Exploration and evaluation of hardly constrained Neural Networks

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MICHELIN

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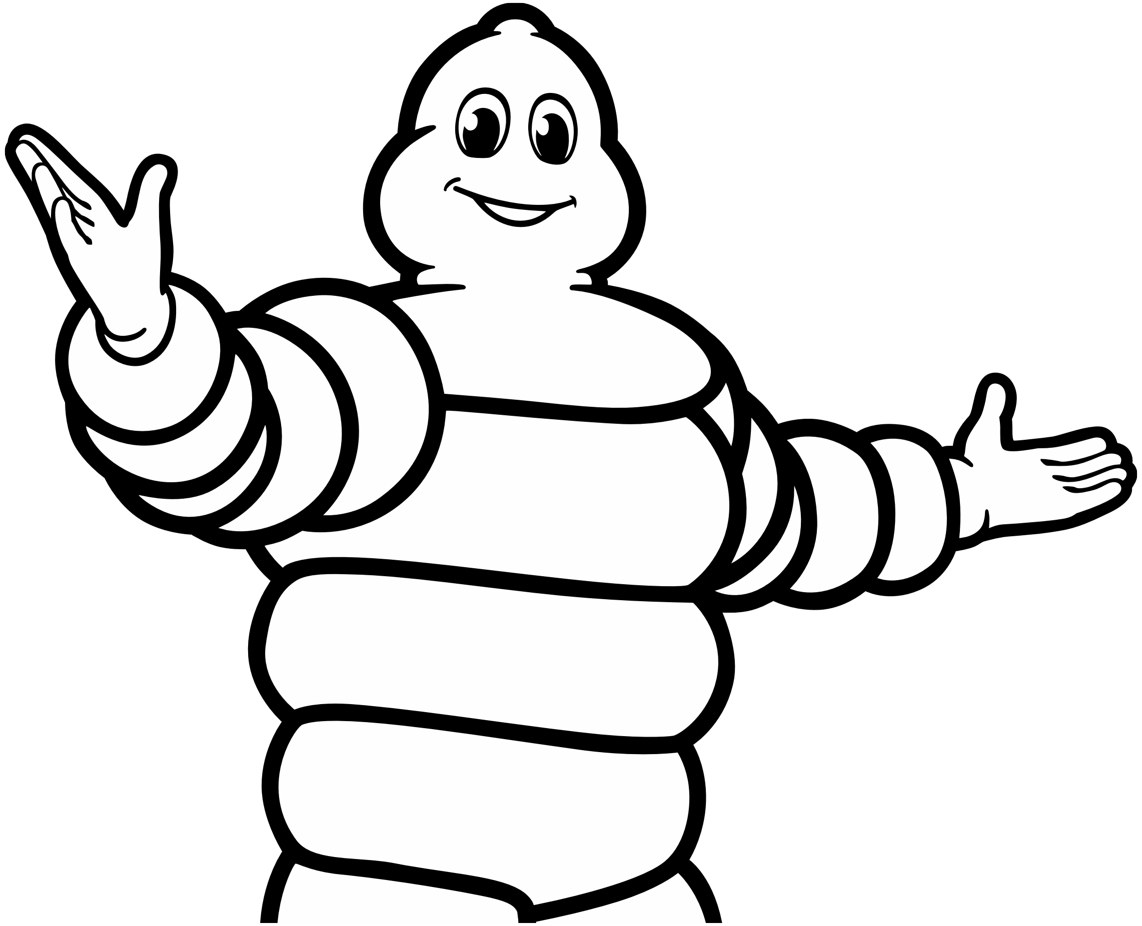
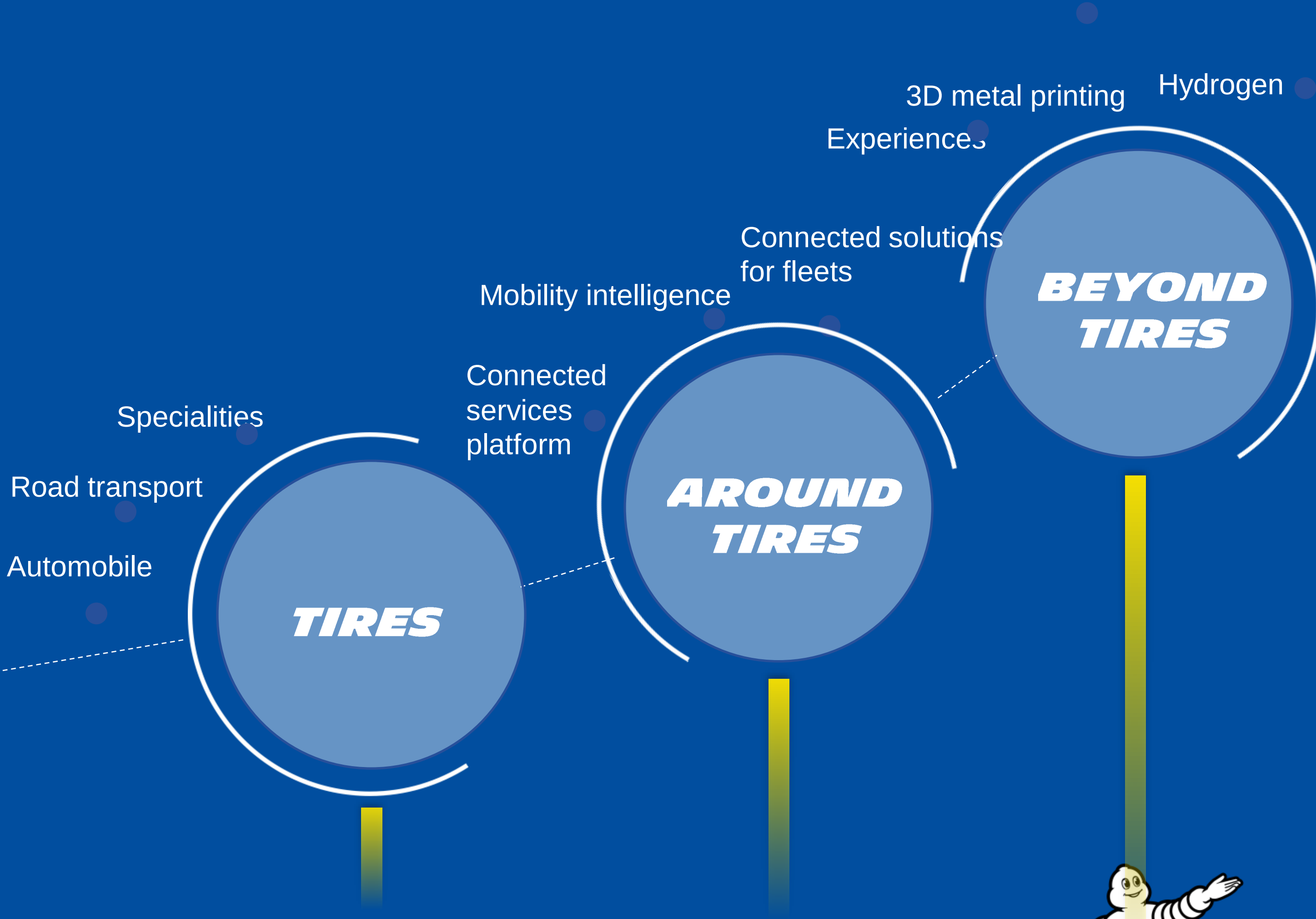


