Webinaire « Doctorants en géotechnique »

Applications of Artificial Intelligence for deciphering strength development of binder-soil mixtures in the context of soil stabilization

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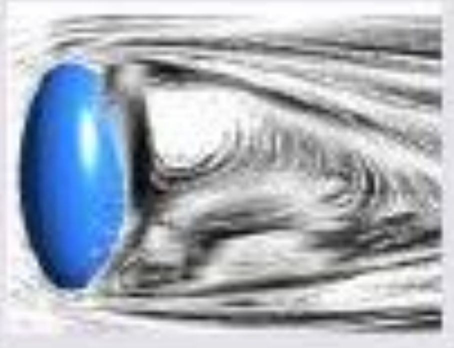
LEMTA – Joint research unit of the University of Lorraine and CNRS

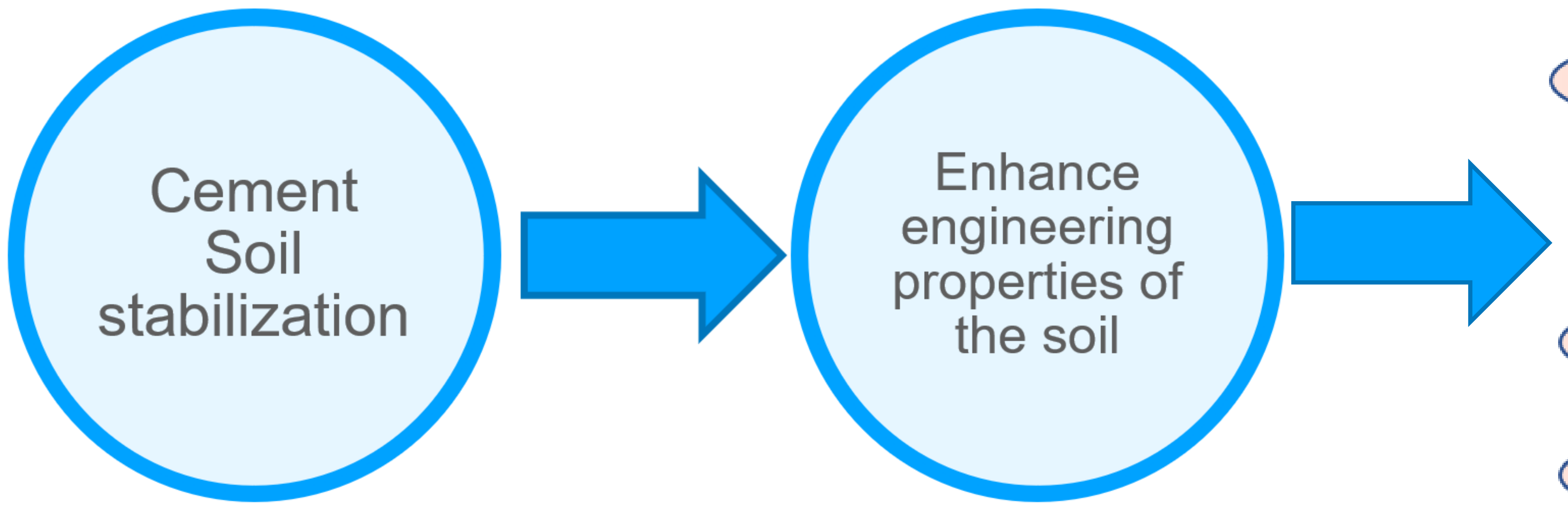
Laboratoire Énergies & Mécanique Théorique et Appliquée

	MILIEUX FLUIDES, RHEOPHYSIQUE	
	Hydrodynamique et rhéophysique	AT IRM POUR L'INGÉNIERIE 
	Transferts dans les fluides	
	Rhéologie de matériaux nano/micro-structurés	
	ENERGIE ET TRANSFERTS	
	Transport dans les milieux complexes	
	Feux	
	Mécanique des sols, géotechnique	
	VECTEURS ENERGETIQUES	
	Hydrogène, systèmes électrochimiques	
	Gestion de la chaleur	
	Gestion de l'énergie électrique	

Mécanique des sols : thématiques de recherche

Cement soil stabilization

- Cement stabilization



- General observation about the strength controlling factors in cement stabilized compacted soils (CSS).

Parameter	General observation
Cement dosage	↑ Higher strength
Curing time	↑ Higher strength
Curing temperature	↑ Higher strength
Soil porosity	↓ Lower strength
Water-cement ratio	↓ Lower strength
Organic content	↓ Lower strength
Dry density	↑ Higher strength
Moisture content	More strength on the dry side of the optimum than on the wet side
Soil type	Require more dosage for FGS than for CGS

Empirical modeling

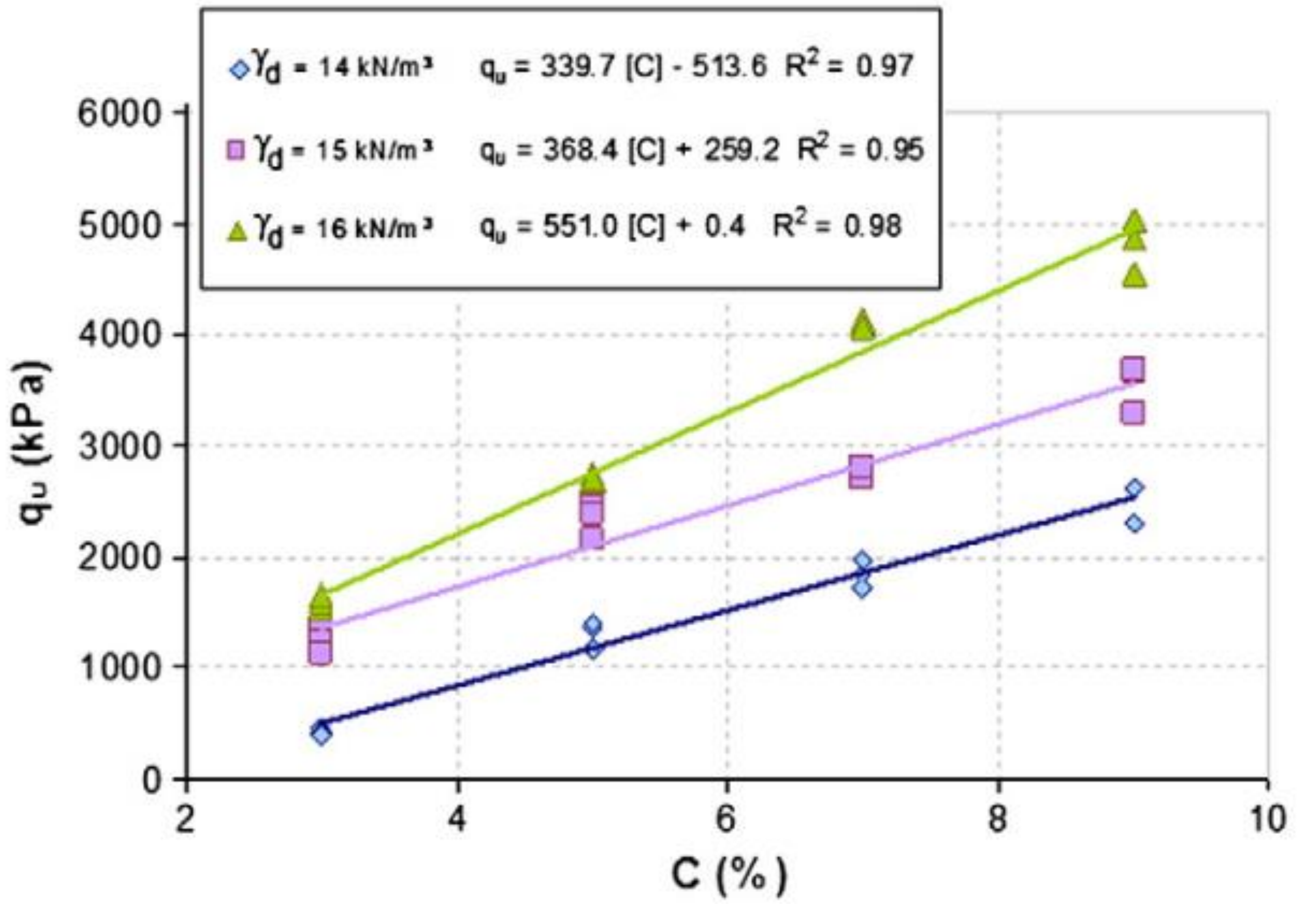
- Mapping the strength controlling factors with the UCS of CSS through laboratory testing

- Limitations ?

