# Fall Workshop

# Machine Learning Surrogate Models for Reliability Assessment of Rockfall Protection Barriers

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**Nice, 13 October 2026**

# Outline

1. Context and Problem Statement
2. Methodology
3. Results and Discussion
4. Conclusions and Perspectives



# 1. Rockfall Hazard

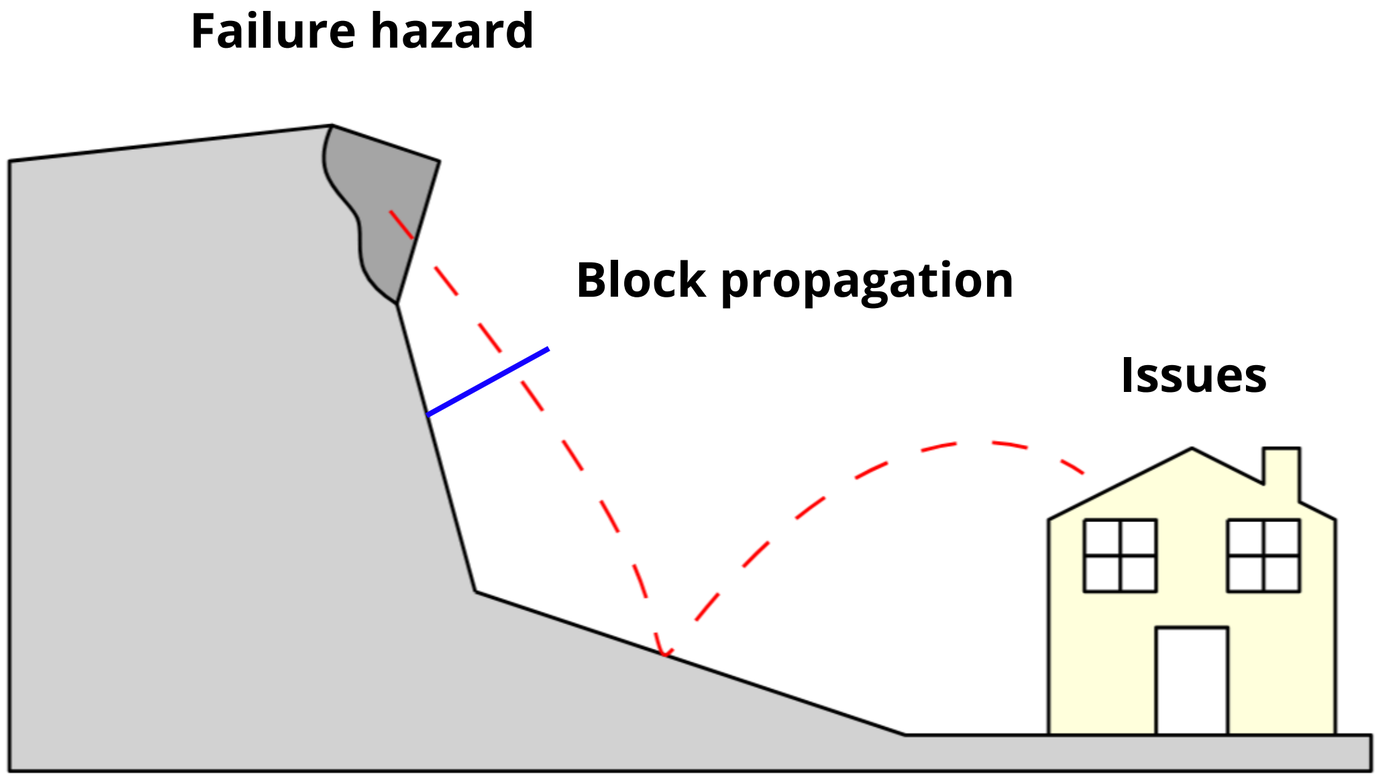



**Illustration of the risk associated with rockfalls [1]**



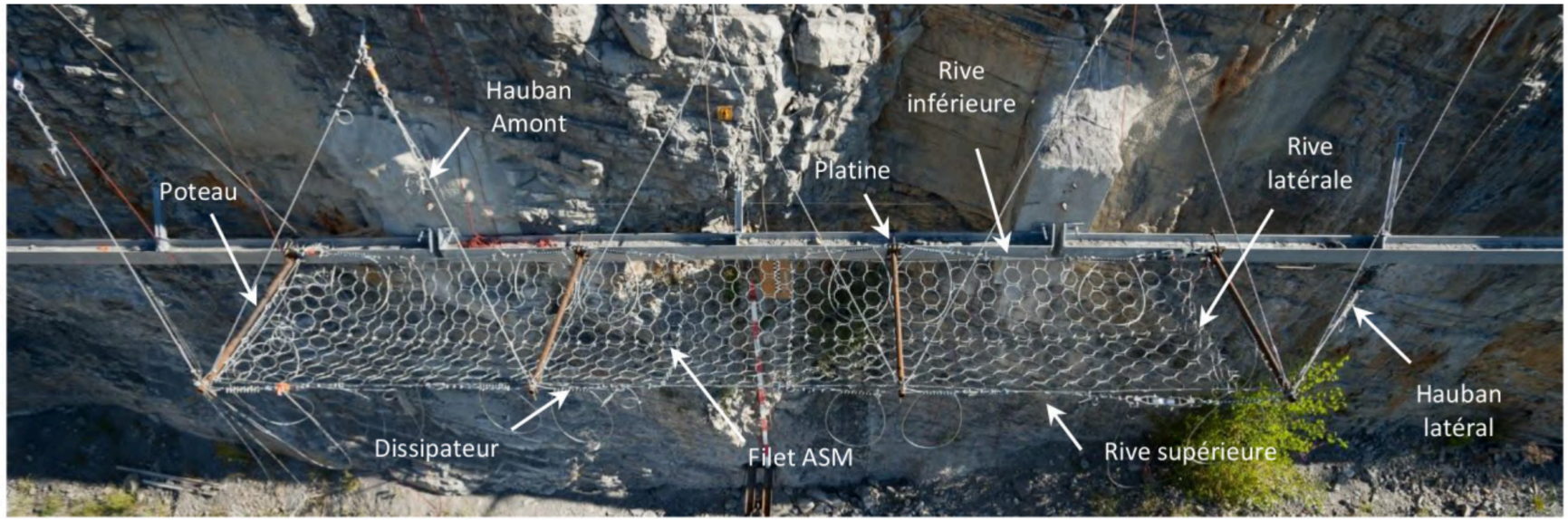
**Rockfall on the RN90 (2025)**



[1] Coulibaly, J. (2017). “Modélisation Numérique Discrète Du Comportement Mécanique Sous ImpactDes Structures d’écrans de Filets Pare-Pierres”. Theses. Université Grenoble Alpes.

