matter Expert

Intuition on “eXplainable AI”



Sensitivities between 2 designs



Importance value over the domain

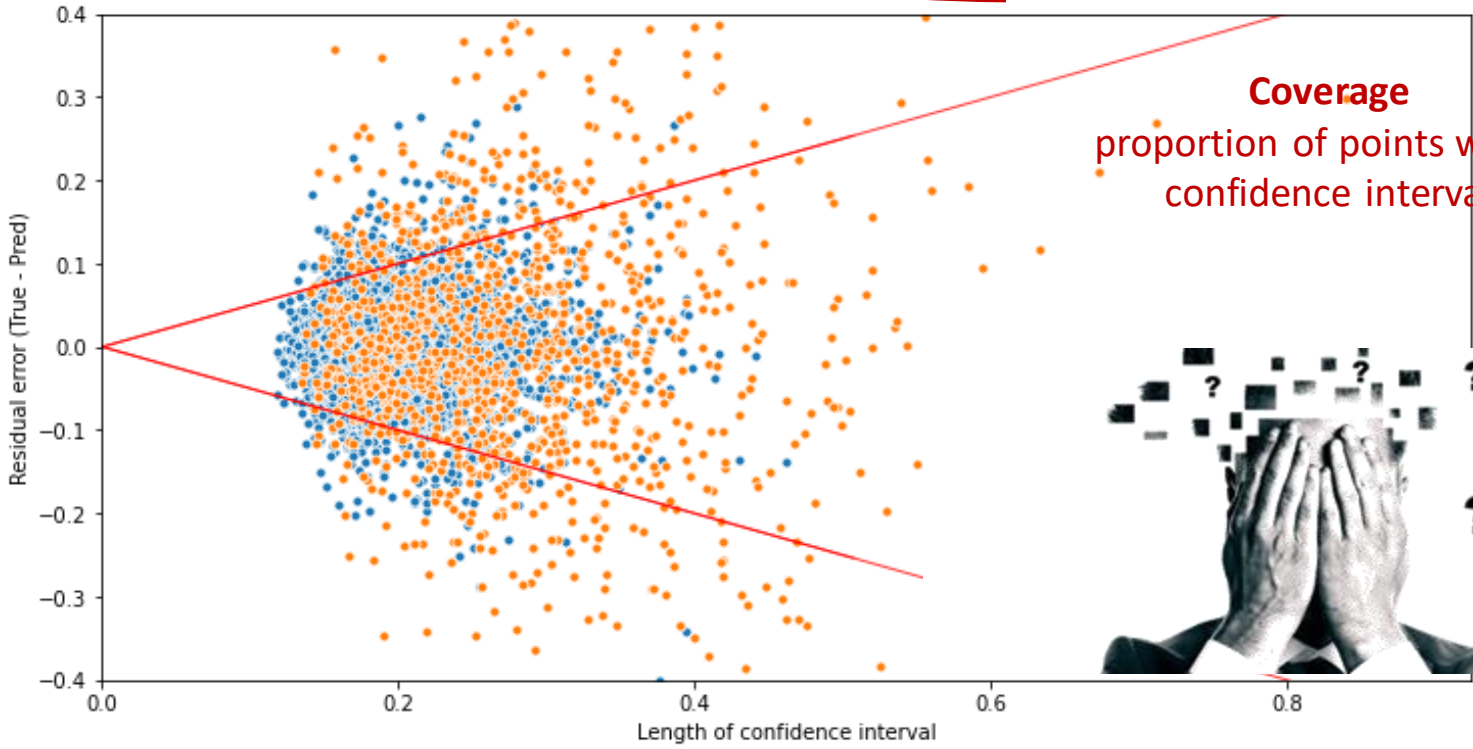




AI Model validation – beyond R^2

Distribution of
Confidence Interval length
« how confident ? »

Precision or Error
(over the domain)
« how precise ? »



Coverage
proportion of points within
confidence interval





Which perimeters are ok ?