1. Michelin

Tires tailored to customers' needs



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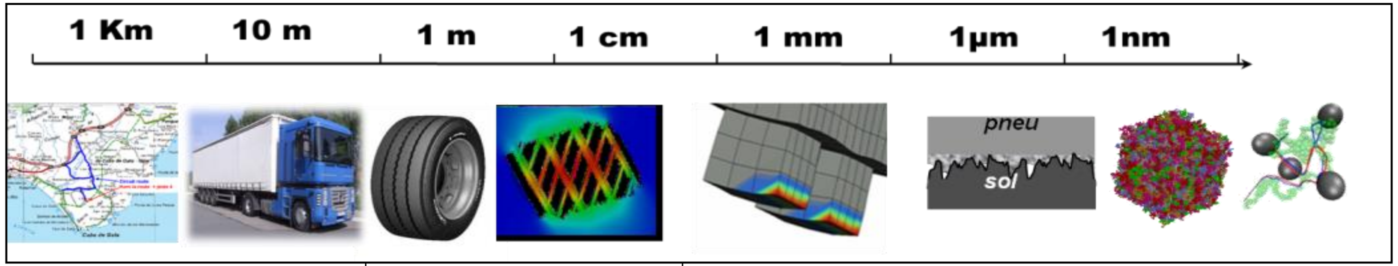
2. General Context