# 1. Rockfall Protection Barriers

- **Protection** structure to stop **rockfalls** to protect people and infrastructure
- **Flexible multi-component system** : net, posts, cables, anchors and energy dissipator devices
- Dynamic impact + Flexible system → highly **nonlinear** mechanical response

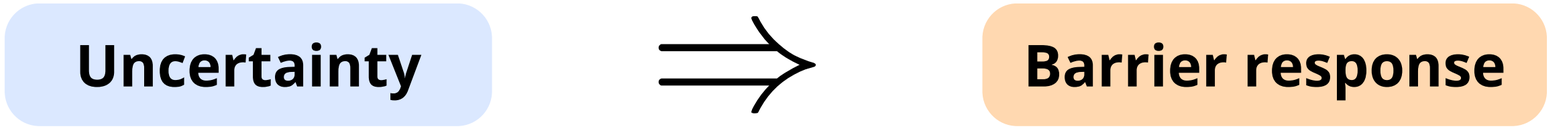



**C2ROP rockfall protection barrier [2]**



[2] Coulibaly, J. B., M.-A. Chanut, S. Lambert et F. Nicot (2019). “Toward a Generic Computational Approach for Flexible Rockfall Barrier Modeling”. Rock Mechanics and Rock Engineering

# 1. Reliability Analysis under Uncertainty



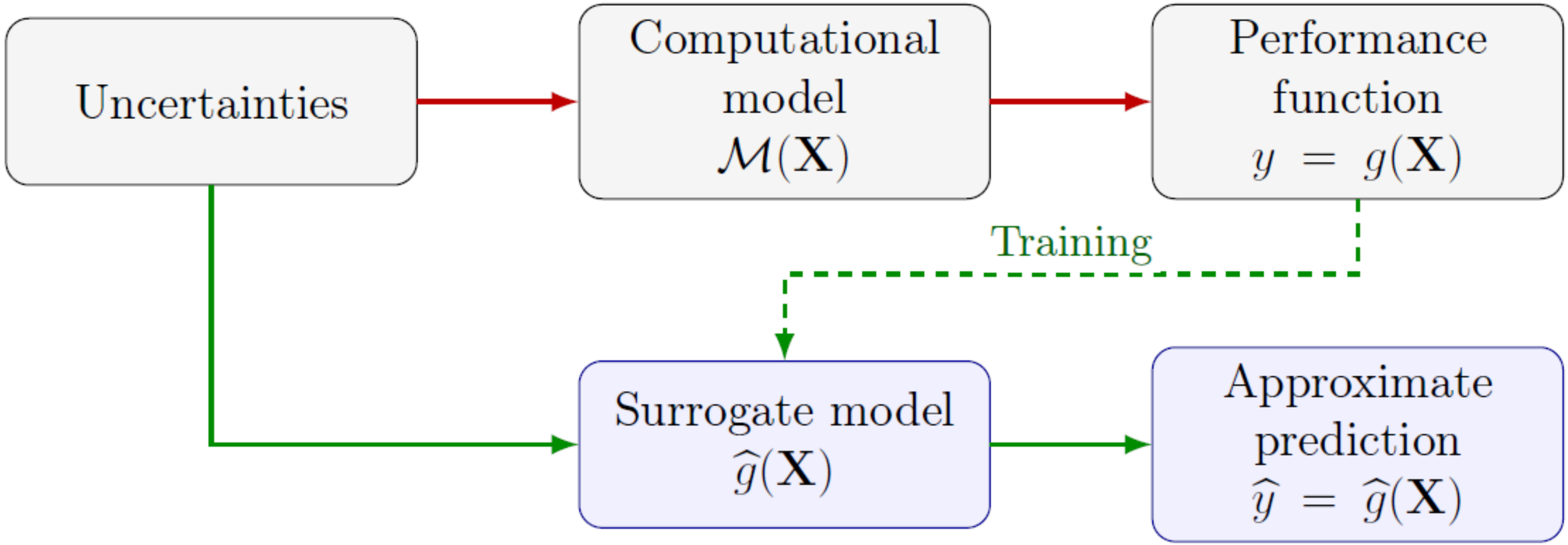

- **Objective** : quantify the probability of failure under uncertain input parameters
- **Limit-state function** $g(\mathbf{X})$ separates safe and failure domains

$$\mathbf{X} \downarrow g(\mathbf{X}) \downarrow$$

$$P_f = P\left[g(\mathbf{X}) \leq 0\right] = \int_{\{g(\mathbf{x}) \leq 0\}} f_{\mathbf{X}}(\mathbf{x})\, d\mathbf{x}$$

# 1. Why Surrogate Models for Reliability Analysis ?

**Large number of model evaluations**
**High computational cost**




**Fast surrogate evaluations**
**Large-scale uncertainty propagation**

# 1. Research Question

**How can surrogate models be reliably used for the reliability assessment of rockfall protection barriers ?**

# 2. Methodology

**Problem specification**

Selected random variables :
$\mathbf{X} = (V, X_{\text{imp}}, Y_{\text{imp}}, \Theta, F_{y,1}, F_{y,2})^{\mathsf{T}}$

Computational model: Generock($\mathbf{X}$)

Performance function: $g(\mathbf{X})$

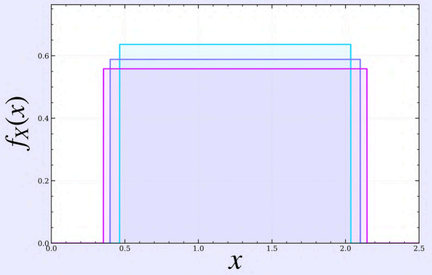
Fixed energy: $E_{\text{tot}} = 272\,\text{kJ}$