1) To identify the perimeters to analyse :

- Summer / Winter / Sporty tires

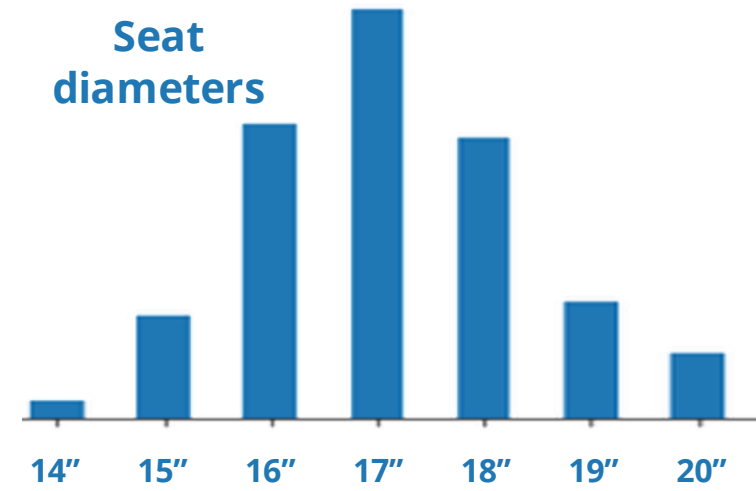


- Tire dimensions / Seat diameters
- Manufacturing process / Plants
- Etc...