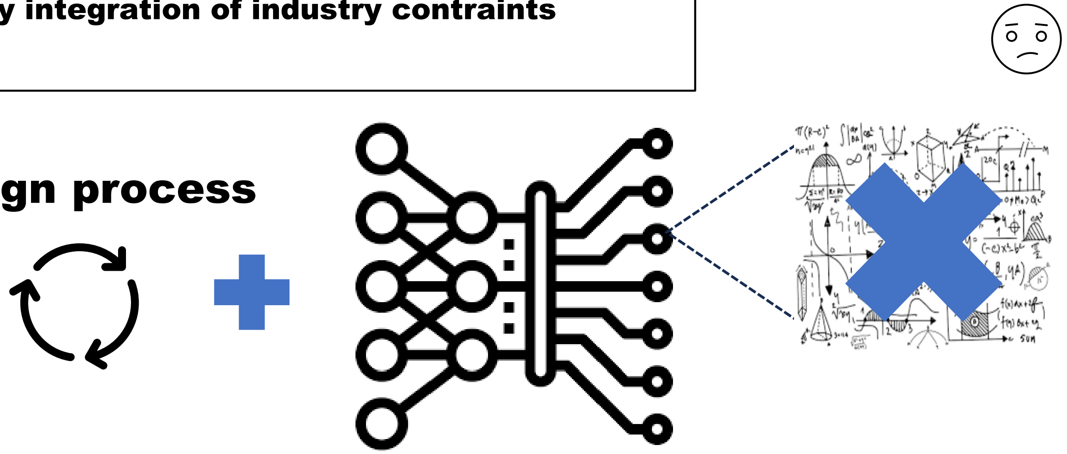
SIM R&D

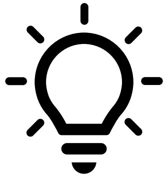


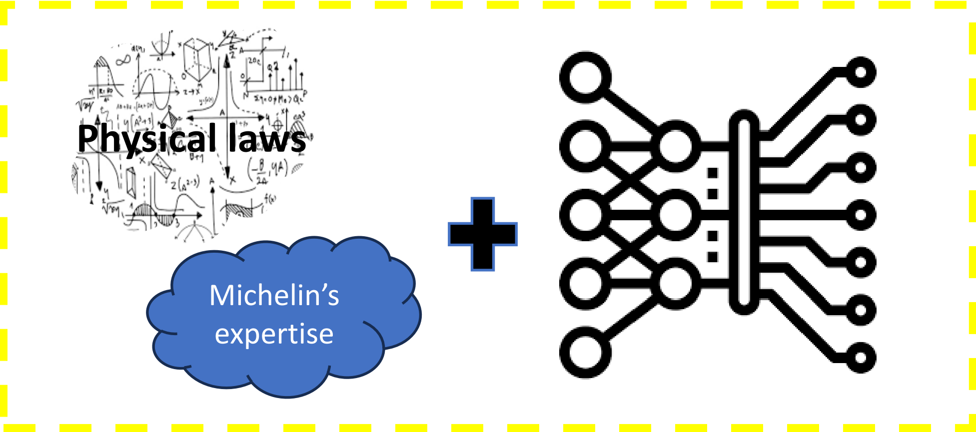
Tire conception levels

- Real-time performance prediction
- Early integration of industry contraints

Design process







Constrained Models

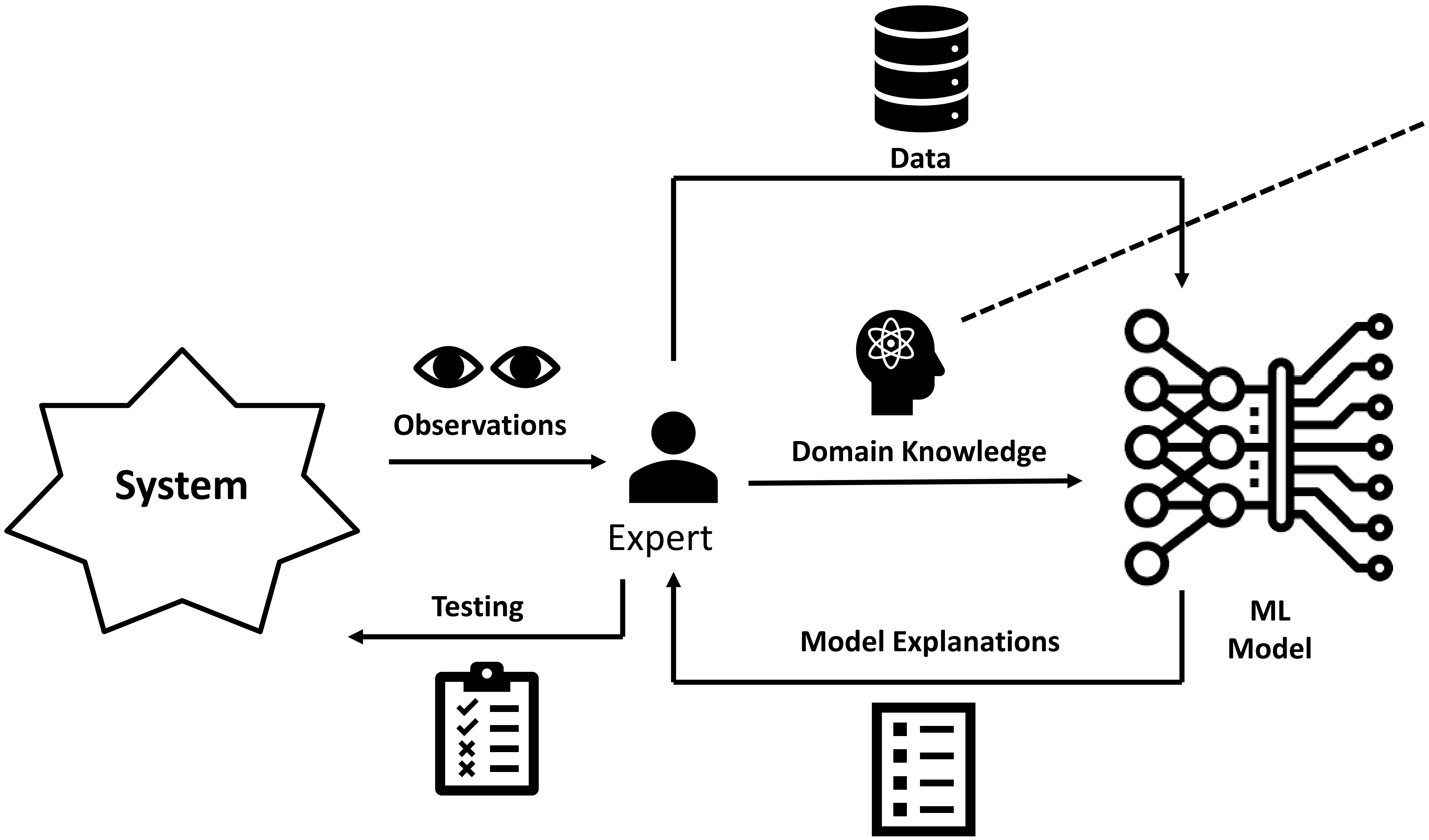
3. Objectives

1. **State-of–the-art review**

2. **Choice of approaches**

3. **Study of use cases**

4. Constrained Models



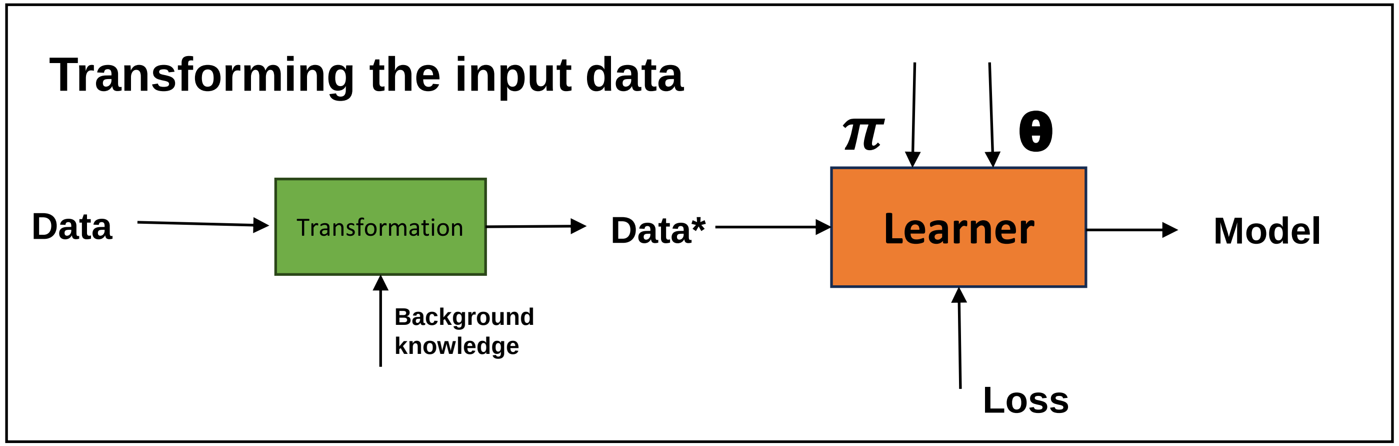
Physical constraints

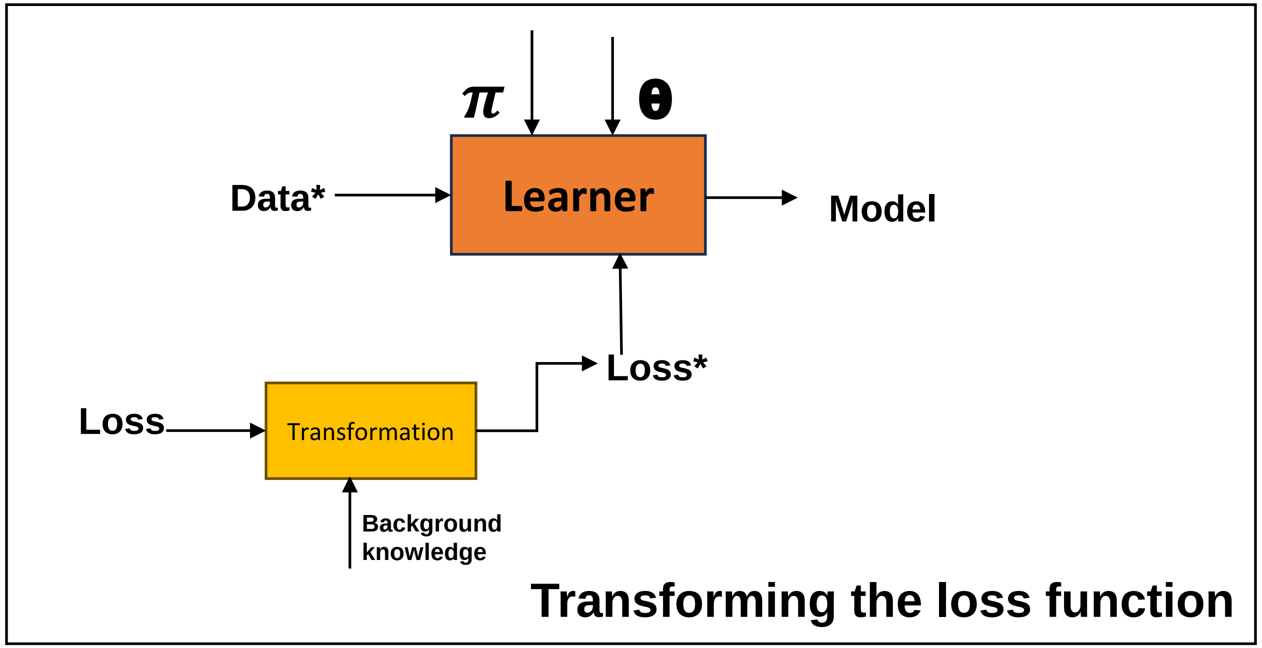
- Physical phenomena
- Material properties
- **Monotonicity**

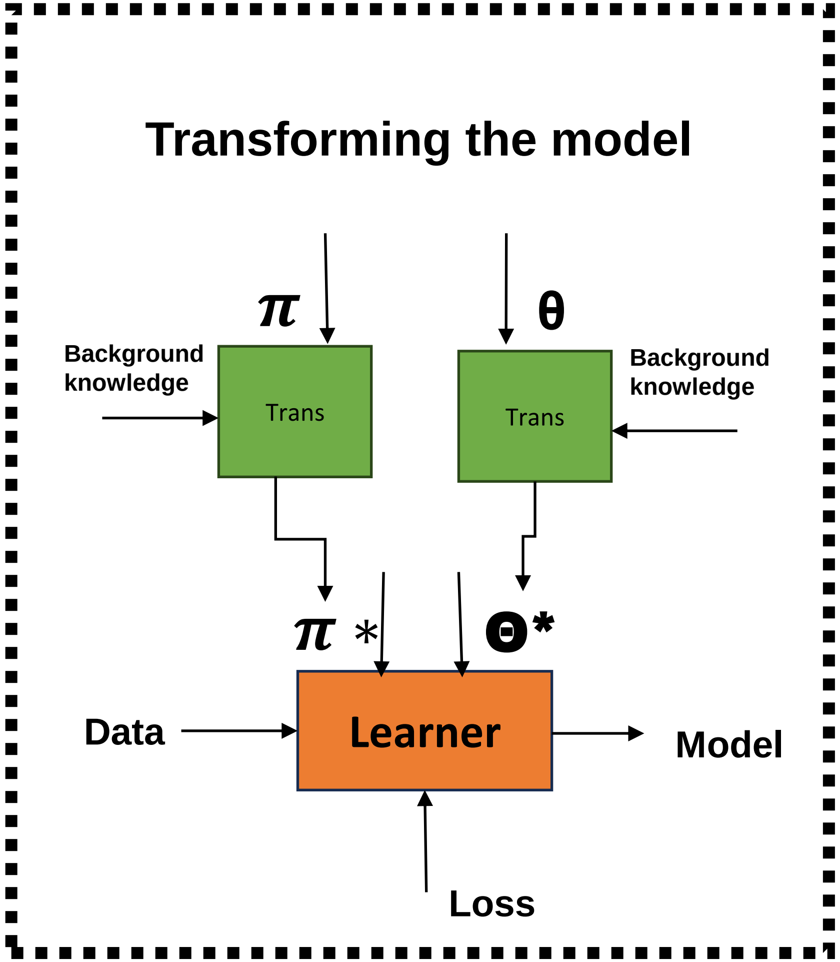
Geometrical constraints

- Regarding the **domain**, **shape,** aspect, size.