Quantity of interest:

$$P_f = \mathbb{P}\left[g(\mathbf{X}) \leq 0\right]$$

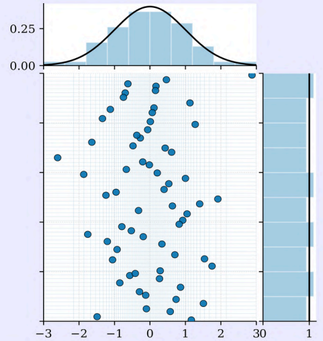
**Uncertainty modeling**

Joint distribution $f_{\mathbf{X}}(\mathbf{x})$




**Design of Experiments**

LHS – 500 samples



Sensitivity analysis

**Computation and post-processing**

Simulations using Generock

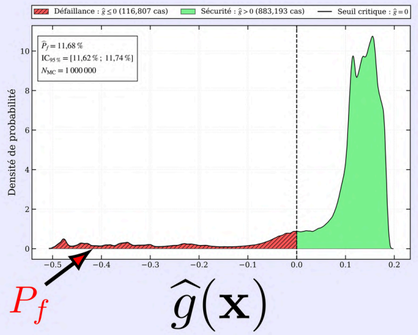
$$\mathcal{D}_N = \left[\begin{array}{c|c} \mathbf{x}^{(1)} & g\left(\mathbf{x}^{(1)}\right) \\ \mathbf{x}^{(2)} & g\left(\mathbf{x}^{(2)}\right) \\ \vdots & \vdots \\ \mathbf{x}^{(N)} & g\left(\mathbf{x}^{(N)}\right) \end{array}\right]$$

**Surrogate modeling**

Training, validation and performance evaluation

$$g(\mathbf{x}) \approx \hat{g}(\mathbf{x})$$

**Reliability assessment**



# 2. Problem Definition – Input Variables

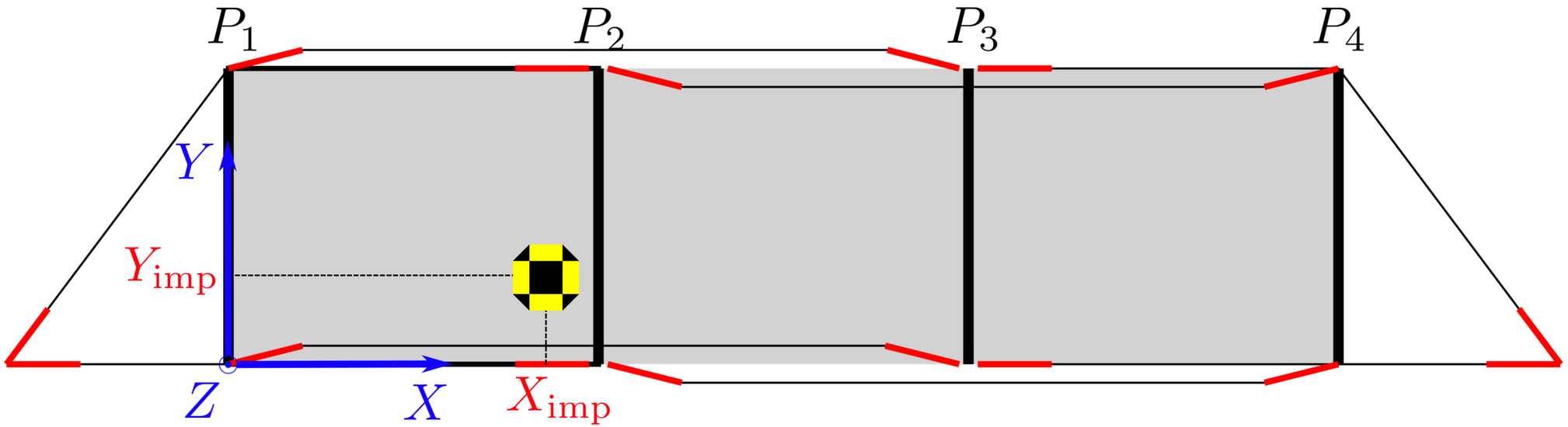



Illustration of impact position (X,Y)