2) For each perimeter, captation of possible biases and their impacts

Coverage and Precision :
key performance indicators to manage biases

Seat diameters



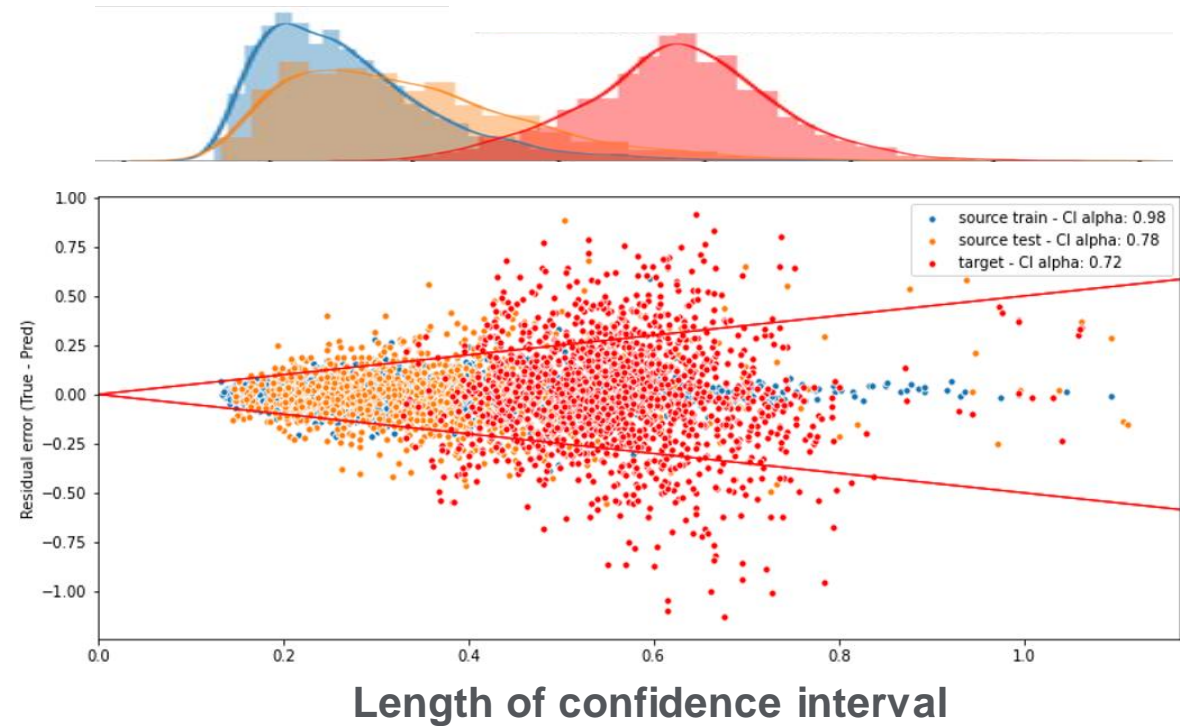
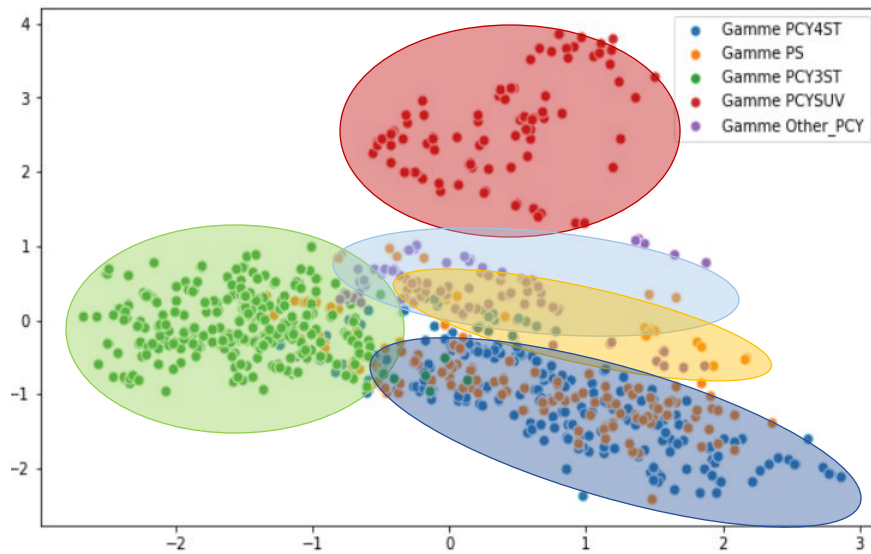