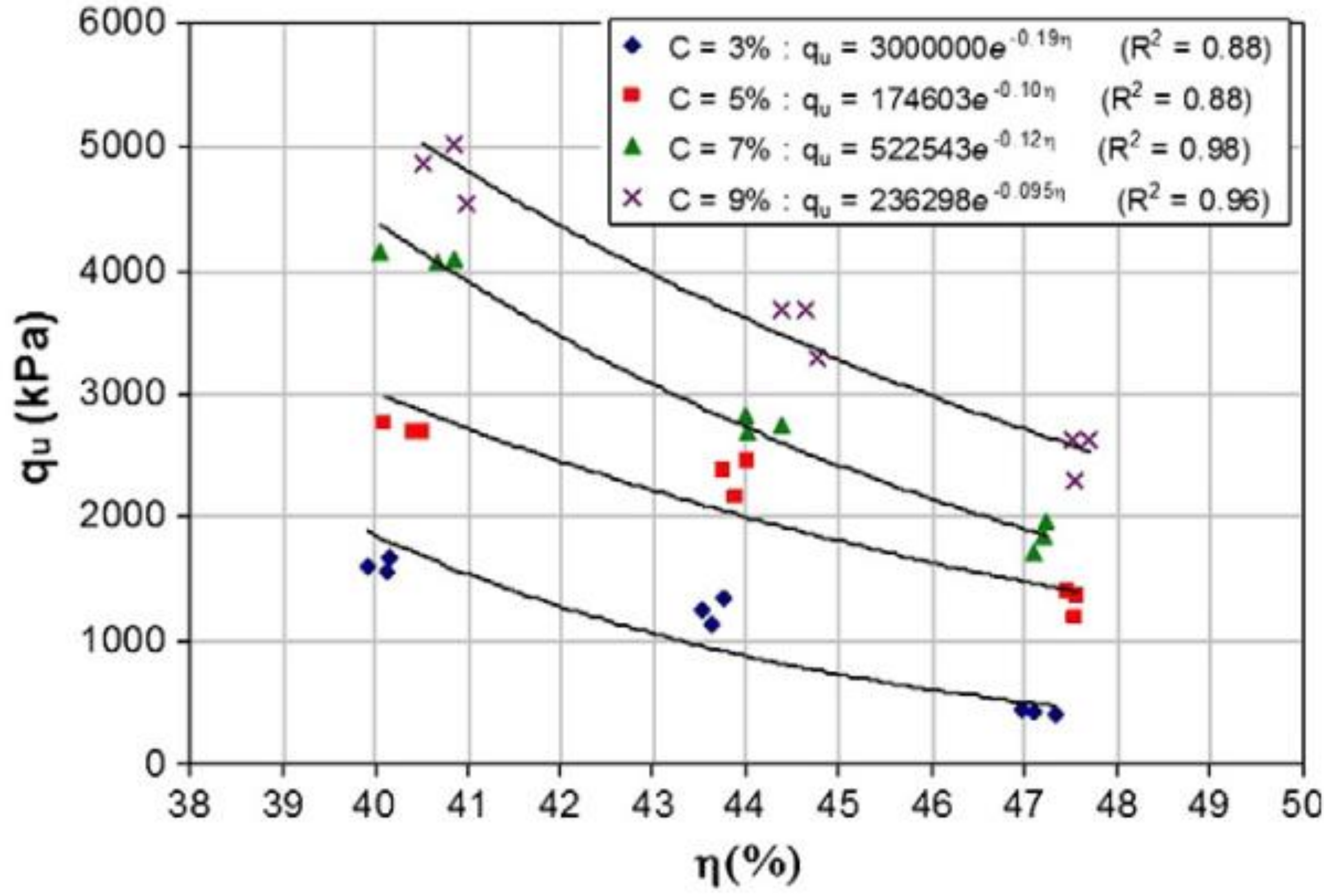
$$qu\ (KPa) = \left[5.45 \times 10^{7}(w) - 5.37 \times 10^{8}\right] \times \left[\frac{\eta}{C_{iv}{}^{0.35}}\right]^{-3.6}$$ (Consoli, et al. 2011)

(Consoli, et al. 2007)	$qu\ (kPa) = \left[5.03 \times 10^{7}\right] \times \left[\frac{\eta}{C_{iv}{}^{0.28}}\right]^{-3.32}$
(Baldovino, et al. 2020)	$qu\ (kPa) = \left[377121 \times t^{0.3}\right] \times \left[\frac{\eta}{C_{iv}{}^{0.45}}\right]^{-2.0}$
(Santana, et al. 2021)	$qu\ (MPa) = \left[3.4 \times 10^{5}\right] \times \left[\frac{\eta}{C_{iv}{}^{0.2}}\right]^{-3.585}$
(Rios, Viana da Fonseca, & Baudet, (2012)	$qu\ (kPa) = \left[4 \times 10^{9}\right] \times \left[\frac{\eta}{C_{iv}{}^{0.21}}\right]^{-4.296}$

- Applicability
- Simultaneous consideration of factors
- Too simple to capture complex relations



Consoli, et al. 2011



A To develop predictive models for strength development in CSS considering a wide range of soil types and cement types

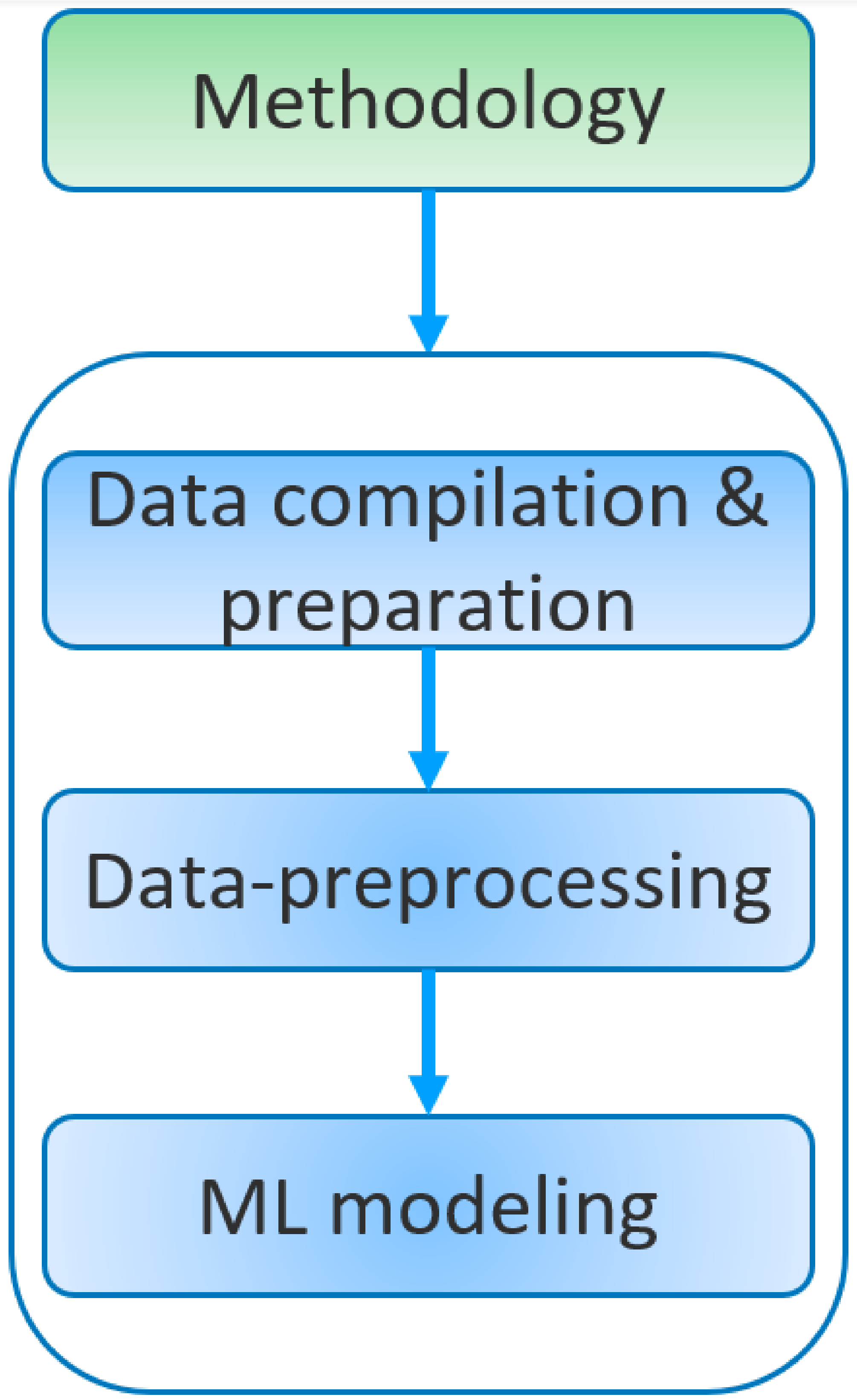
B To Identify the most important features and their contribution to the strength

C To provide design charts by optimizing the strength of CSS based on compaction parameters.

Data compilation and preparation

Compiled dataset on cement-stabilized compacted soils			
Author	USCS	Cement type	Datapoints
Baldovino, et al. (2020)	High plastic silt (MH)	Type-III	36
Abdallah, A. et al. (2023)	Lean Clay (CL)	CEM-II	120
Beckett, C. (2014)	Crushed limestone	OPC	18
Dong, Xinxin, et al. (2022)	Silty sand (SM)	CEM-II	20
Mengue, et al. (2017)	High plastic silt (MH)	CEM-II	36
Chamling, P. K., et al. (2021)	Silty sand (SM)	OPC Grade-53	30
Minh-Duc, et al. (2020)	High plastic silt (MH)	PC-40	20
		Total	**280**

Liquid limit	Fine contents	Cement type	Norm. Initial dry density	Norm. Initial water content	Cement dosage	Curing time	Porosity-cement ratio	UCS
LL	FC	-	ρ_{norm}	ω_{norm}	C	T	η/Civ	qu
(%)	(%)	-	-	-	(%)	(days)	-	(KPa)



Data preprocessing

- Accessing the correlation between features and UCS

- Multi collinearity check !