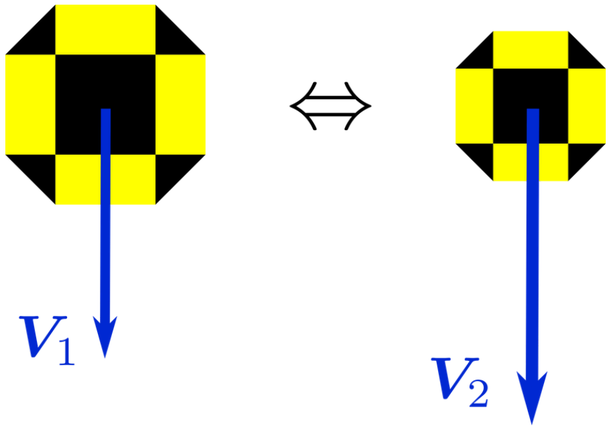



Illustration of translational velocity

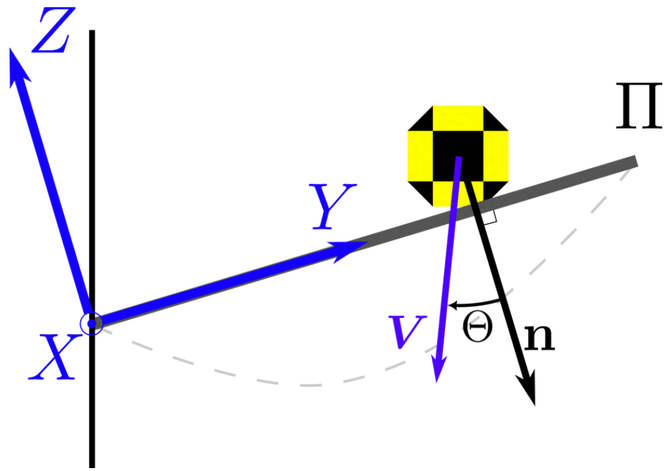



Illustration of impact angle

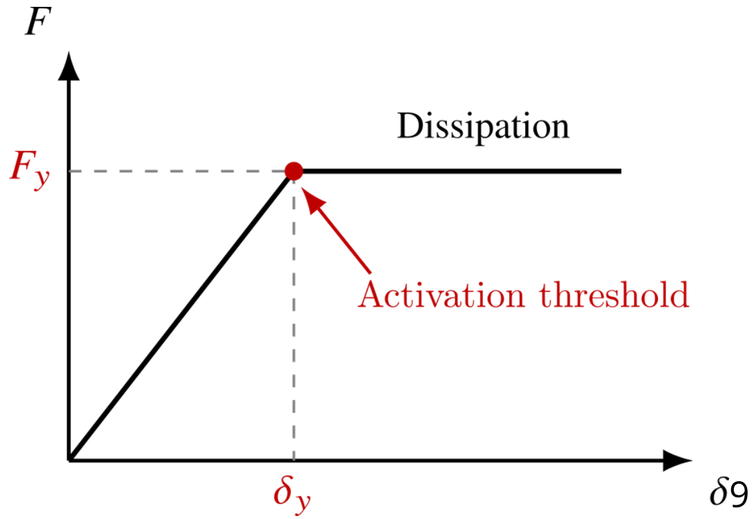


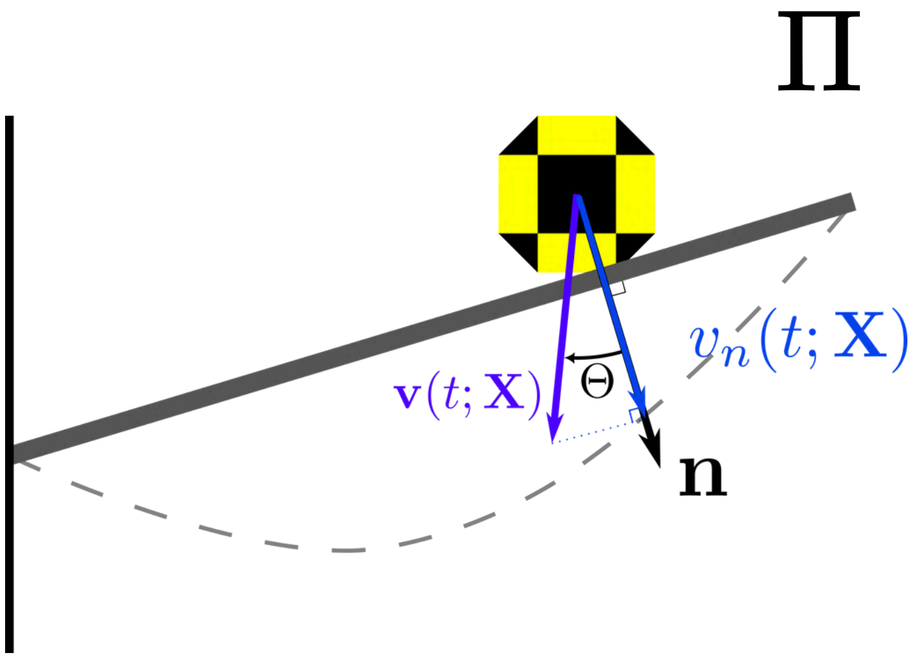

Illustration of activation threshold

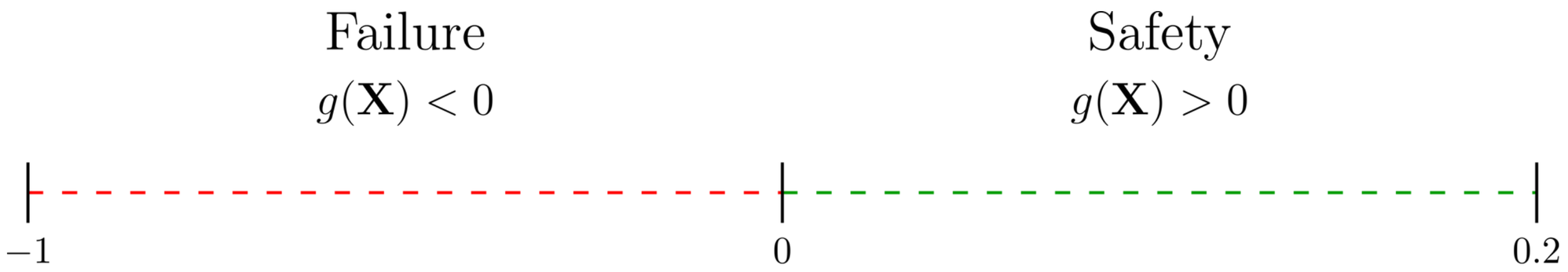
# 2. Problem Definition – Output

$$v_{n,\min}(\mathbf{X}) = \min_{t \in \mathcal{T}(\mathbf{X})} v_n(t;\mathbf{X})$$

$$r(\mathbf{X}) = -\frac{v_{n,\min}(\mathbf{X})}{v_n(0;\mathbf{X})}$$

$$g_\alpha(\mathbf{X}) = \begin{cases} r(\mathbf{X}), & \text{if } r(\mathbf{X}) \le 0 \\ \dfrac{1-\exp\left[-\alpha r(\mathbf{X})\right]}{\alpha}, & \text{if } r(\mathbf{X}) > 0 \end{cases}$$