4.1 Constrained Learning approaches

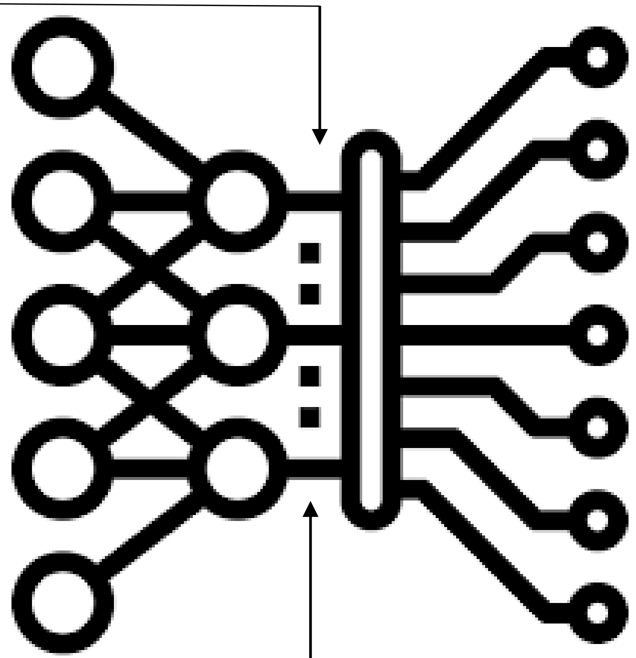






4.2 Chosen approaches

Standard NN Architecture



Monodense

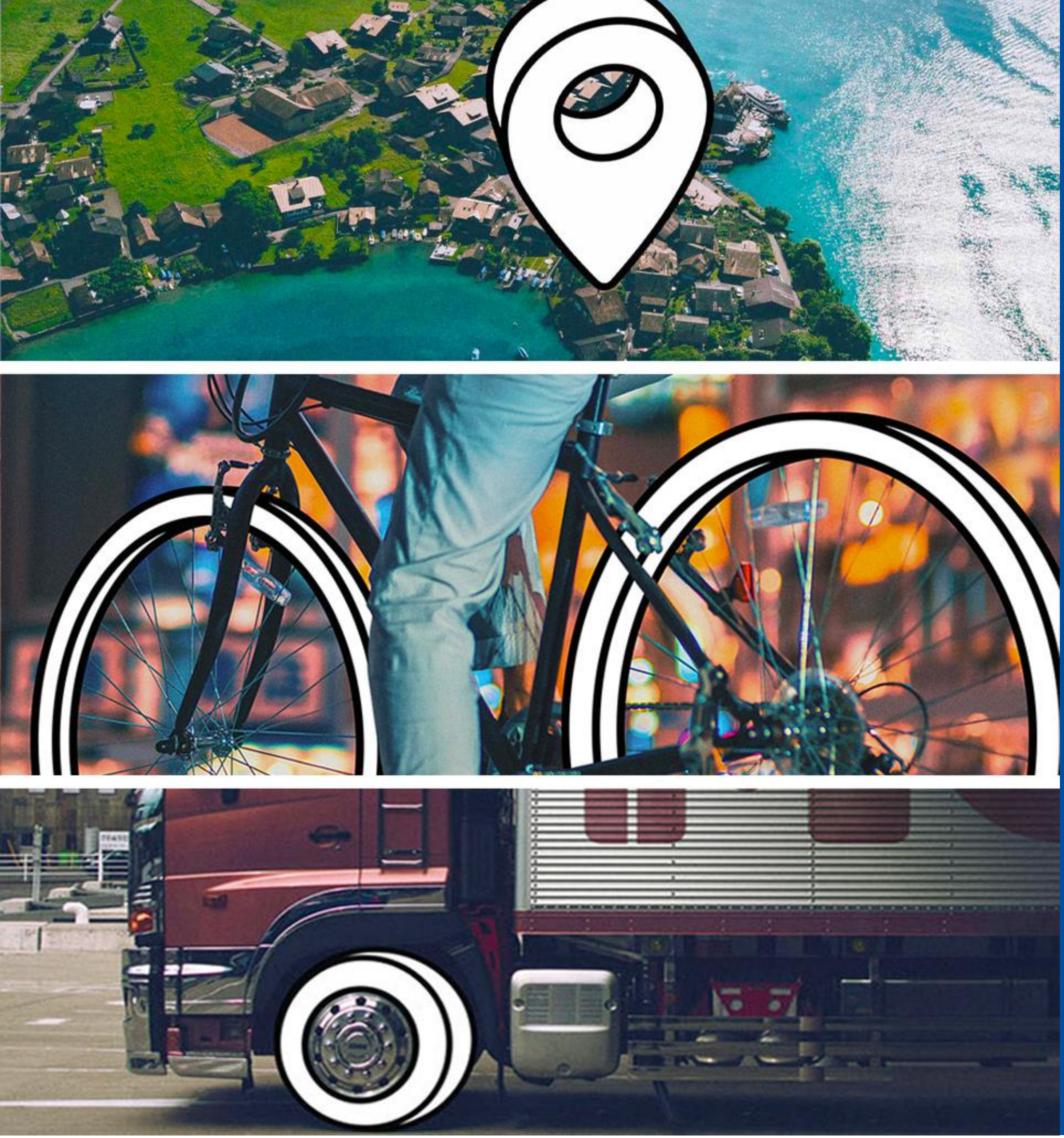
- To enforce monotonicity constraints by defininf a new type of layer called Monodense.

MultiplexNet

- To enforce multiple domain constraints directly in the output layer of a NN.

Domain Constraints

- To enforce domain constraints defined as a differentiable layer.