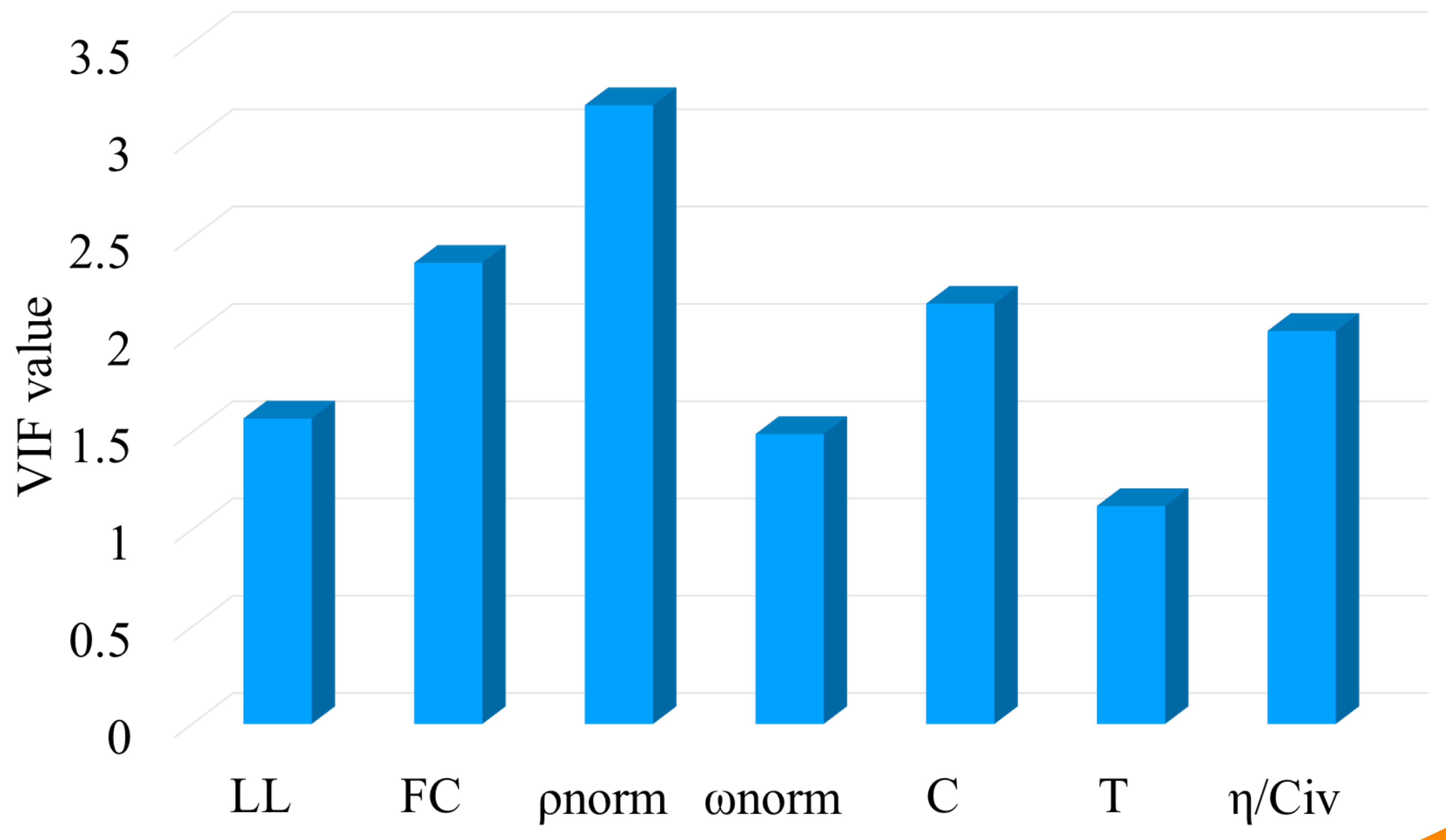
Pearson correlation

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 (y_i - \bar{y})^2}}$$

	LL	FC	ρnorm	ωnorm	C	T	η/Civ	qu
LL	1.0							
FC	-0.14	1.0						
ρnorm	0.37	-0.66	1.0					
ωnorm	0.078	-0.071	-0.23	1.0				
C	0.17	-0.016	0.025	-0.24	1.0			
T	-0.023	0.23	-0.013	0.010	-0.064	1.0		
η/Civ	0.031	0.12	-0.21	0.095	-0.61	-0.020	1.0	
qu	0.11	-0.49	0.55	0.0085	0.14	0.20	-0.51	1.0

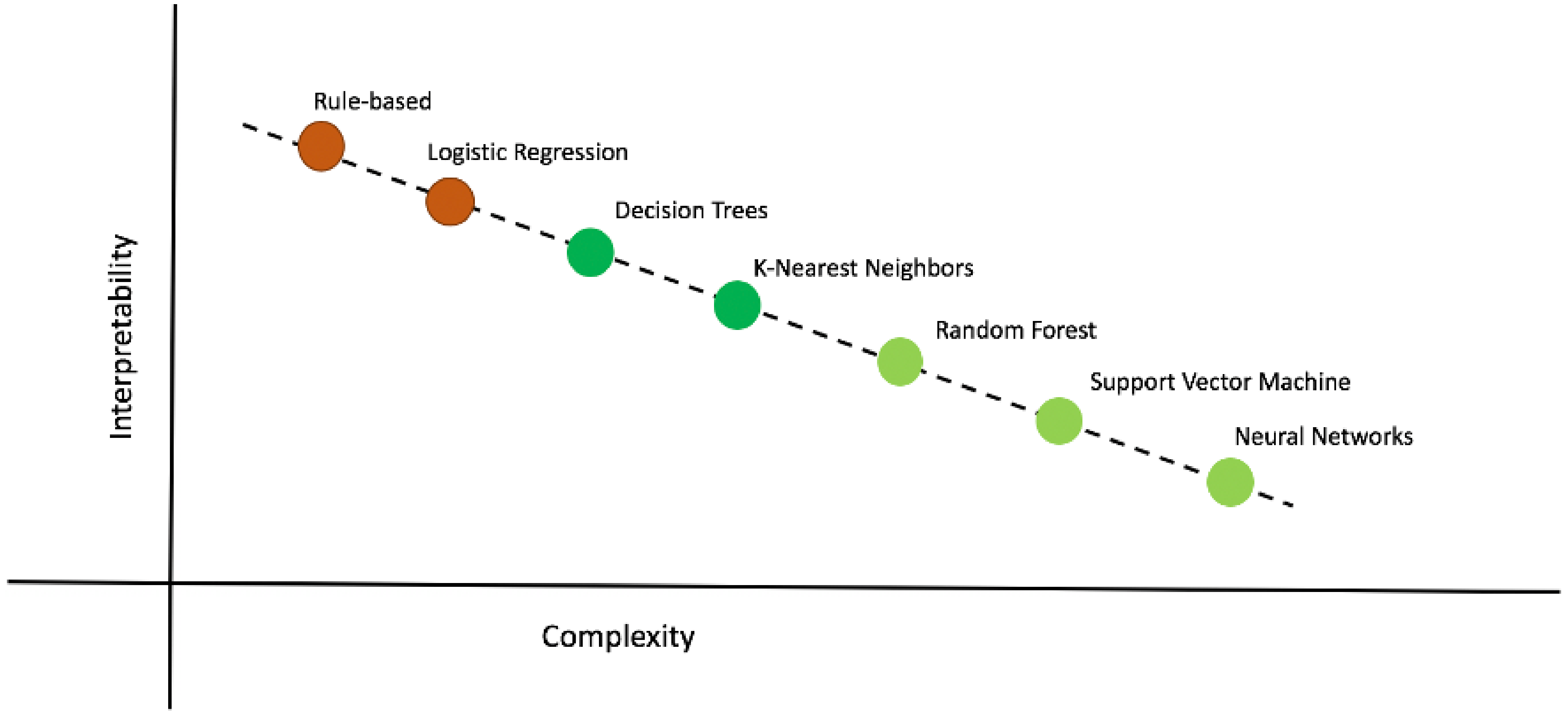
Variance inflation factor

$$VIF = \frac{1}{1 - \hat{R}^2}$$



Machine learning modeling

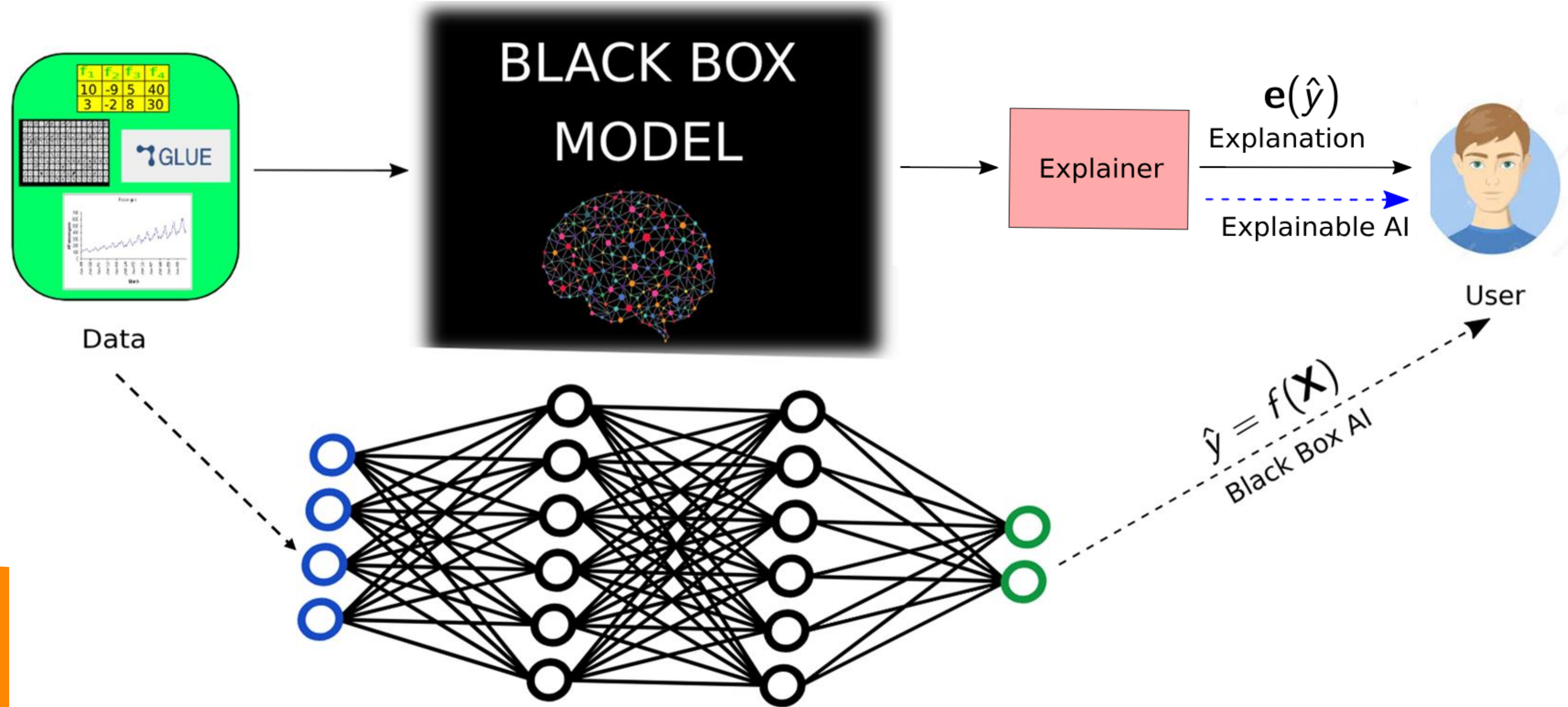
- Interpretability and complexity in ML modeling



(https://medium.com/@analyttica/understanding-shap-xai-through-leaps-e648c77310e8)

- What is a black box model ?