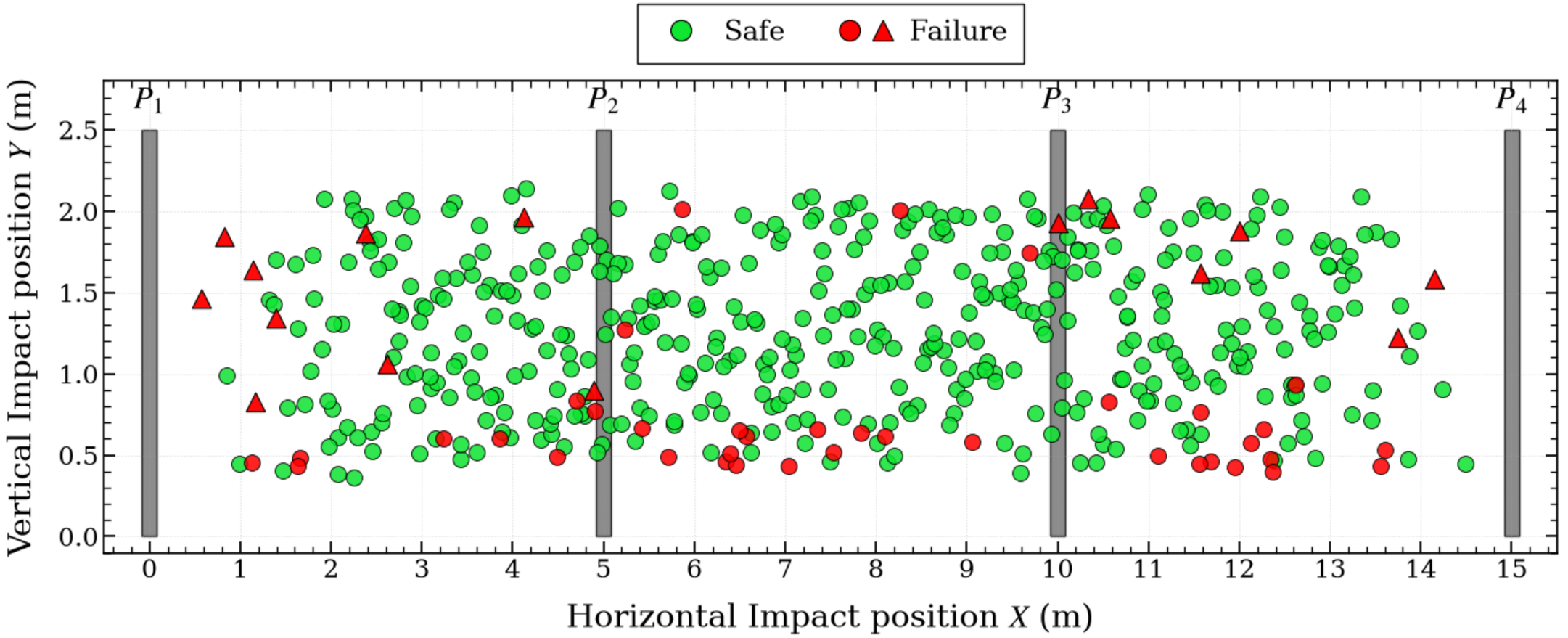

**Quantifies the barrier's ability to stop the impacting rock block**

# 2. From Problem Definition to Surrogate Modelling

- **How many simulations ?**
  - Limited computational budget
- **Which learning task ?**
  - Regression or classification ?
- **Which surrogate model ?**
  - RF, XGBoost, SVM, MLP, GPR, PCE…
- **How to train and validate it ?**
  - Imbalance, hyperparameters, validation strategy…

**Our approach :** start with 500 simulations and use **Exploratory Data Analysis** to guide the surrogate-modelling strategy

# 2. Design of Experiments & Exploratory Data Analysis



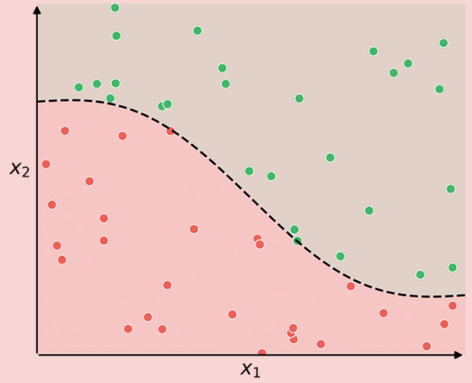

- Latin Hypercube Sampling
- 500 numerical simulations
  (~13 h computational time)
- 54 failure / 446 safe cases

- **Imbalanced dataset** → ~11% failure
- Nonlinear response and potential discontinuities
- Different physical failure mechanisms

# 2. Surrogate Modelling Strategy

## Classification

Learn to distinguish safe and failure cases

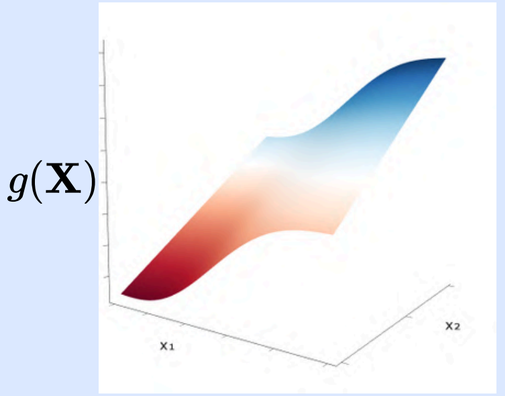



**Model families**

- Random Forest
- XGBoost
- MLP (neural network)

## Regression

Learn the continuous performance function $g(\mathbf{X})$

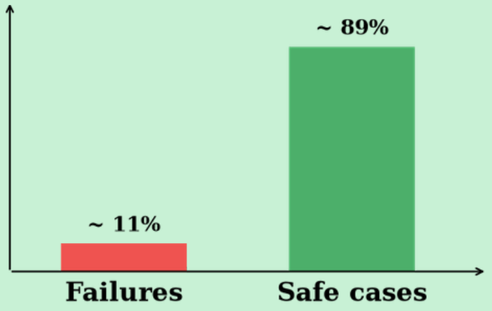



**Model families**

- Random Forest
- XGBoost
- MLP (neural network)
- Gaussian Process Regressor
- Polynomial Chaos Expansion

## Class imbalance

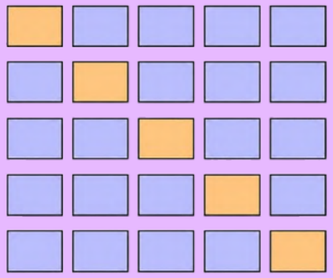
Different strategies tested




- **Weighting**
- **Random Undersampling**
- **SMOTE**
- **Custom loss functions**