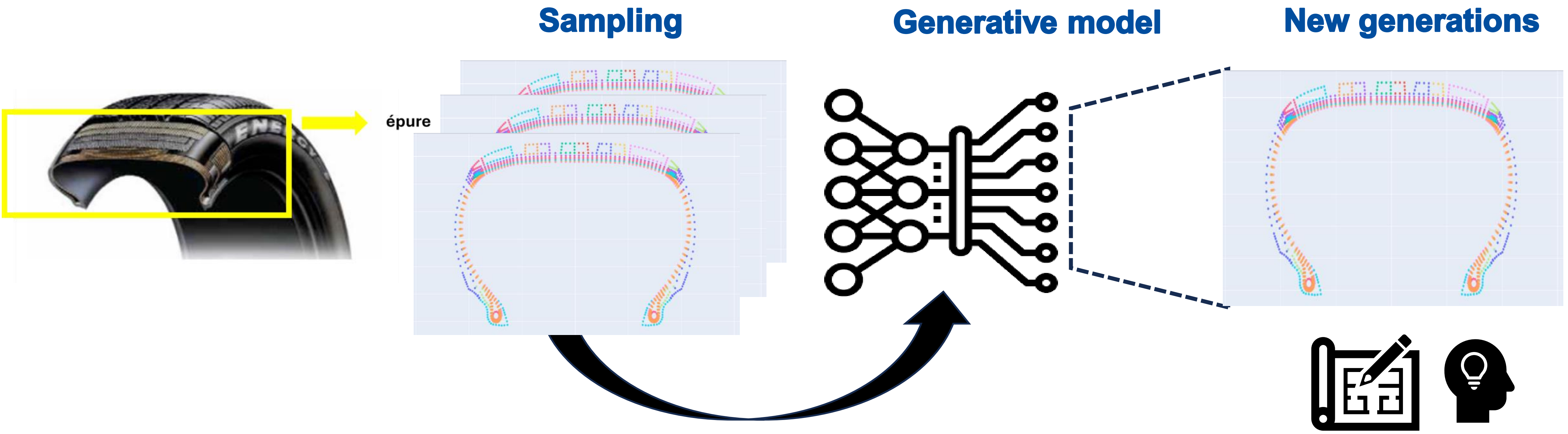


USE CASES

5.1 Generative design of tire's components

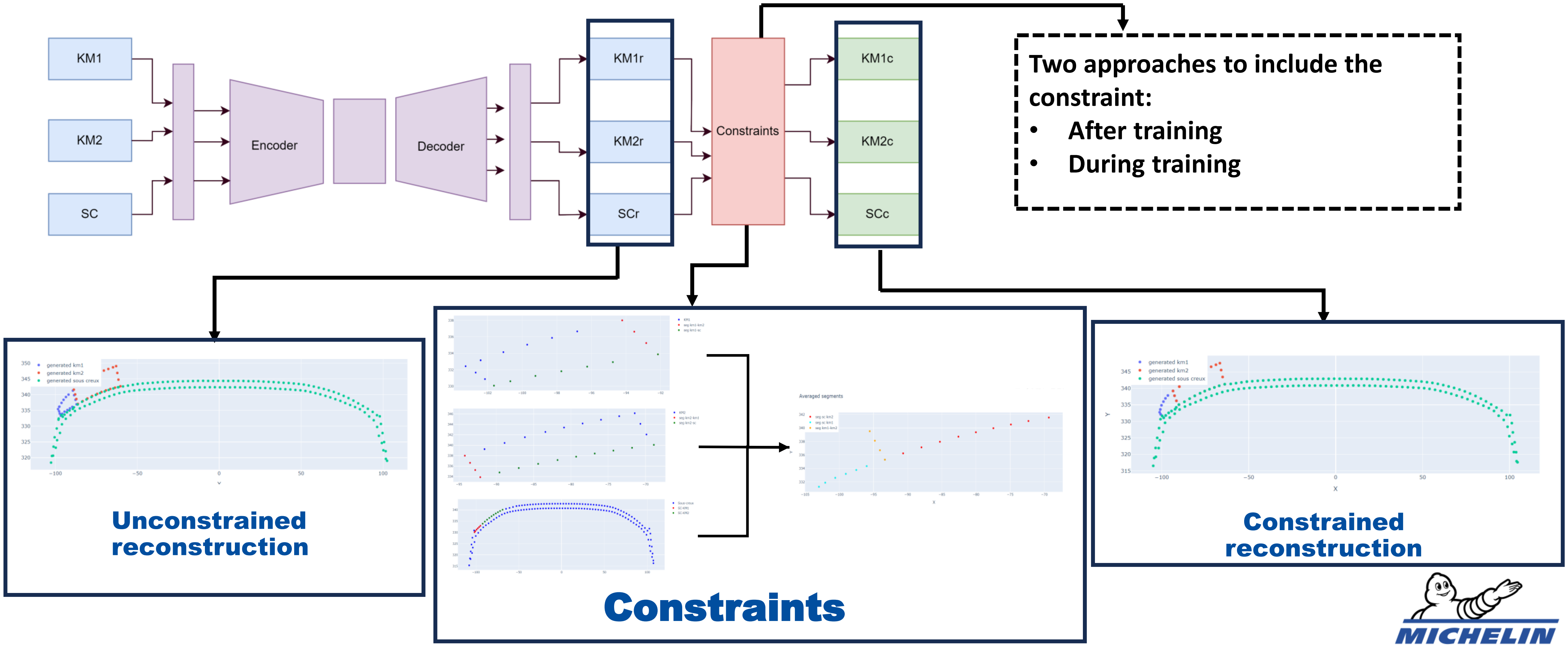
Data description:

- 279 samples
- 27 products conforming an « épure »