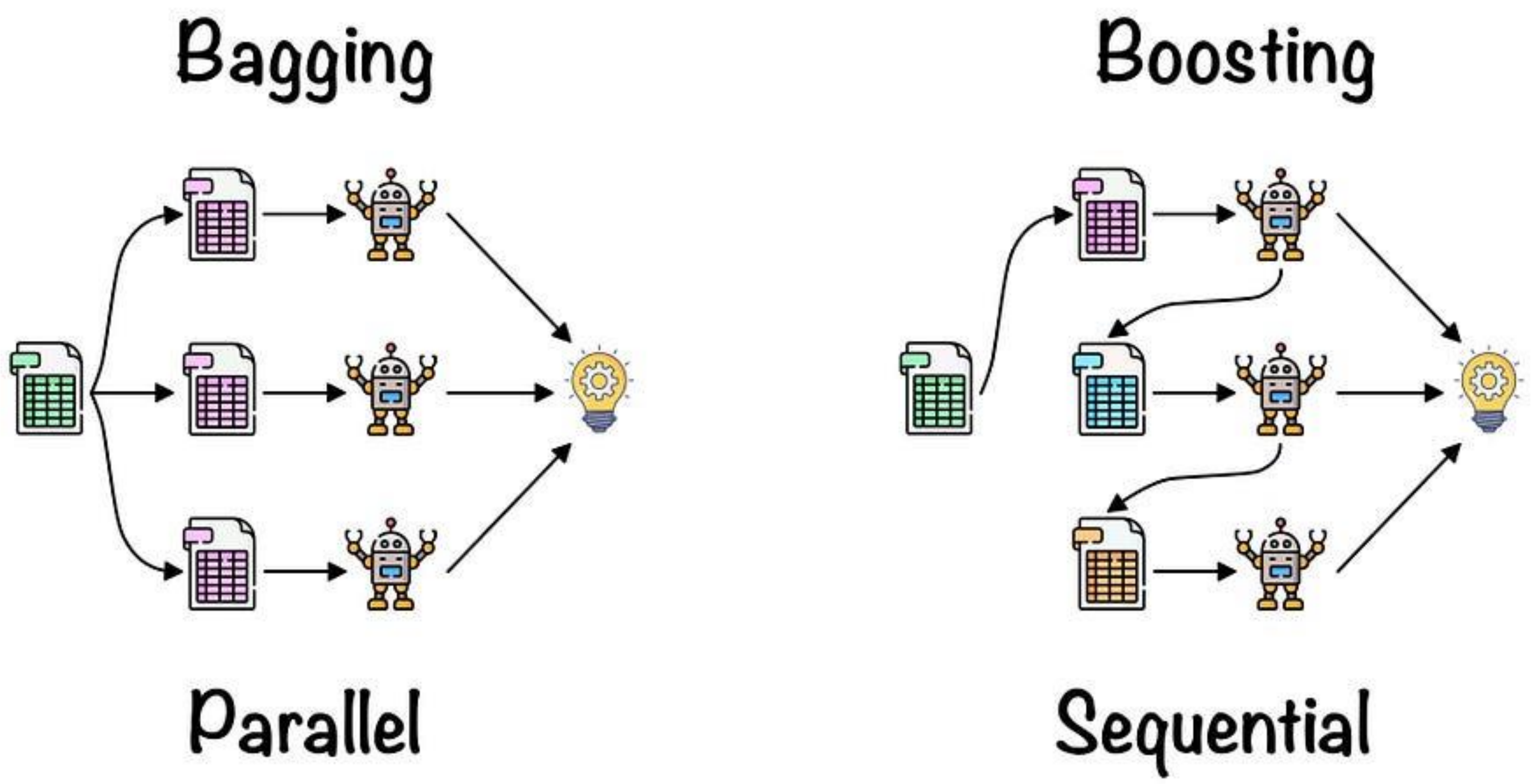
- How can we interpret a black box model (Explainable AI) ?



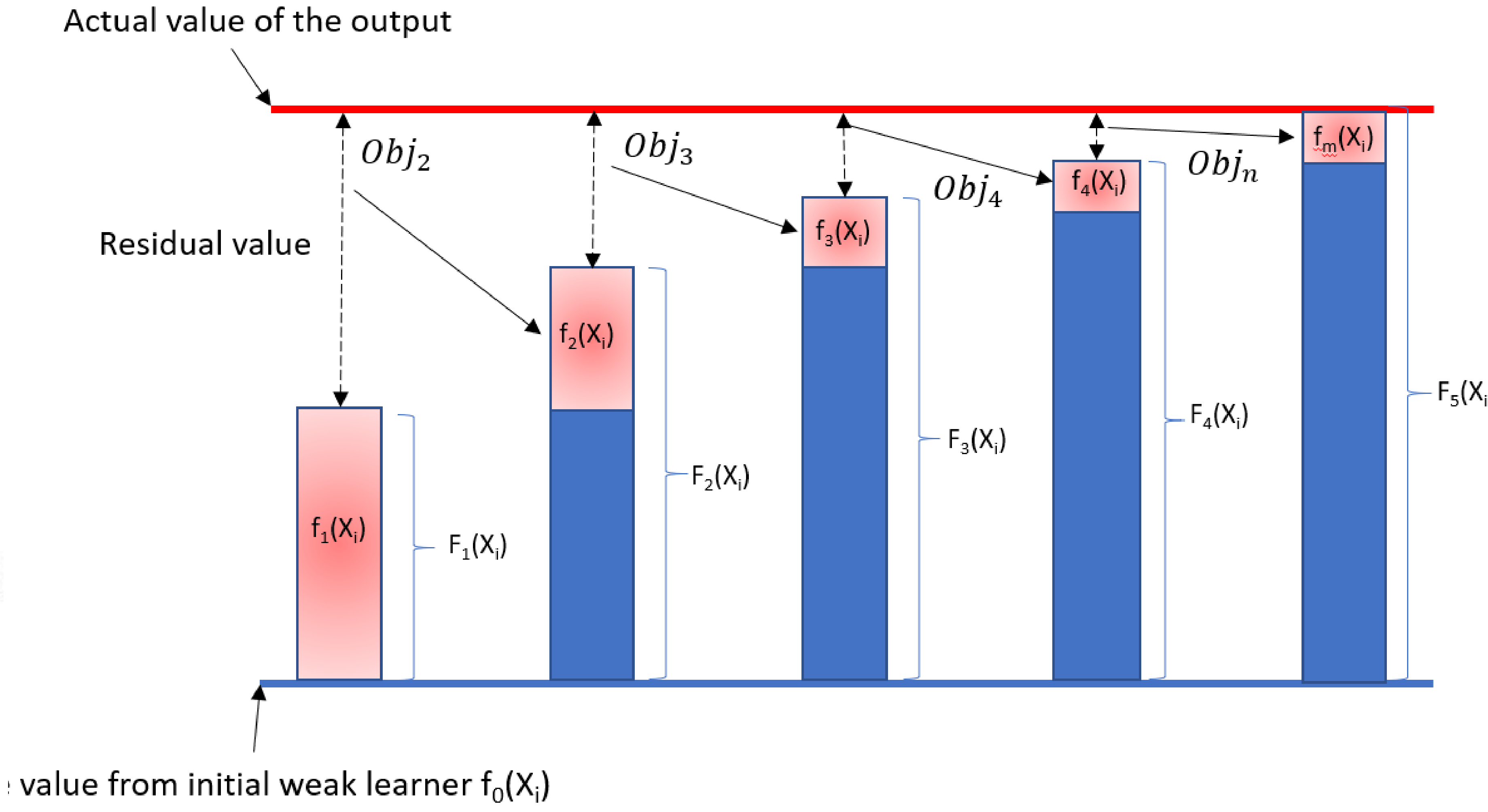
(https://spectra.mathpix.com/article/2021.09.00007/demystify-post-hoc-explainability)

eXtreme Gradient Boost (XGBoost)

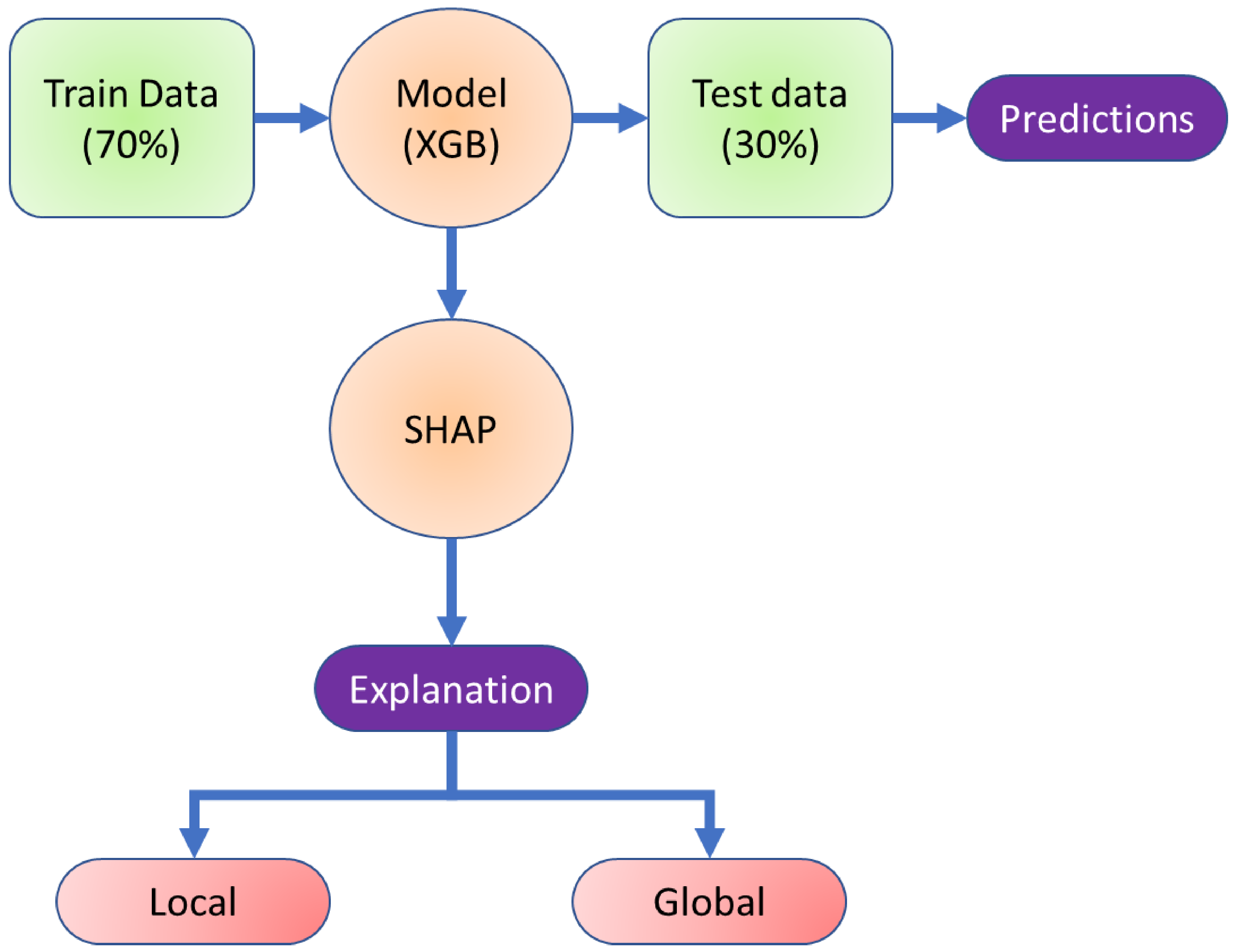
- XGBoost: A boosting ensemble learning technique
- A series of weak learners try to fit the residuals in the predictions made by previous weak learners.
- Grid-search algorithm was used to obtain optimal values of hyper-parameters