## Training & Validation

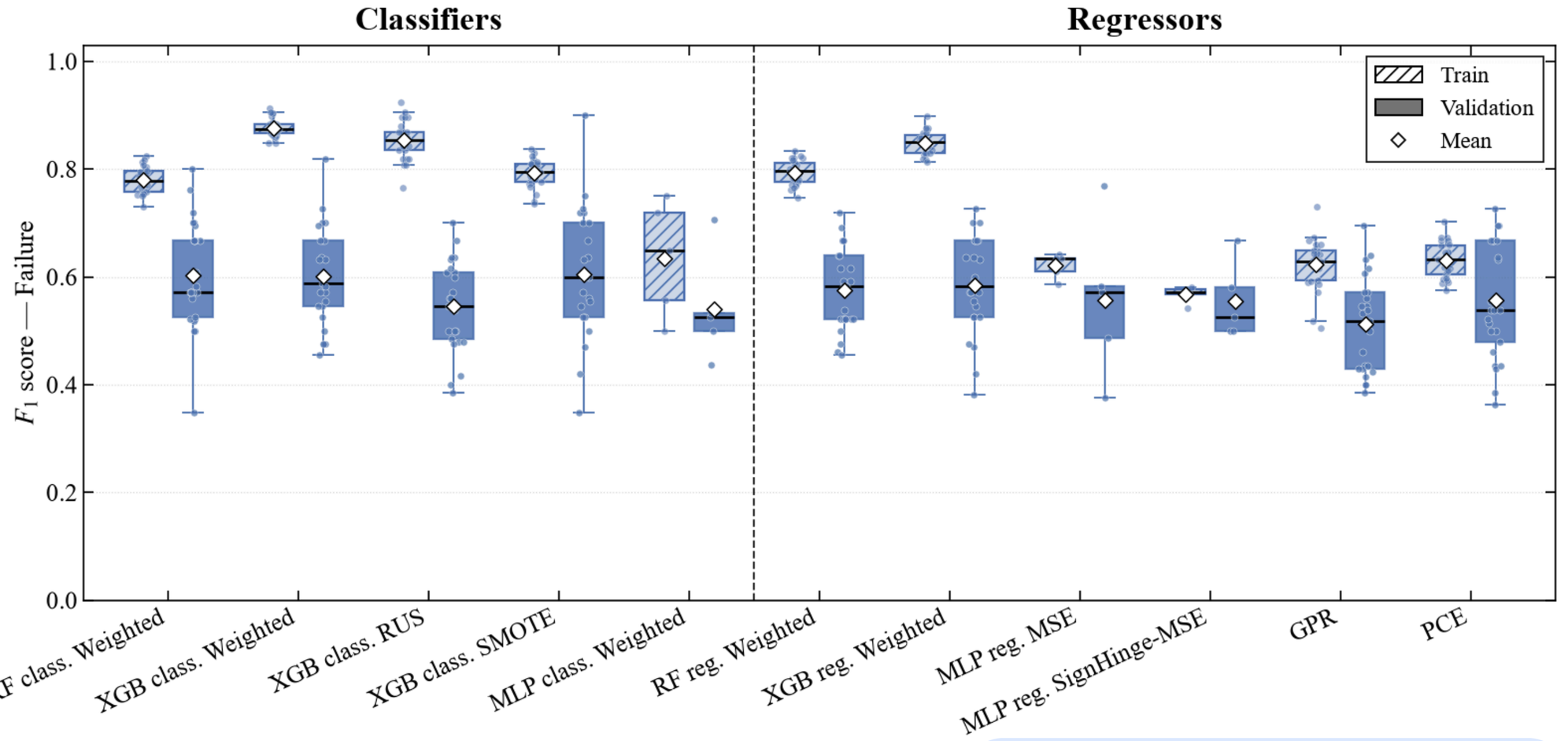
Stratified 5-fold cross-validation and hyperparameter search



