EPFL

Machine Learning projects

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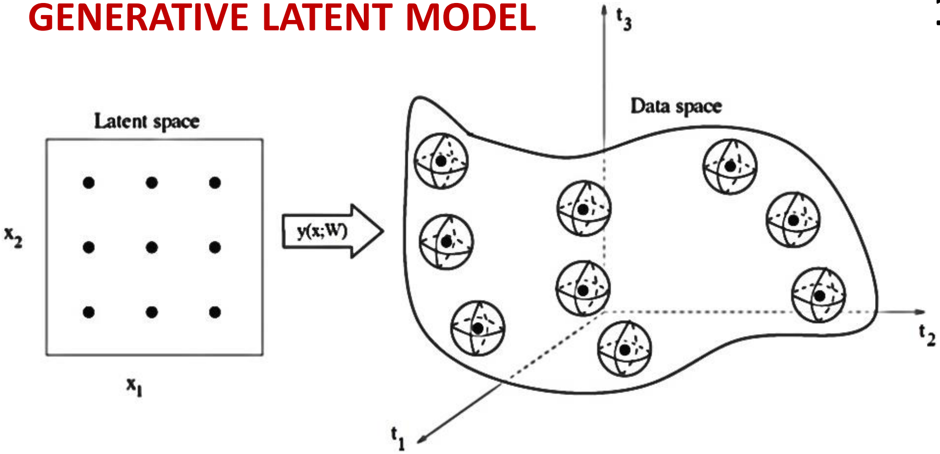
Swiss
Plasma
Center

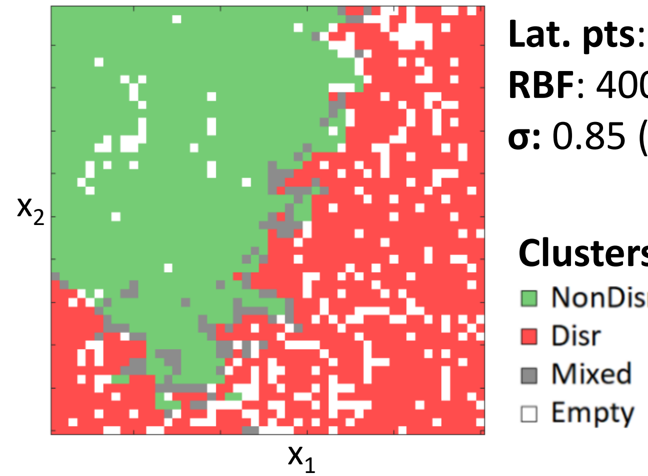
Tokamak disruption prediction: Supervised learning with Random Forests

GENERATIVE LATENT MODEL



REF: [Pau et al IEEE 2018]
REF: [Pau et al NF 2019]

1) GTM 2D-MAPPING OF JET-ILW 7D INPUT SPACE (NonDisruptive vs Disruptive)

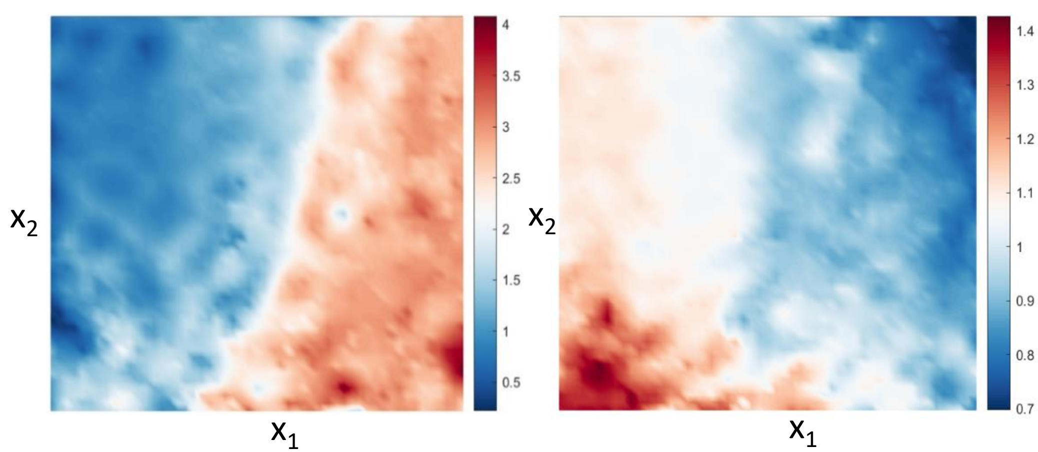


Lat. pts: 2500
RBF: 400 (gaussians)
σ: 0.85 (RBFs width)