How to maintain AI performance over time ?

We played a game...

What if I remove one tireline, am I able to « detect » uncertainty zone ?

Tire design space projection



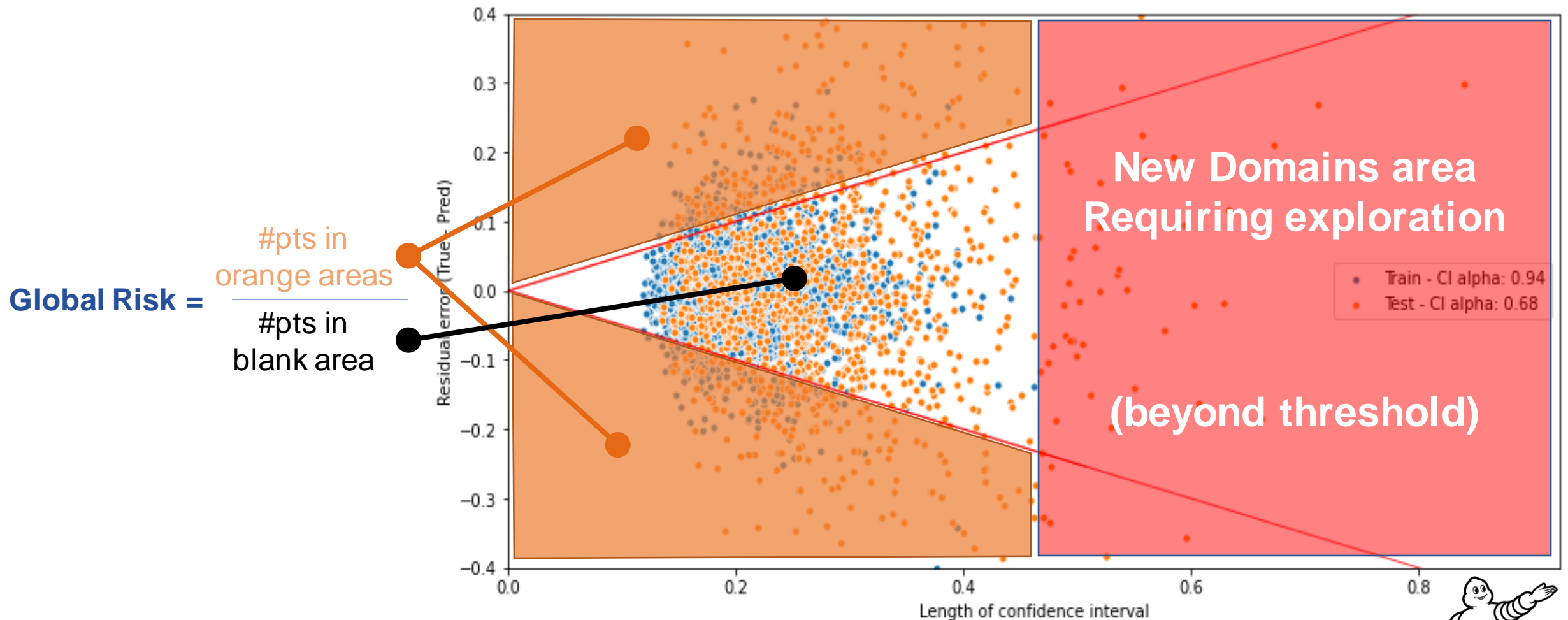
Such indicator enables

- the maintenance of our model in operations – continuous learning – frugal
- the risk management on local decision





Uncertainty prediction to manage error risks ?



Global risk estimation must be evaluated with respect to business stakes





Toward a model Audit framework

Different metrics for different actors

Expertise	Actors	Questions & Interactions with AI
High AI expertise Low <i>Metier</i> expertise	AI designer data scientist	<ul style="list-style-type: none"> - what is the performance of my model ? Its uncertainty ? - what are the key drivers of the model ? - Is there any bias in my dataset ?
Medium AI expertise High <i>Metier</i> expertise	Performance engineer AI co-designer	<ul style="list-style-type: none"> - Is the model aligned with its usage chain ? - Can I learn new rules from that model ? <i>sensitivity</i> - What is the validity domain of the model ? <i>Stress test</i>
Low AI expertise High <i>Metier</i> expertise	AI consumer Mat/Tire designer	<ul style="list-style-type: none"> - What is the confidence in the prediction ? - What are levers around that conception point ? - How can we explain evolution between those 2 designs ?
Medium AI expertise High <i>Metier</i> expertise	AI Audit Fellow <i>metier</i>	<ul style="list-style-type: none"> - do we have an identity card of the model ? Validation, explicability, validation domain, risk assessment