**Hyperparameter search**

- Model-dependant search space
- Optimization based on a chosen metric

# 3. Surrogate Model Performance

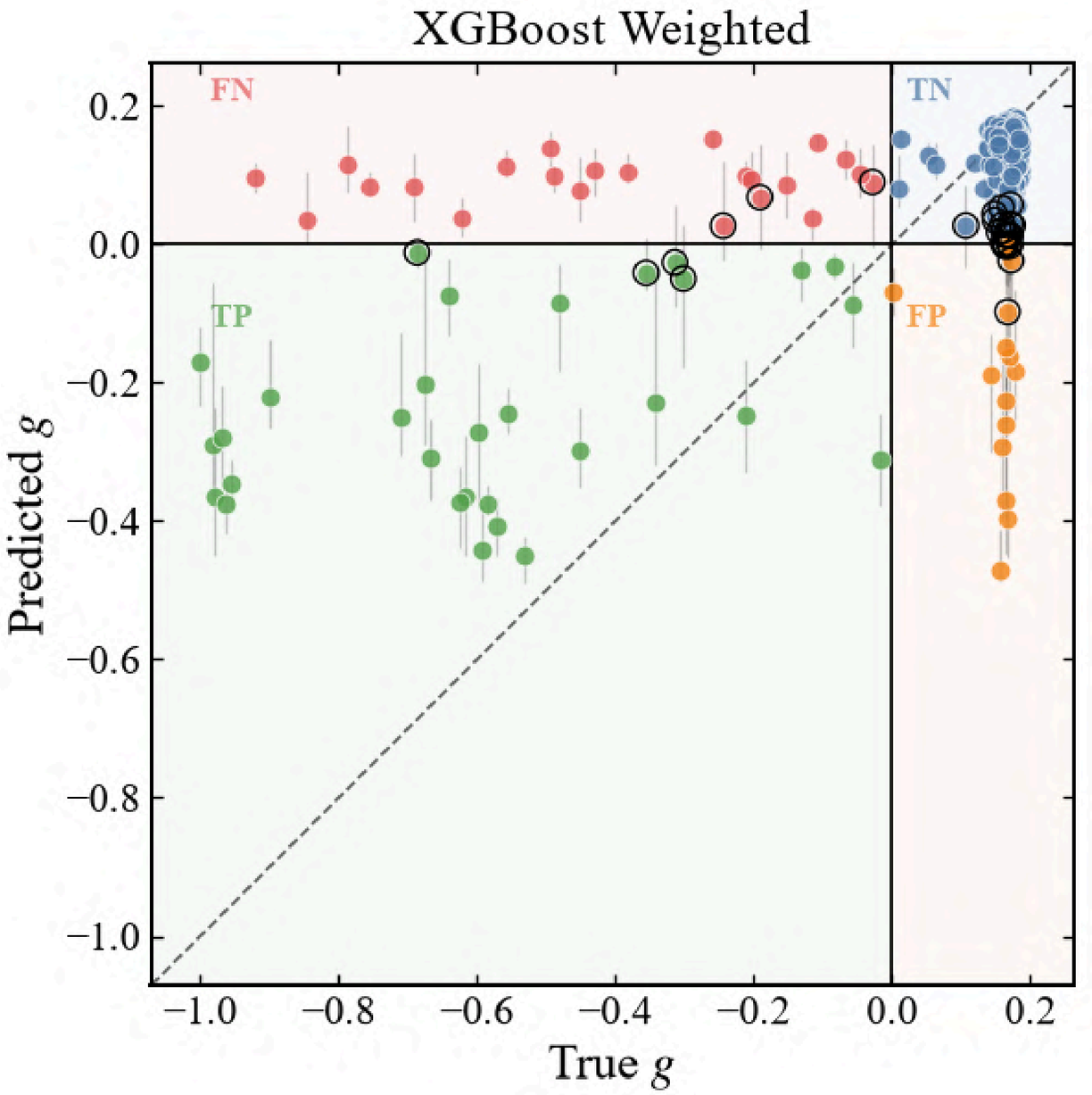



- Validation F1 score stabilizes around 0.6
- Performance remains insufficient for reliability assessment

**No clear improvement with :**

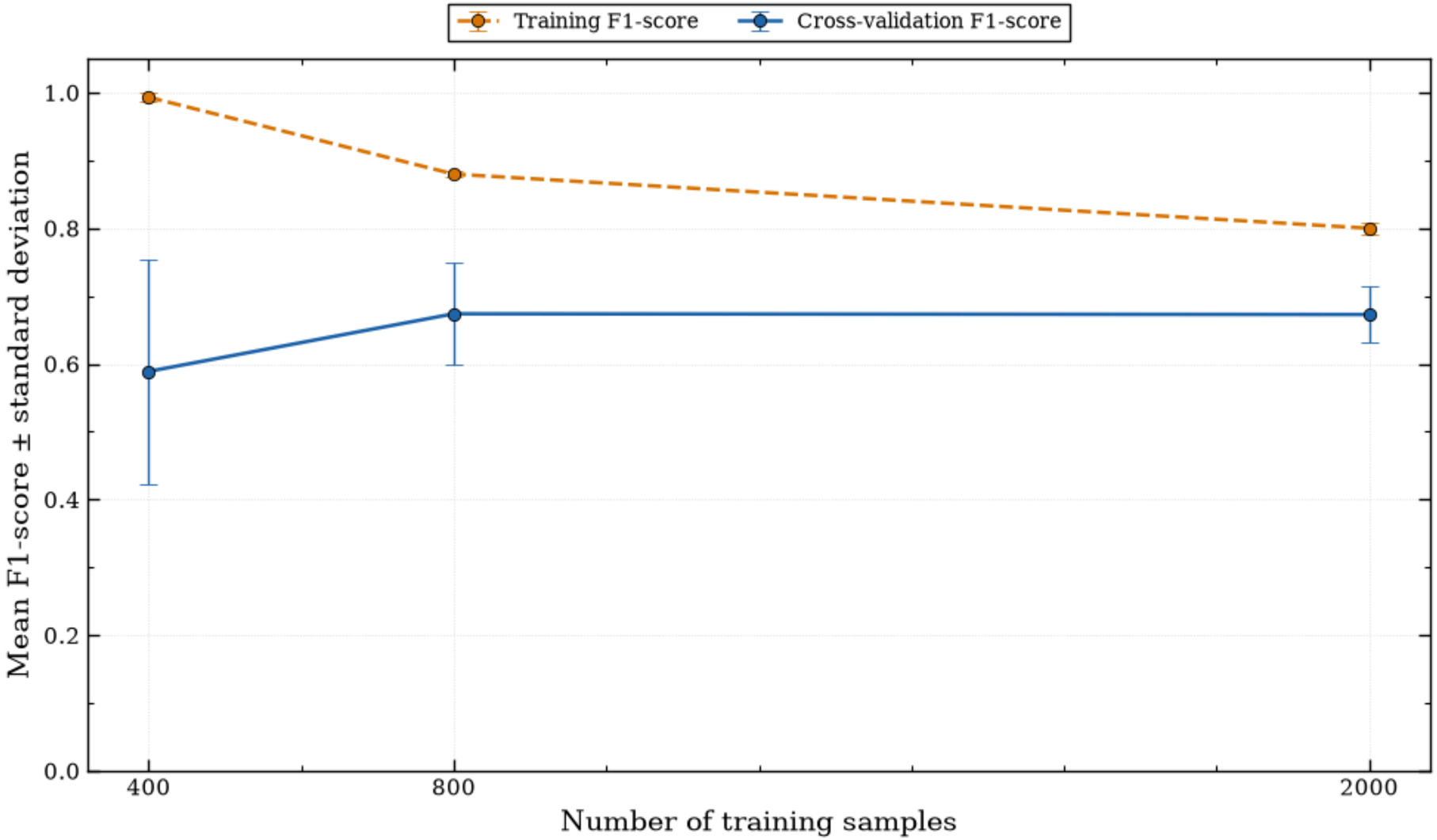
- Classification vs. regression
- More complex models
- Class-imbalance strategies