1) **2D GTM Map:** modes of the posterior probability distribution in the latent space, obtained by 'reversing' the mapping (*Bayes' theorem*) from the 7D [input] data-space to the 2D [output] latent space.
2) **GTM component planes:** distribution of the input parameters associated with the mapping and allow to analyze patterns and not straightforward relations among the different features.

2) GTM input parameters component planes

Radiation peaking [a.u.]   Internal Inductance [a.u.]



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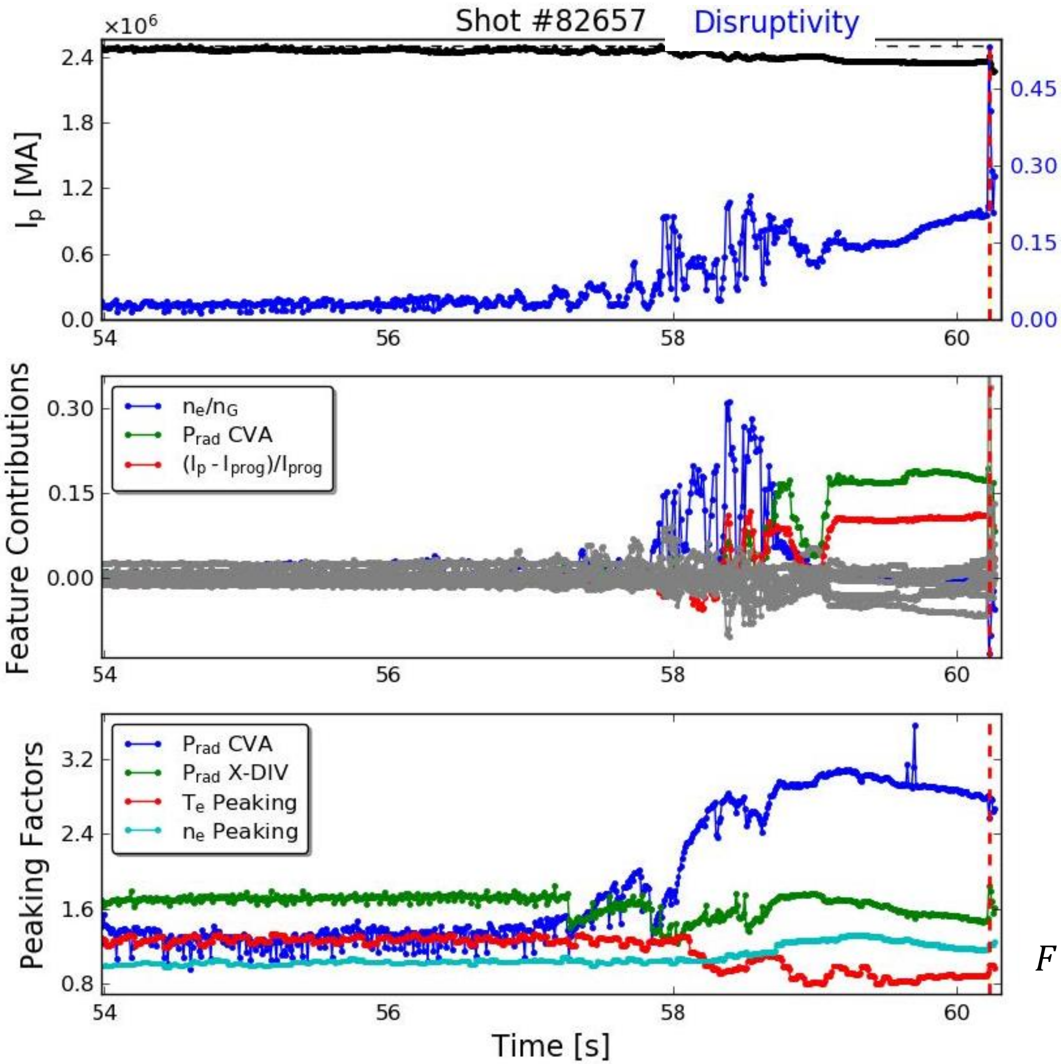
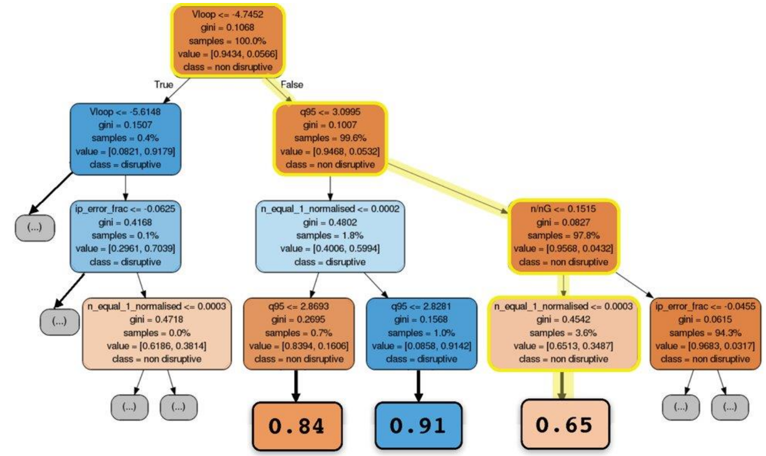
➢ INTERPRETATIVE RANDOM FOREST:

REF: [Rea et al FST 2020]





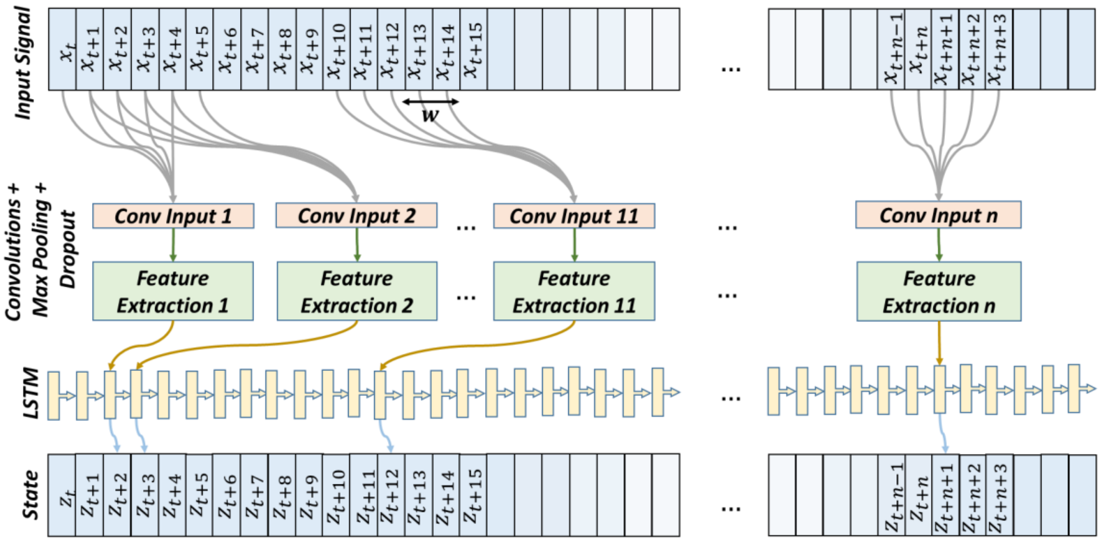
- **Impurities accumulation** in the plasma core is well captured by "**feature contribution**", prior to the disruption.
- **Predictions** for forest of *M* trees can be **decomposed** in the *K* **contributions** from each evaluated input feature:

$$F(x) = \frac{1}{M}\sum_{m=1}^{M} \text{bias}_m + \sum_{k=1}^{K}\left(\frac{1}{M}\sum_{m=1}^{M} \text{contrib}_m(x,k)\right)$$