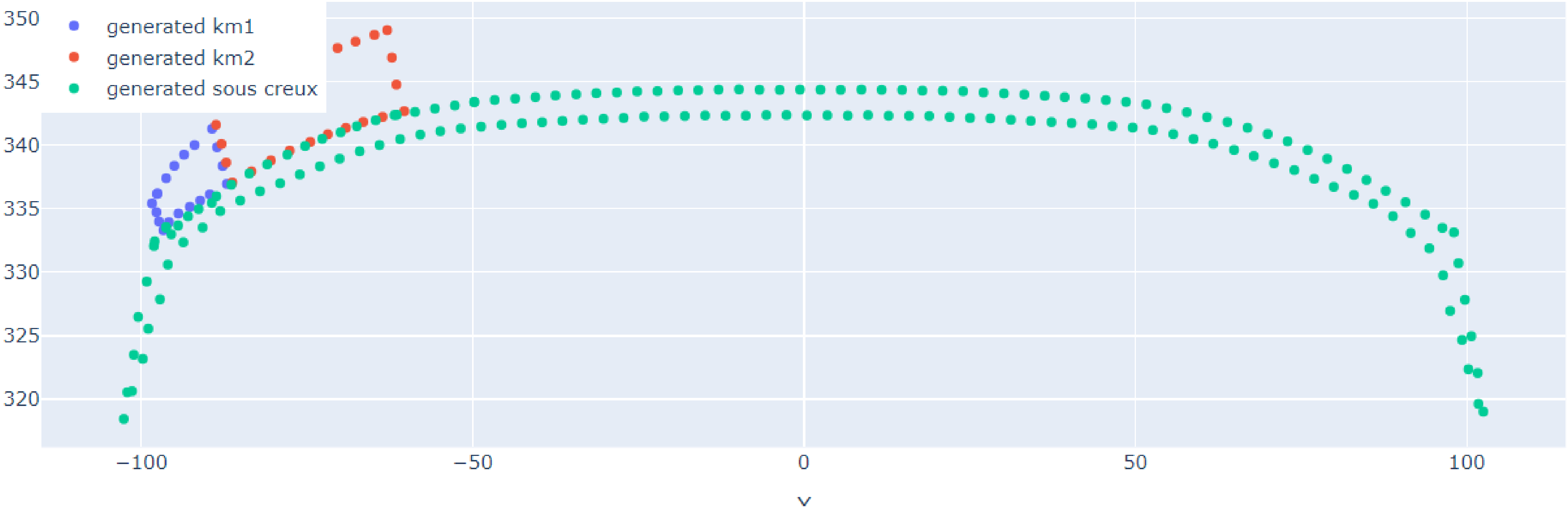


5.1.1 Model architecture and constraint definition

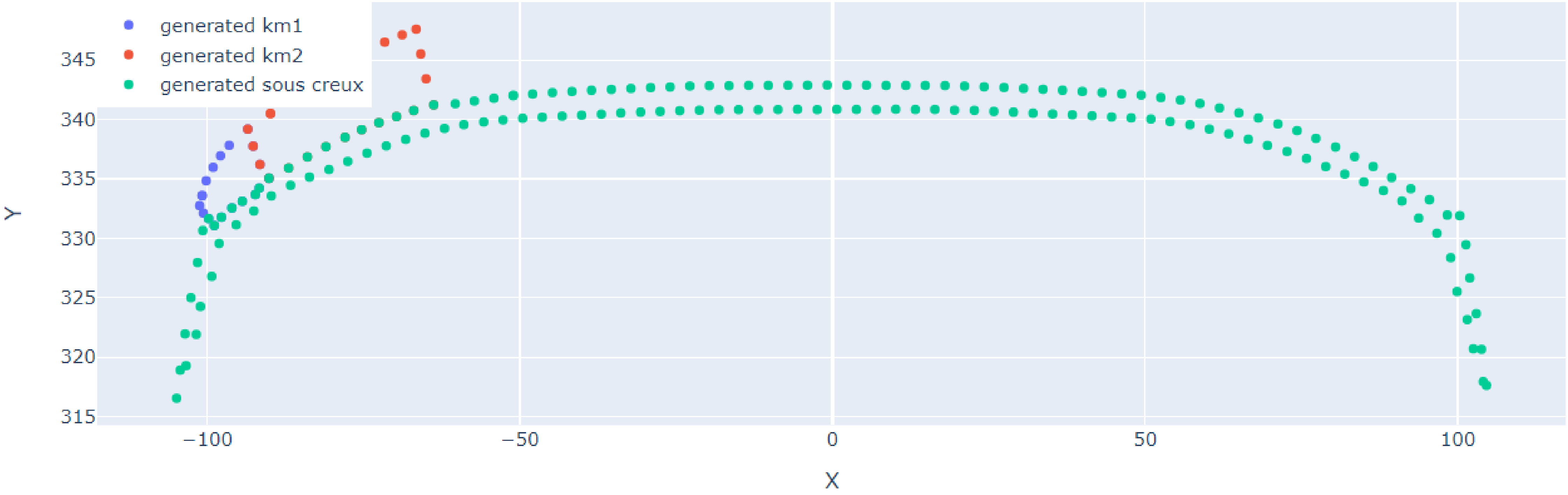
Architecture



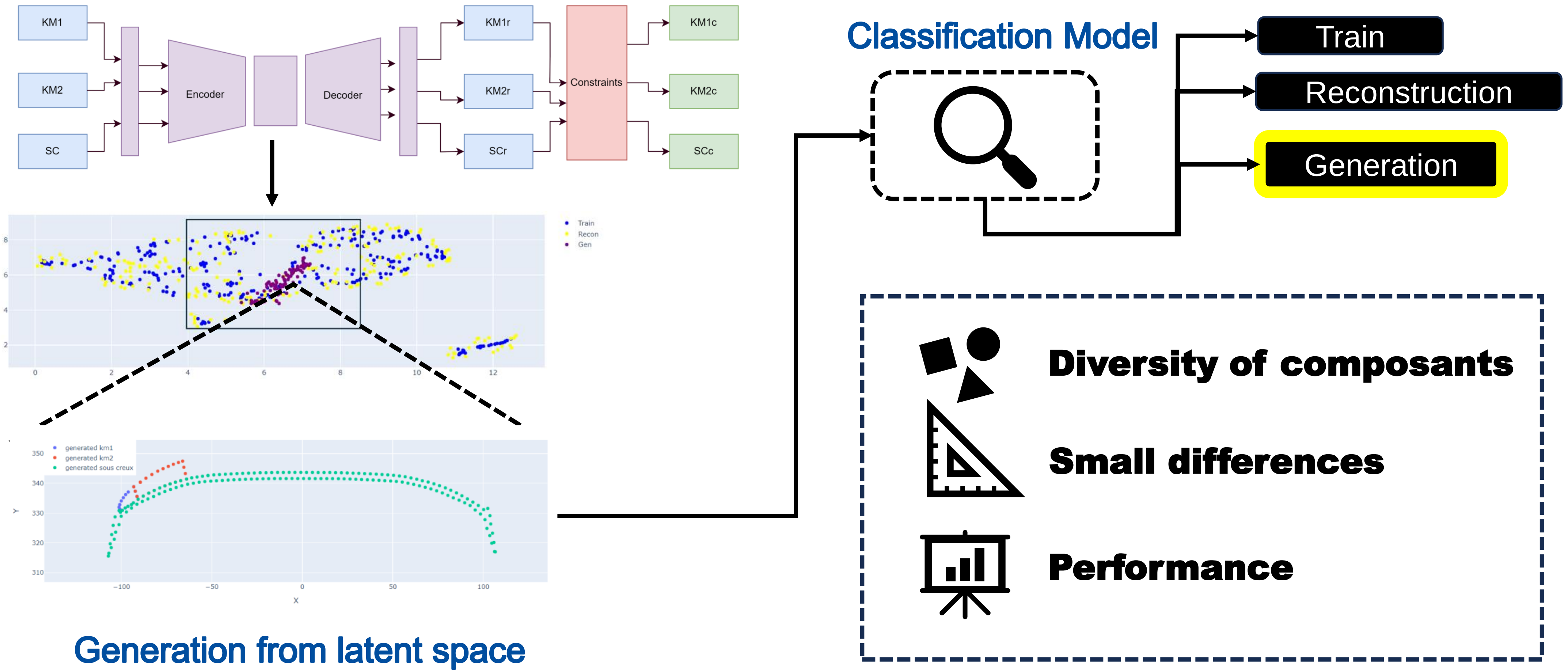
UNCONSTRAINED RECONSTRUCTION



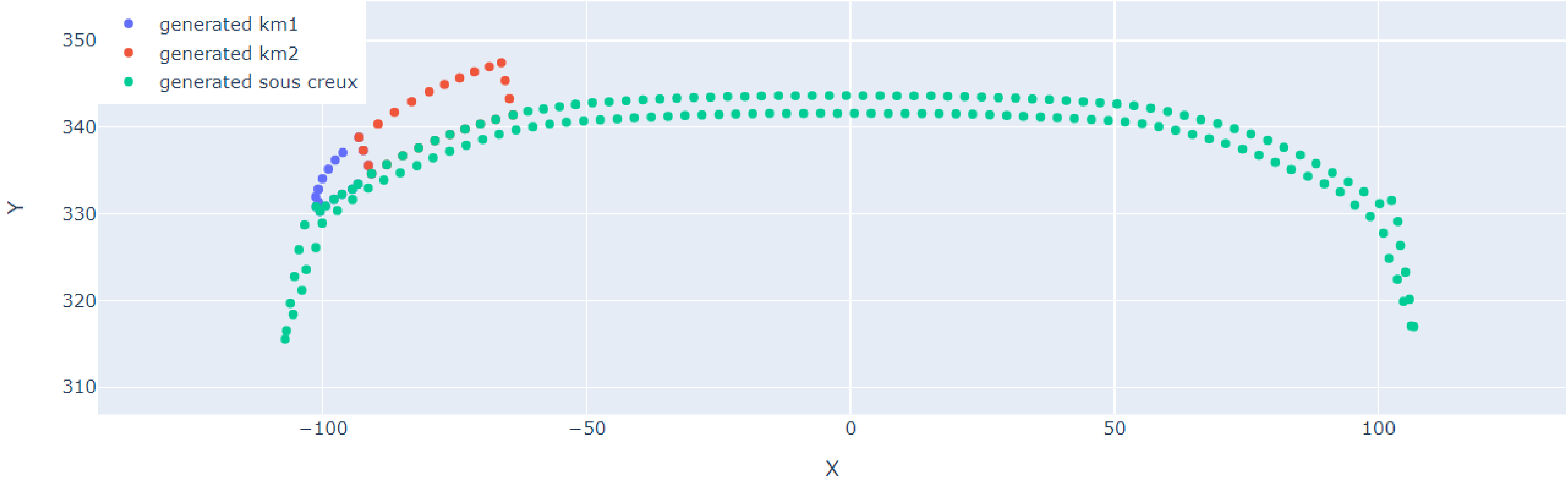
UNCONSTRAINED RECONSTRUCTION



5.1.2 Diversity study

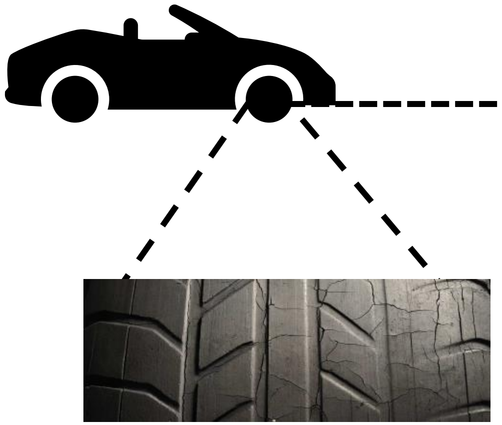


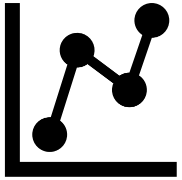
GENERATION FROM LATENT SPACE



5.2 Damage prediction case

Prediction of the cumulative damage and final damage.