# 3. Where Do the Errors Occur ?



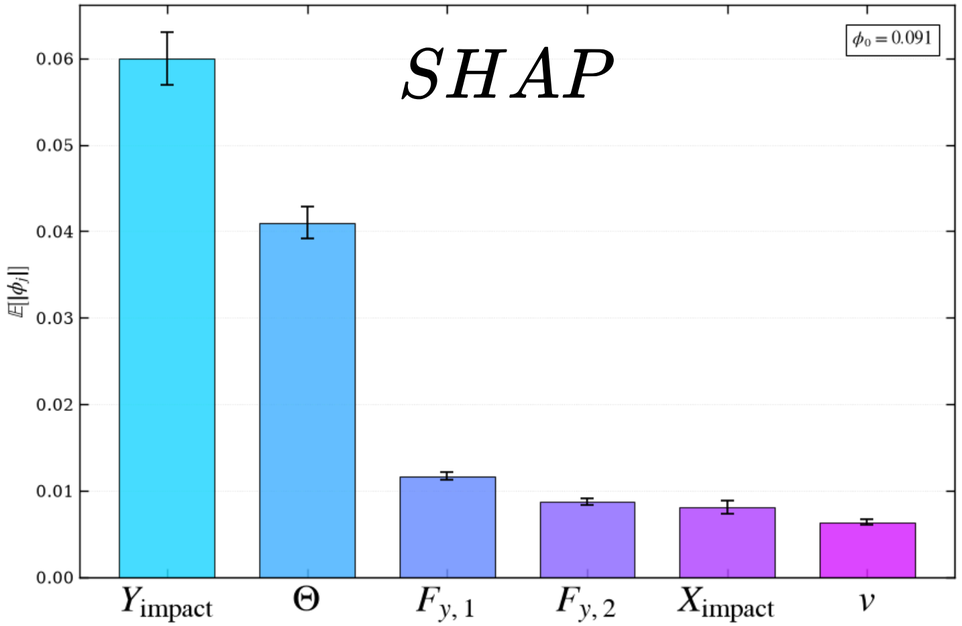

- **Errors are not restricted to the limit-state boundary**
- **Errors occur across different values of the performance function**
- **No simple error pattern emerges**

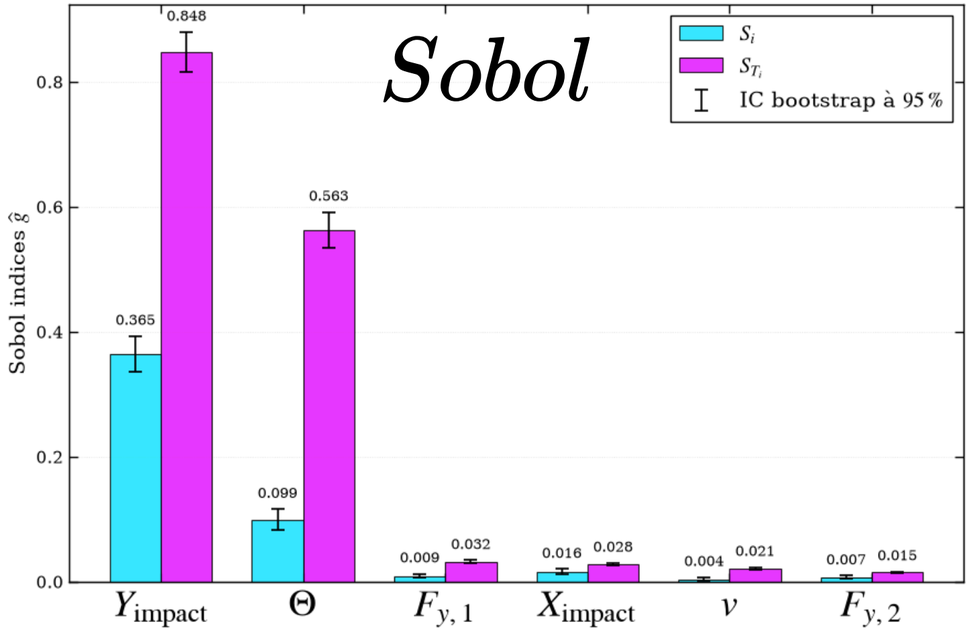
# 3. Can More Data Solve the Problem ?

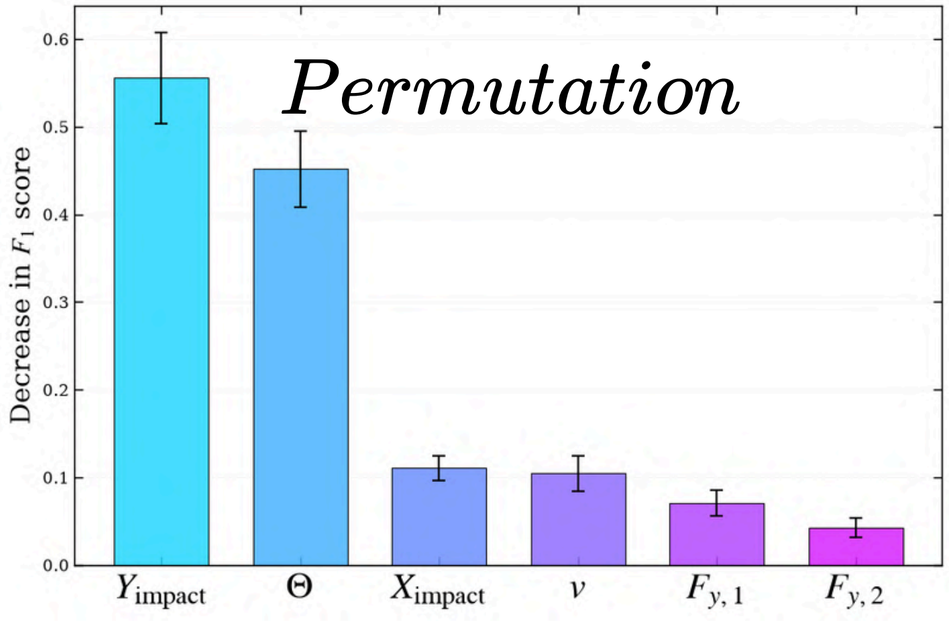



**Increasing the training-set size within the available computational budget does not lead to a clear improvement in predictive performance.**

# 3. Surrogate Interpretation & Sensitivity Analysis




- Consistent importance of **Yimp** and **θ**
- Strong interaction effects revealed by Sobol total-order indices
- Sensitivity results remain conditional on surrogate performance

# 4. Conclusion & perspectives

**Surrogate models provide a promising framework for reliability analysis, but their predictive reliability remains a key issue**

- **No surrogate model clearly solves the problem**
- **Class-imbalance treatments are not sufficient**
- **Errors are not restricted to the limit-state boundary**
- **Sensitivity analysis provides physically meaningful insights**

**Perspectives :**

1. **Improve the simulation framework**
2. **Improve the learning strategy**
3. **Explore advanced Machine Learning architectures (GNNs, PINNS, DNO…)**

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**Thank you for your attention !**

**Questions ?**