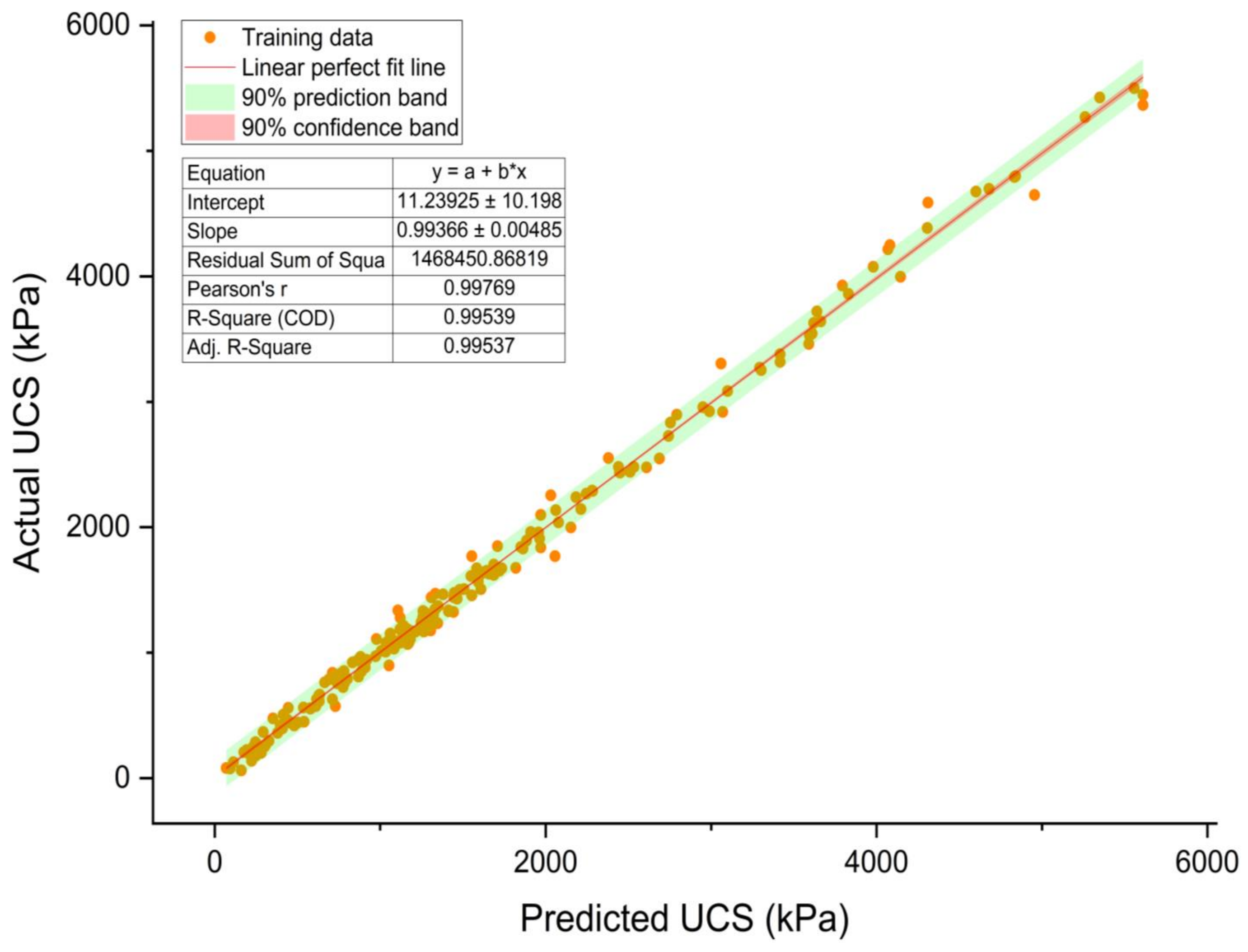
https://medium.com/@roshmitadey/bagging-v-s-boosting-be765c970fd1



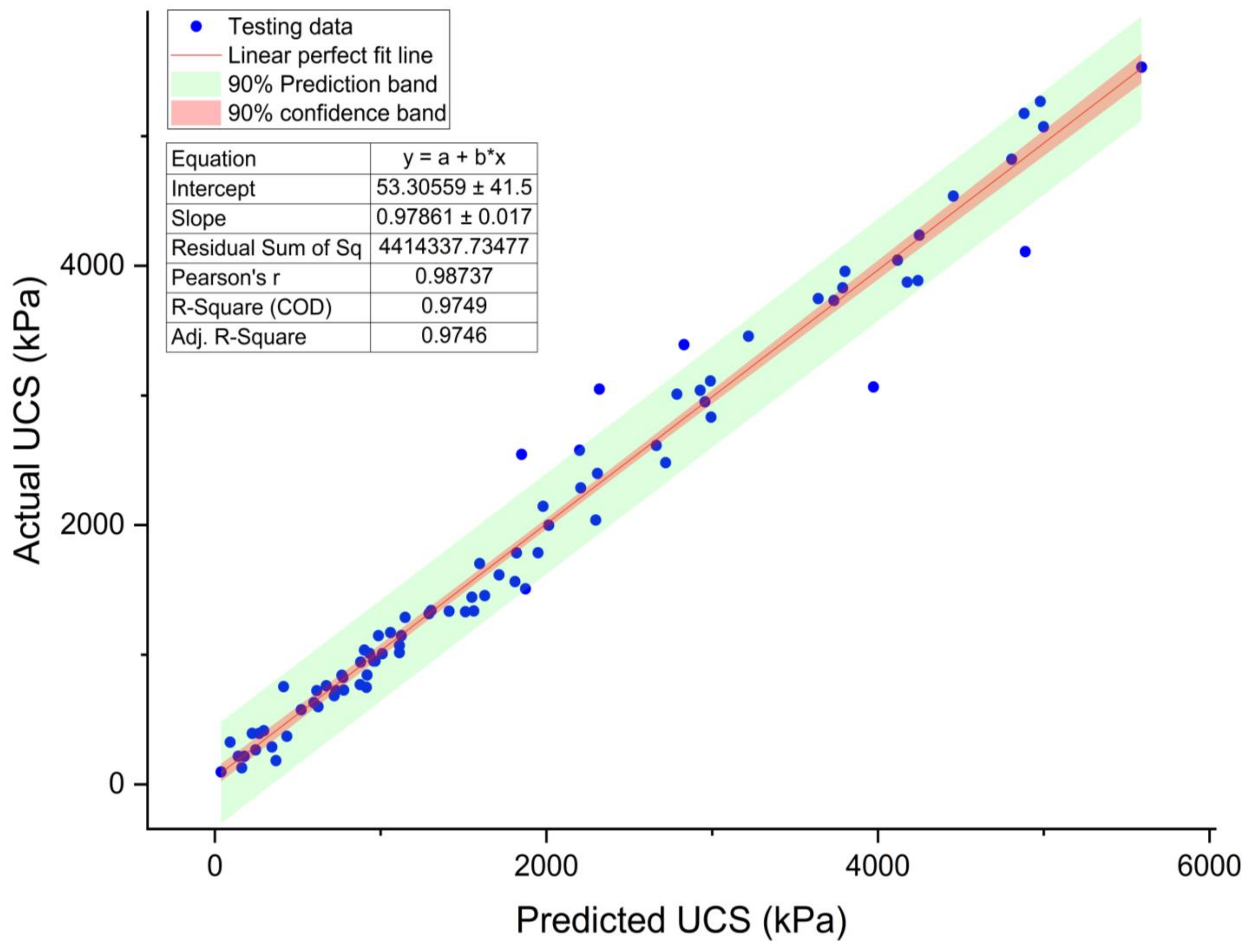
Hyperparameter	Function	Defined grid space	Optimal values
max_depth	Controls maximum depth	2, 3, 4, 5, 6, 7	5
learning_rate	Controls the step at each iteration to reduce loss	0.1, 0.2, 0.3, 0.4	0.2
n_estimators	Controls the number of trees to be generated	50, 100, 150, 200	150
min_child_weight	Defines the minimum sum of weights of all observations required in a child	7	7
subsample	Specifies the fraction of observations to be randomly sampled for each tree	0.7, 0.8	0.8
colsample_bytree	Specifies the fraction of features to be randomly sampled for each tree.	0.5, 0.6, 0.7, 0.8	0.6
reg_lambda	Penalizes the loss function and prevents overfitting	0.3, 0.4, 0.5, 0.6	0.6