Synthetic data to predict damage

Models

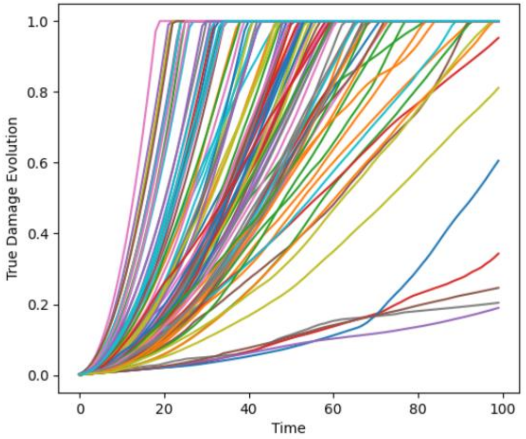
LSTM | **Transformer** | **Convolution**

Dense | **MonoDense**

+ Constraints

The predicted wear (d) should be:

- $0 \leq d \leq 1.0$
- Monotonically increasing. ↑

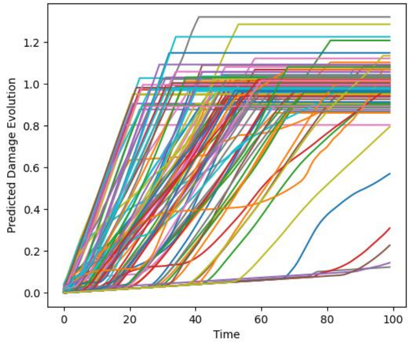


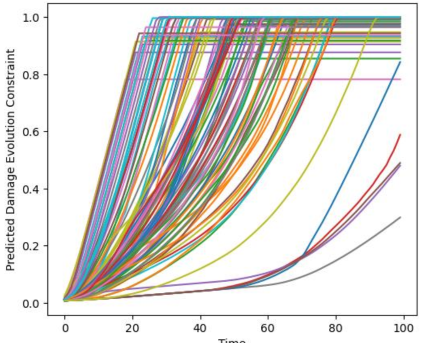
Expected damage evolution

5.2.1 Results domain constraints

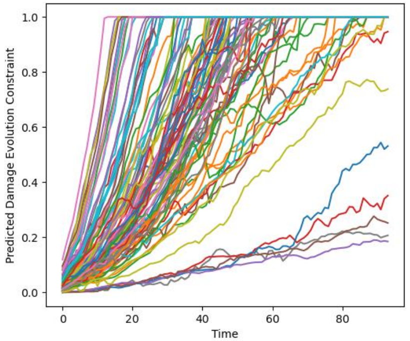
Constrained | Unconstrained | Constrained | Unconstrained

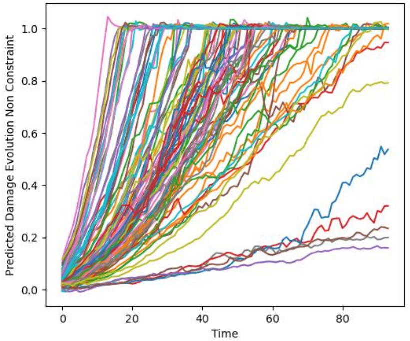
Transformer



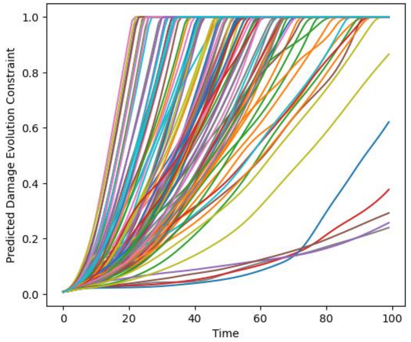


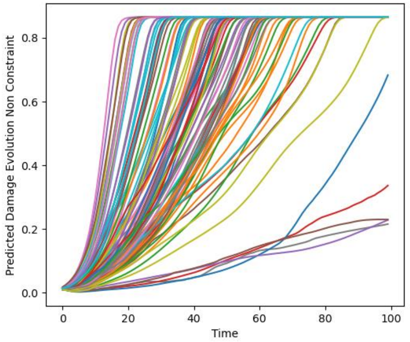
Dense SW



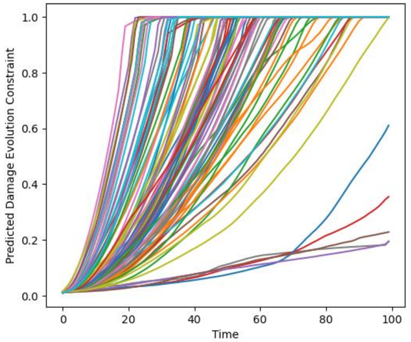


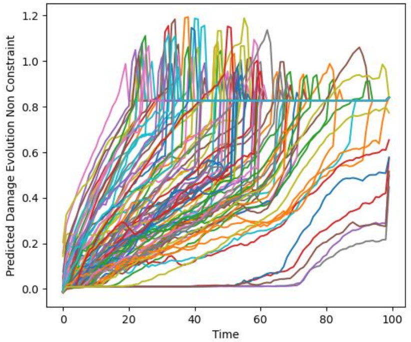
LSTM





Convolution

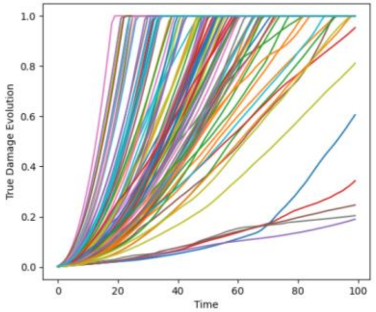




Constrained

Model	MSE	MAE	RMSE	R2
LSTM	3.2197	1.0895	1.7943	0.9979
Dense	23.9143	2.3130	4.8902	0.9828
Convolution	6.2355	1.2263	2.4971	0.9960

True



Unconstrained

Model	MSE	MAE	RMSE	R2
LSTM	6.2355	1.2263	2.4971	0.9960
Dense	26.3848	2.4132	5.1366	0.9811
Convolution	1838.6836	35.4744	42.8799	-0.1837

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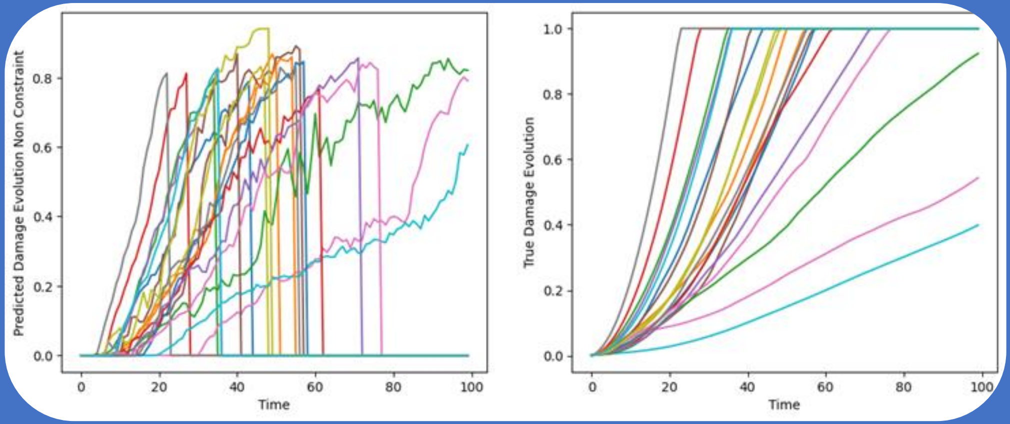
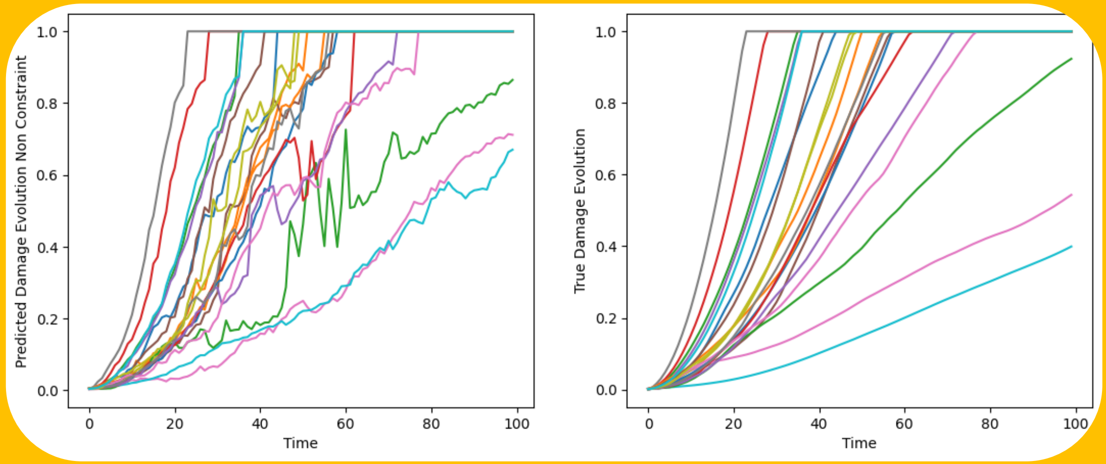
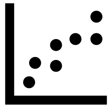
5.2.2 Monotonicity constraints