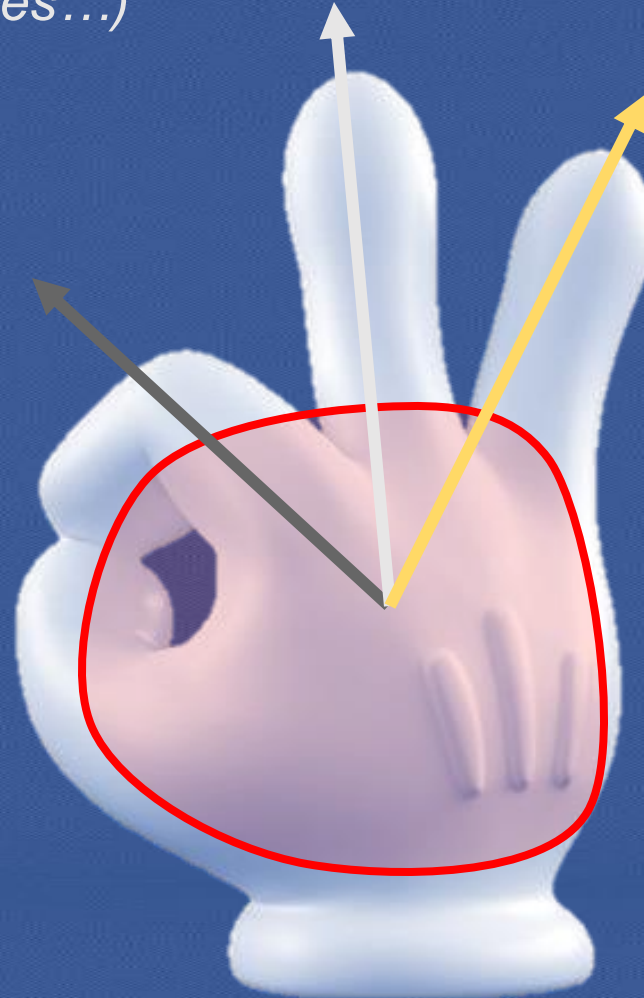
Validating models fits on Mickey's hand

*Which domains are ok ?
(tirelines, process, zones...)*

*How long model stays
valid ? (new tireline ?)*

*Physical validity ?
(ok with knowledge ?)*

*What are the usage
limitations to manage
error risks ?*



To validate, a multidisciplinary team is key

Domains and bias

- *Product owner*
- *Data Scientist*

Physical validity

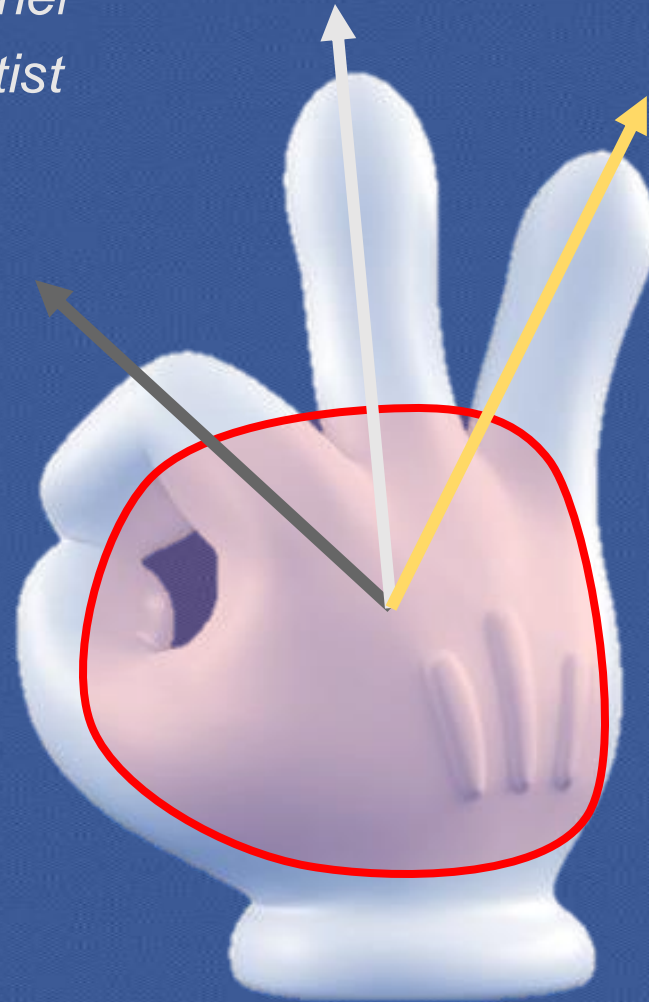
- *Performance analysts*
- *Experts*

Validity with time

- *Data Scientist*

Risk management

- *Quality partners*
- *Decision making process management*





***It looks like ...
Uncertainty
Quantification***





What seems new on AI has been around in engineering

Simulation / Physical models	Data models (Statistics inc.)
Code quality, CI/CD	MLOps
Computation verifications	Error metrics
Uncertainty quantification	Prediction uncertainty
Sensitivity analysis	Explainability
Reproductibility	Model monitoring
Validation perimeter	Drift monitoring
H&Q with business	Human in the loop
Non-regression test basis	Data gouvernance & quality
Reception test-cases	Model score-card

Thus, a revival of interest for UQ (by true interest or fear ...)





- UQ is getting a **new dynamic** from the data transformation with a better share of responsibilities
- Levers of models are more **business centric** in a way ?
- Business is asking to **homologate** product through models (even more since AI) – expecting more maybe ?
- **Not only** a Michelin challenge !



CERTIFIED

The way AI models are validated need to be certified ?



Thanks for your attention !