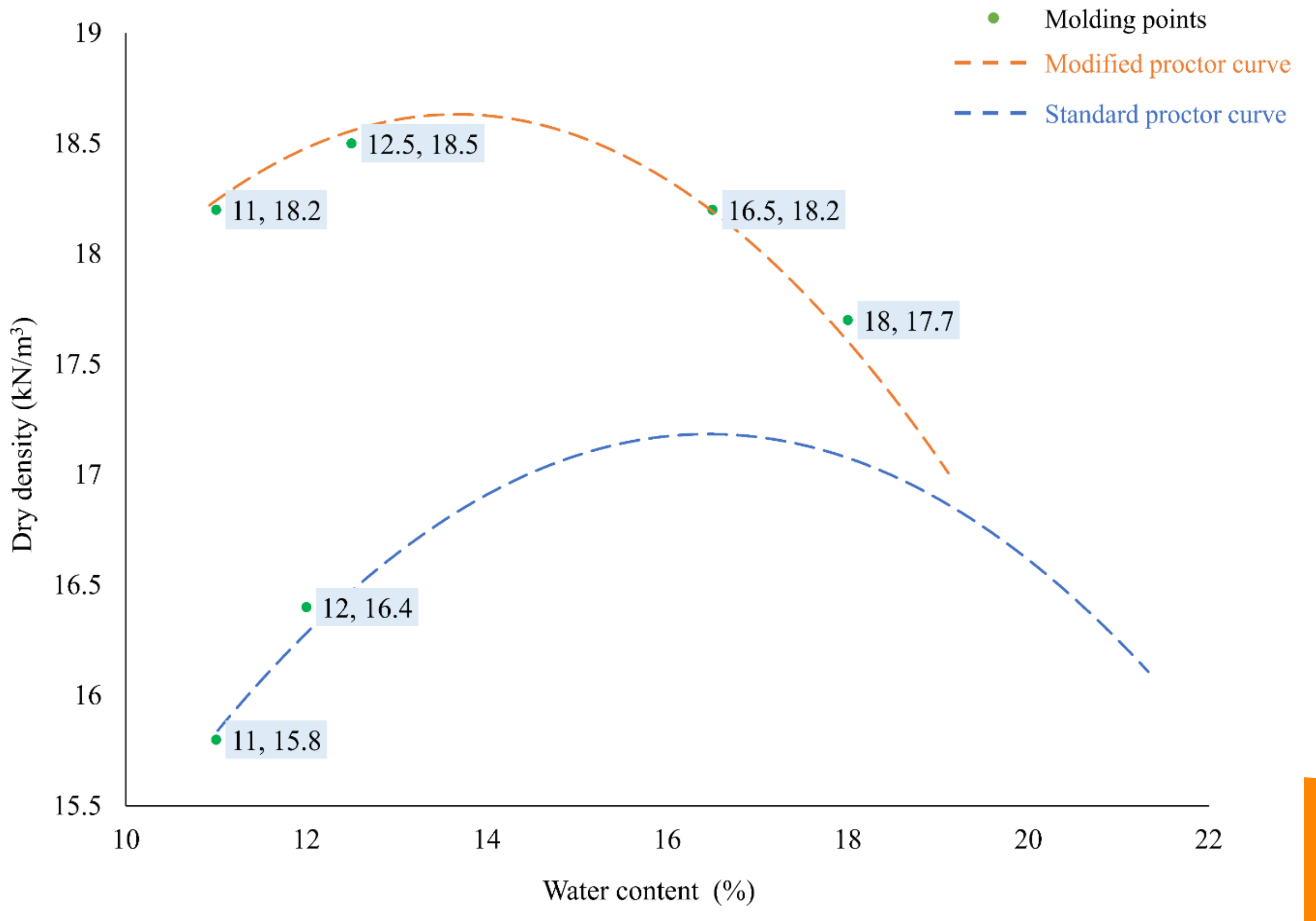
Training set



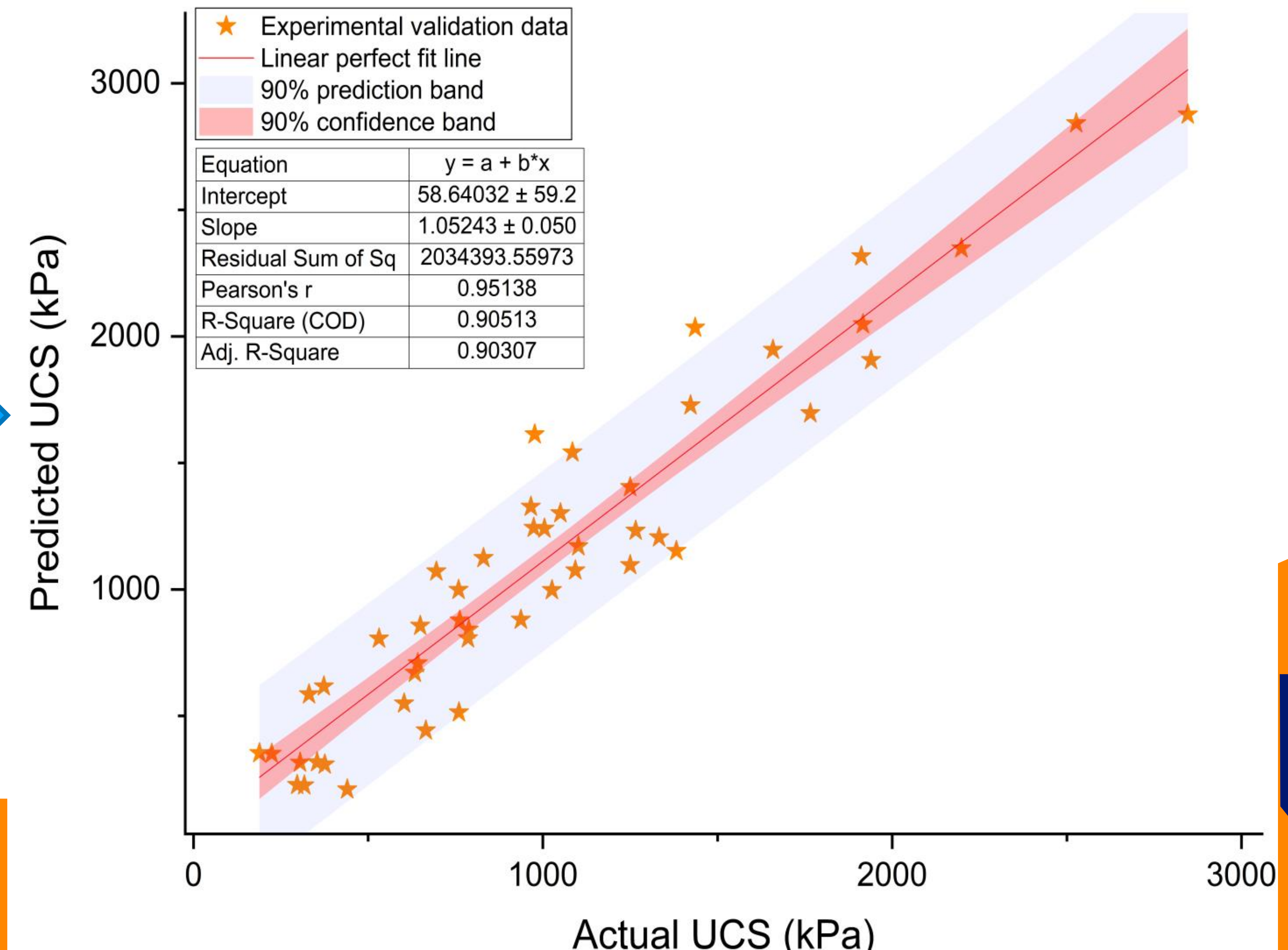
Testing set



Initial conditions for lab testing



Experimental validation



Shapley additive explanations (SHAP)

- SHAP is based on game theory and interprets the predictions of black-box models
- SHAP value of a feature is the **marginal contribution** of that feature to the output

$$\phi_i(f) = \sum_{S\subseteq N\setminus\{i\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}[f(S\cup\{i\}) - f(S)]$$

Price Money

1st	2ND	3rd
1000 €	750 €	500 €

A **B**

Coalitions

$$C_{AB} = \mathbf{1000}$$
$$C_A = \mathbf{750}$$
$$C_C = \mathbf{500}$$
$$C_0 = \mathbf{0}$$

Marginal contributions

A

$$C_{AB} - C_B = \mathbf{500}$$
$$C_A - C_0 = \mathbf{750}$$
$$\boxed{\frac{500 + 750}{2} = \mathbf{625€}}$$