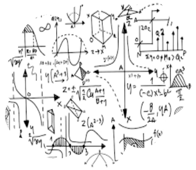
Only Monodense layers model



Monodense and dense layers model



Model



Constraints

Balance should be found

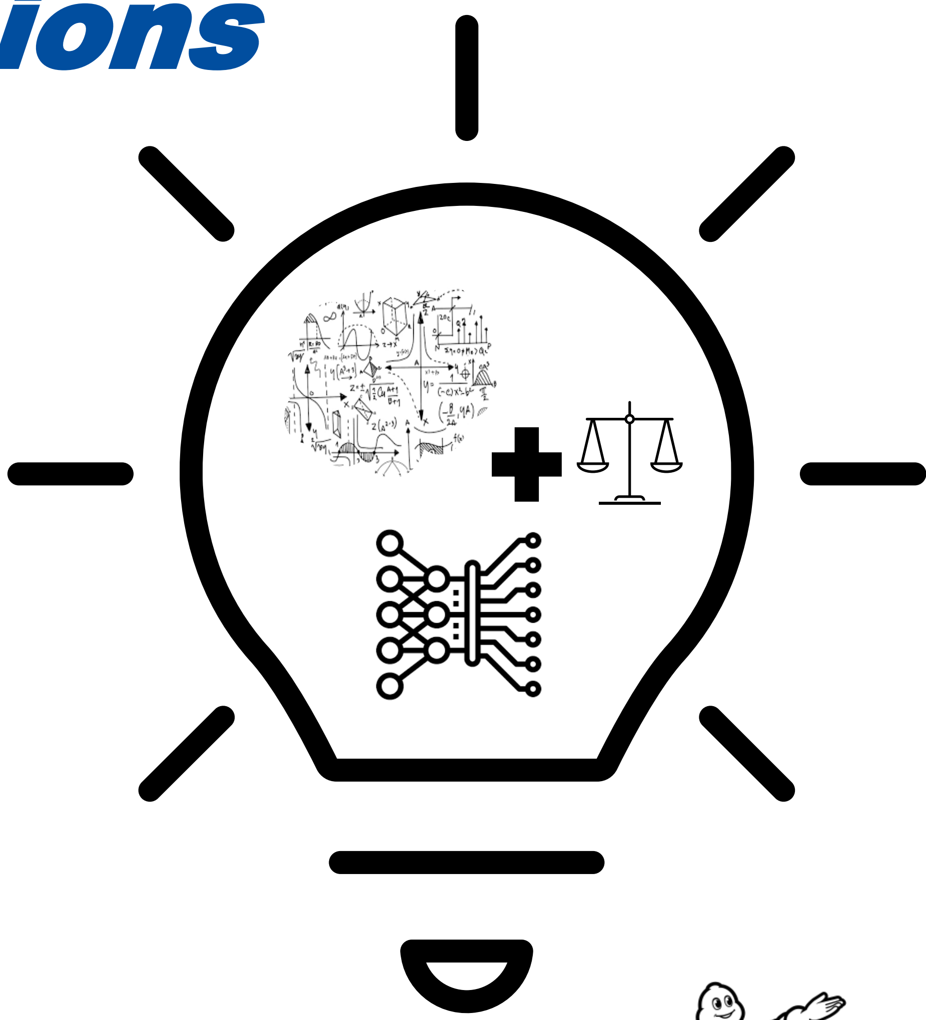
6. Analysis and Conclusions

1st case

- Scalability
- Constraints respect
- Diversity study

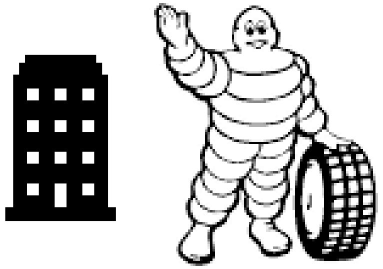
2nd case

- Help the model to focus
- Simpler models
- Monotonicity constraints

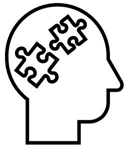


Python Library

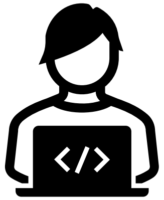
7. Retrospective and Feedback



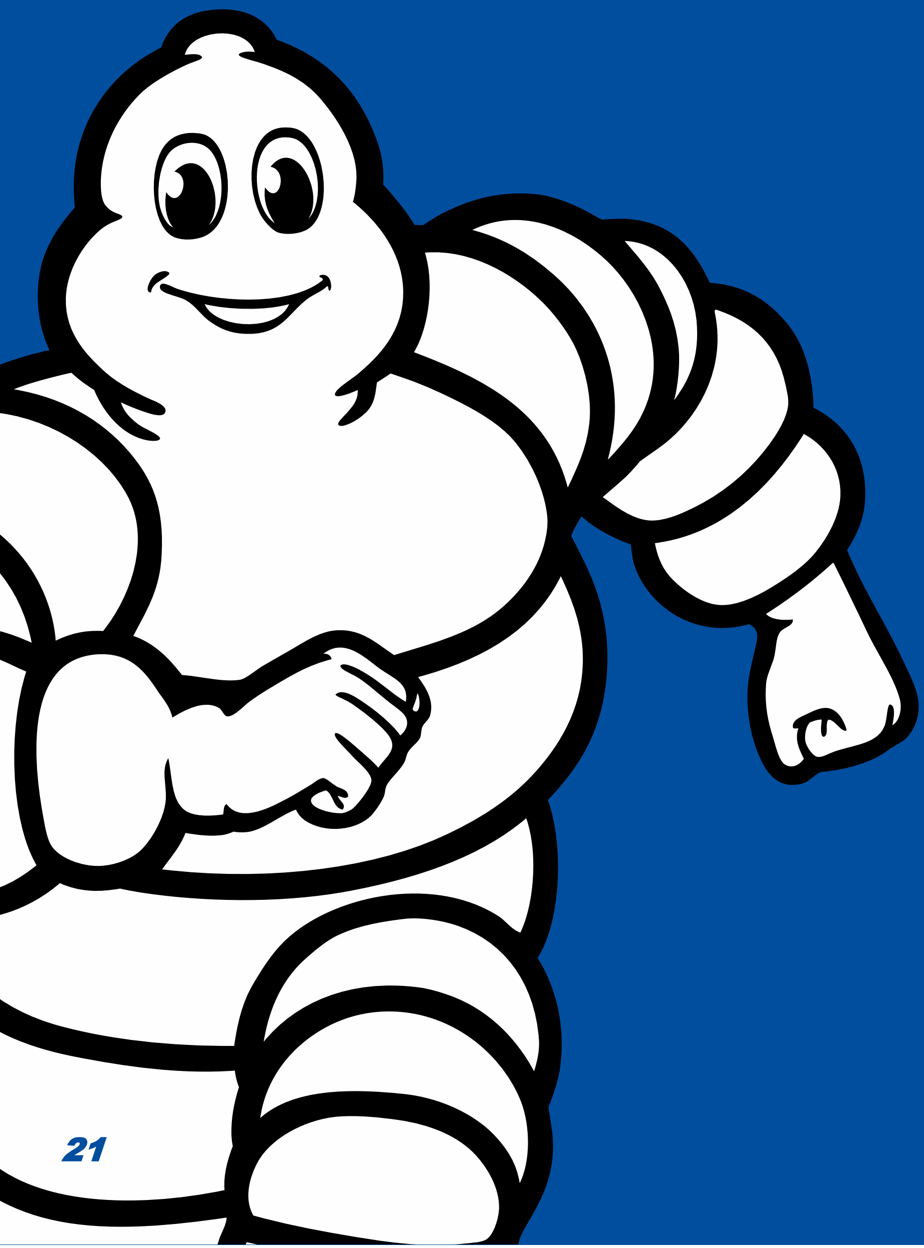
Experience at Michelin



Skills development



Future career



Thank you!