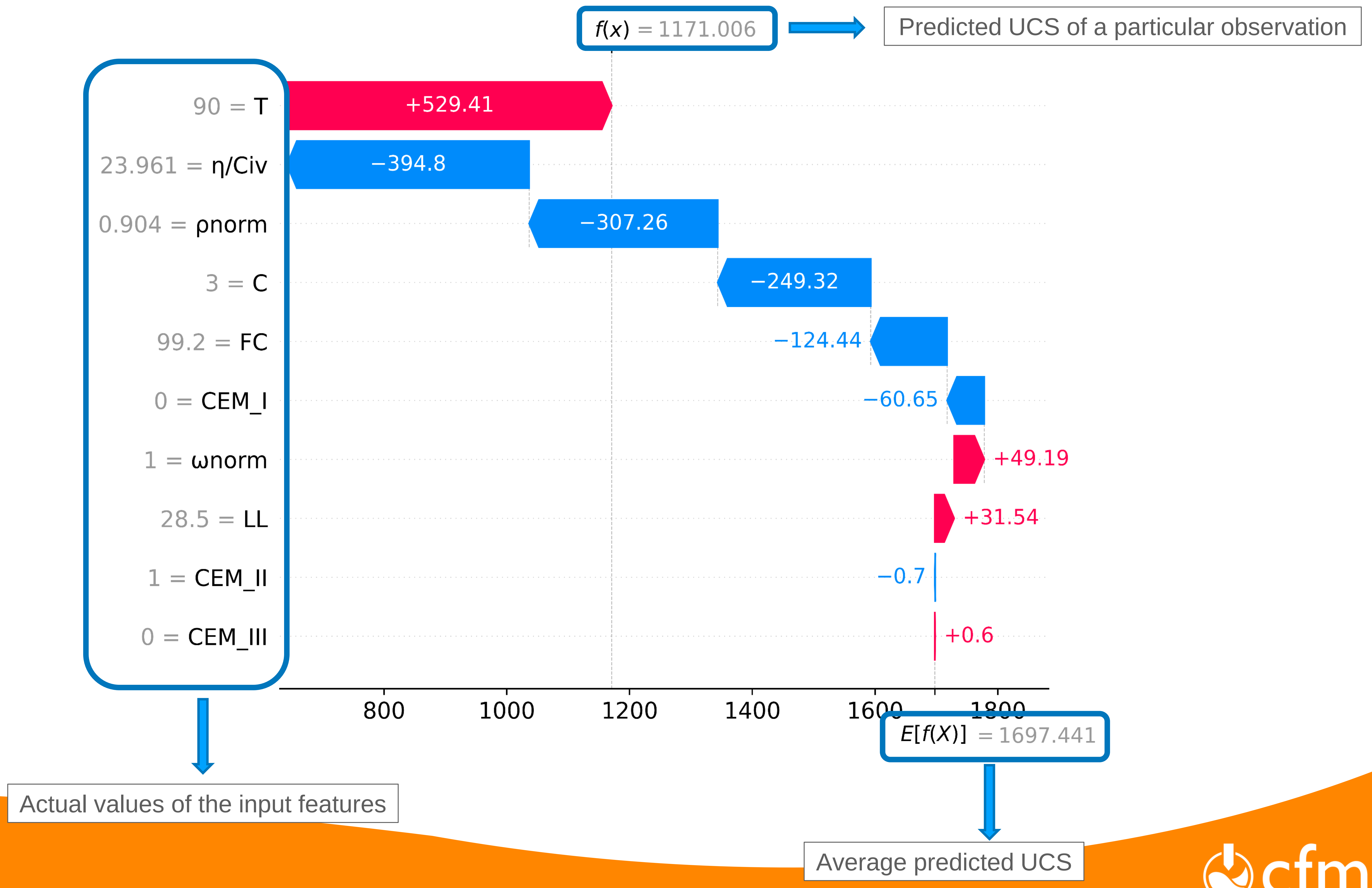
B

$$C_{AB} - C_A = \mathbf{250}$$
$$C_B - C_0 = \mathbf{500}$$
$$\boxed{\frac{250 + 500}{2} = \mathbf{375€}}$$

Shapley additive explanations (SHAP)

- SHAP **local interpretations**
- Local interpretations help evaluating the individual predictions.

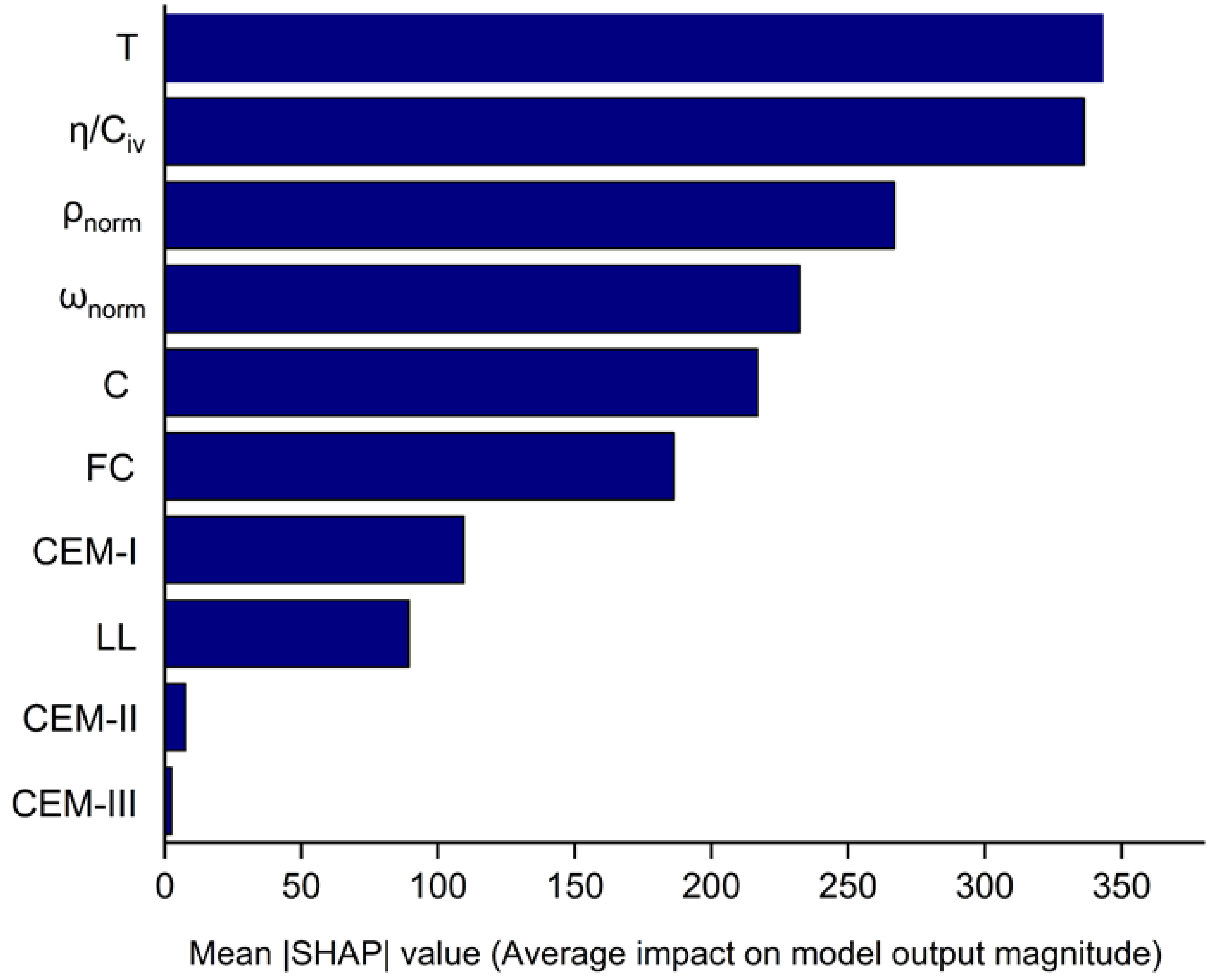
SHAP explanation of a single observation



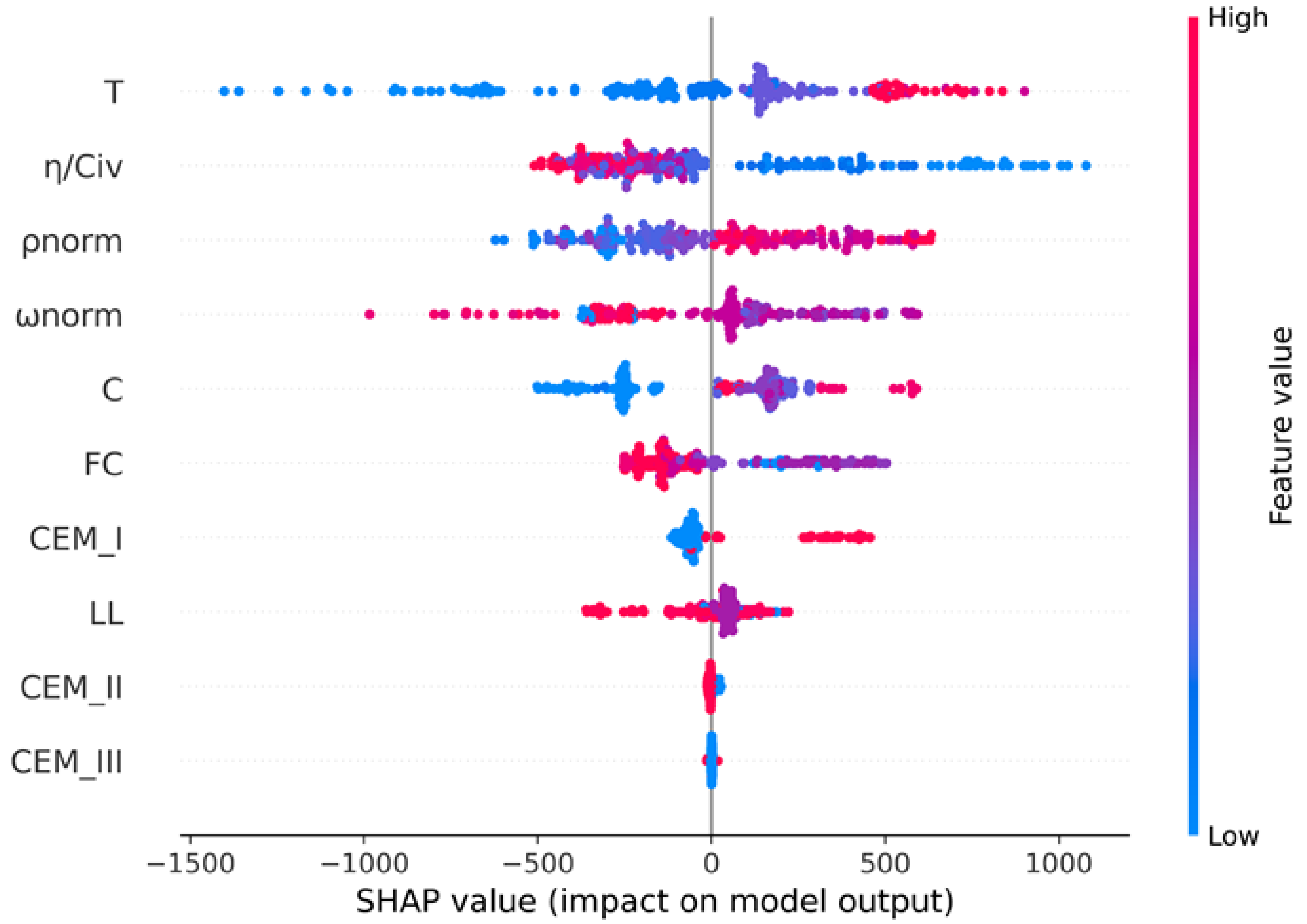
Shapley additive explanations (SHAP)

- SHAP **global Interpretations**
- Global interpretations evaluate the overall behavior of the model across the entire dataset
- T has the highest individual impact followed by η/C_{iv}, and compaction parameters.

SHAP feature importance



SHAP summary plot



Design charts

Feature values

LL (%)	0, 30, 54
FC (%)	1, 50, 99
ρ_{norm}	0.9, 0.95, 1.0, 1.05, 1.1
ω_{norm}	0.9, 0.95, 1.0, 1.05, 1.1
C (%)	3, 6
T (days)	28

Possible combinations

3×3 ×5 ×5 ×2 ×1 = **450**

Assumptions for η/C_{iv} calculation

Specific gravity of the soil = 2.7

Specific gravity of the cement = 3.11

Soil's MDD = 17 kN/m^3

Soil's OMC = 17 %

Saturation Check

Saturation check and filtering out the initial conditions leading to full saturation of the soil.

Reduced datapoints

Reduced datapoints after saturation check = 396

Assuming cement type

CEM-I	CEM-II	CEM-III
396	396	396

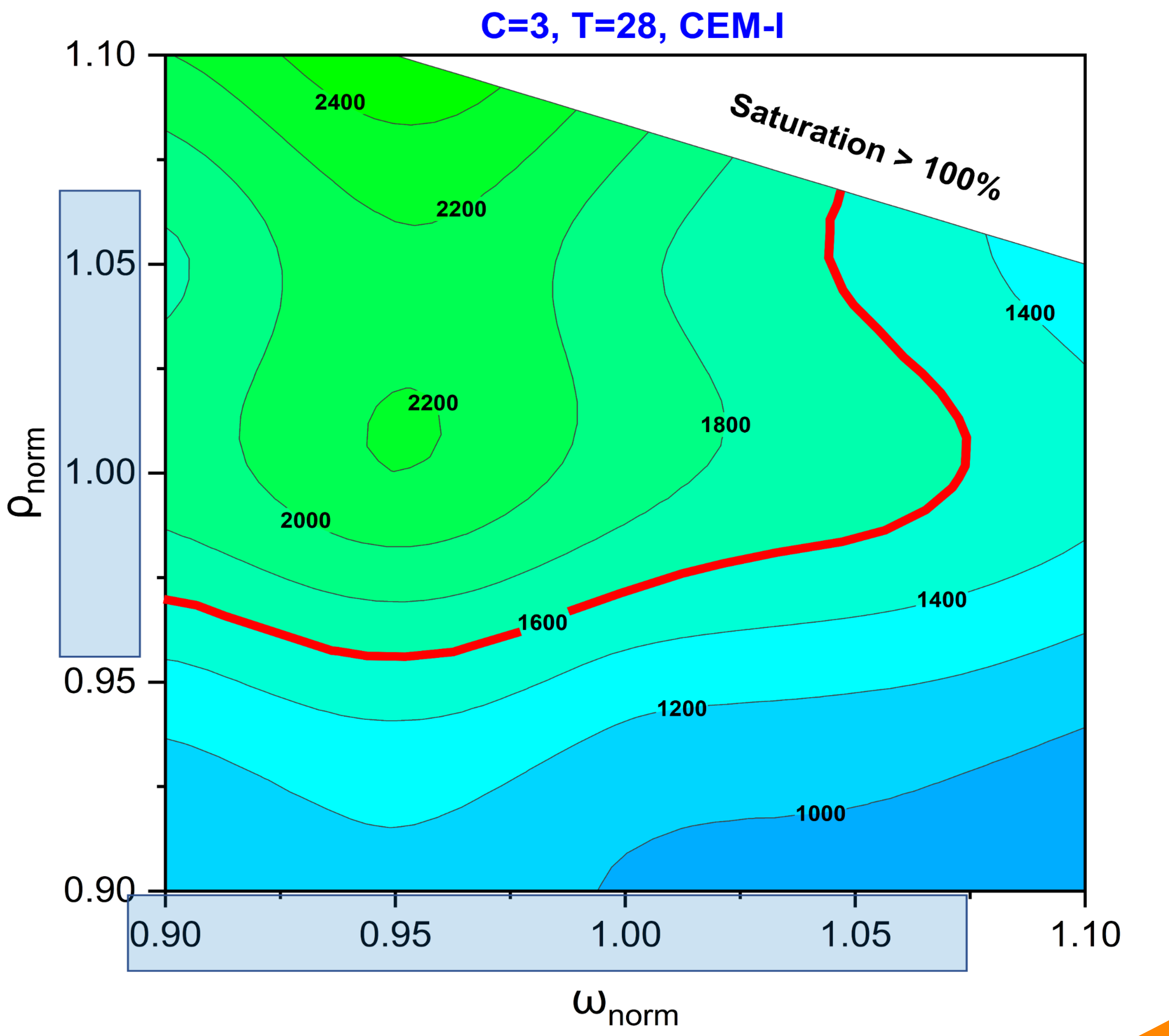
(Total 1188 datapoints)

Using XGB model for prediction

Using the optimized XGB model to make predictions for the 1188 datapoints

Design Charts

Plotting the XGB predictions as contour maps



User interface

- Streamlit library in Python was used to develop a user interface for the model.
- The app asks for the input values within the given range and predicts the UCS
- To access the model, can the QR code.

Estimation of the UCS of cement-treated soils using XGBoost model

Step 1: Initial conditions and consistency check

Initial dry density of the soil (ρi) [g/cm³]: 1.50

Specific gravity of the soil grains (ρss): 2.65

Maximum dry density of the soil (ρmax) [g/cm³]: 1.80

Specific gravity of the cement (ρsc): 3.16

Initial water content of the soil (wi) [%]: 24.00

Cement dosage (%) - Range [1-10]: 6.00

Optimum water content of the soil (wopt) [%]: 28.00

Saturation is: **81.23**%

Calculated η/Civ value: **16.34**

Calculated Normalized dry density: **0.83** [0.82, 1.06]

Calculated Normalized water content: **0.86** [0.32, 1.82]

Step 2: Additional parameters

Liquid Limit (%) - Range [0-60]: 40.00

Select Cement Type: CEM-I

Fine Contents (%) - Range [0-99]: 30.00

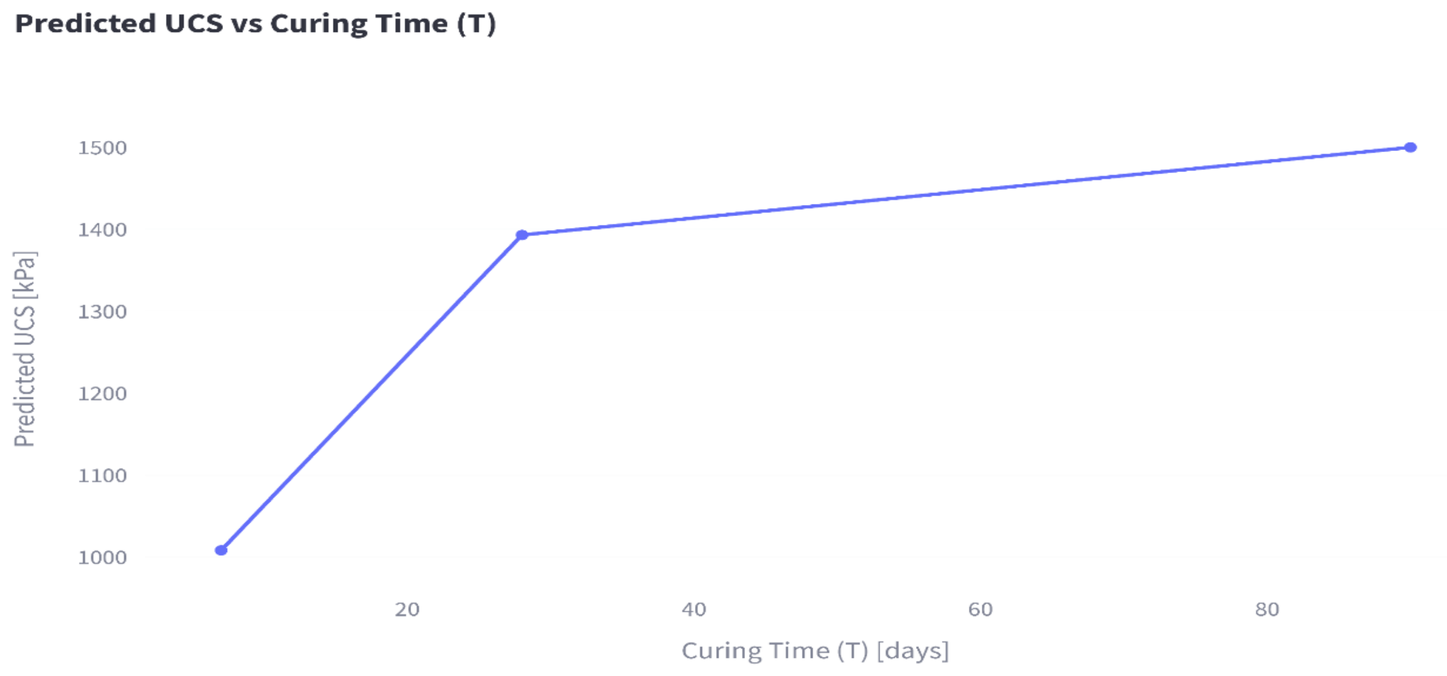
Predict UCS

Predict UCS

The predicted UCS value at T=7 days is: **1008.0** kPa

The predicted UCS value at T=28 days is: **1392.8** kPa

The predicted UCS value at T=90 days is: **1499.7** kPa



- A grid-search-based XGB model was developed to evaluate the strength of cement-treated compacted soils (CSS).
- The XGB model showed high predictive performance during model training, testing and experimental validation phases.
- SHAP revealed T, n/C_{iv}, ρ_{norm}, and ω_{norm} to be the most important features contributing to the strength development in CSS
- Design charts are presented offering the possible combination of dry density and water contents to obtain the target UCS.
- This research, with the help of explainable AI, was able to offer valuable insights into the strength development in CSS and provided a model can conveniently be applied in diverse conditions pertaining to soil type, and cement type.

References

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THANK YOU FOR YOUR ATTENTION !