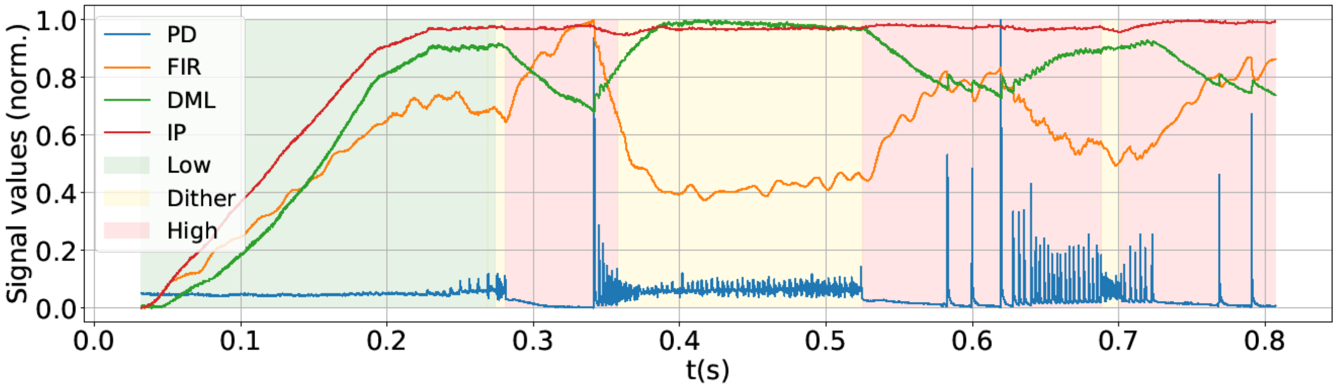
Machine Learning supporting HDL studies (1)

➢ AUTOMATIC CLASSIFICATION OF PLASMA CONFINEMENT STATES:

➢ **DEEP LEARNING** model based on a convolutional-RNN (LSTM)
- ***Probability*** *of the plasma of being in a given confinement state (accounting for temporal evolution)*
- *Preliminary* ***RT*** *implementation*



REF: *[Matos et al NF 2020]*



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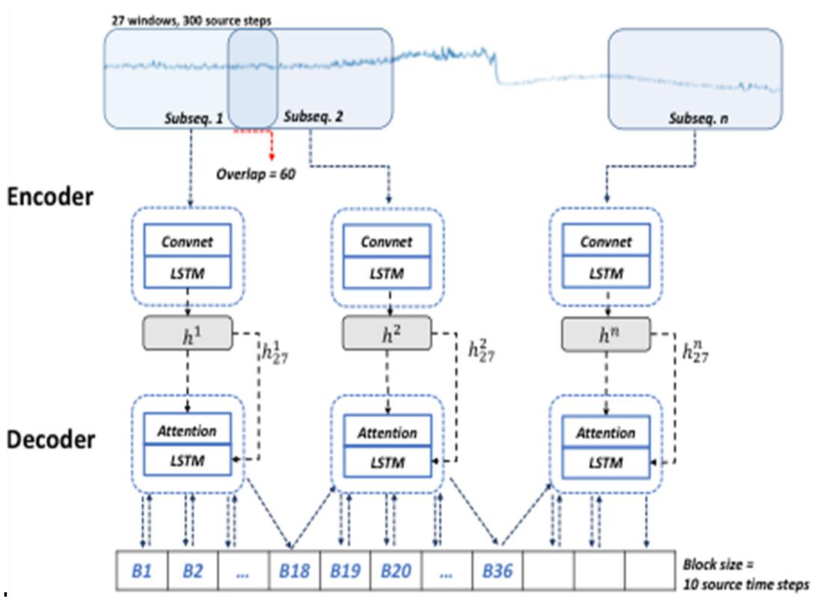
Machine Learning supporting HDL studies (2)

➢ AUTOMATIC CLASSIFICATION OF PLASMA CONFINEMENT STATES:

➢ SEQUENCE 2 SEQUENCE MODEL:

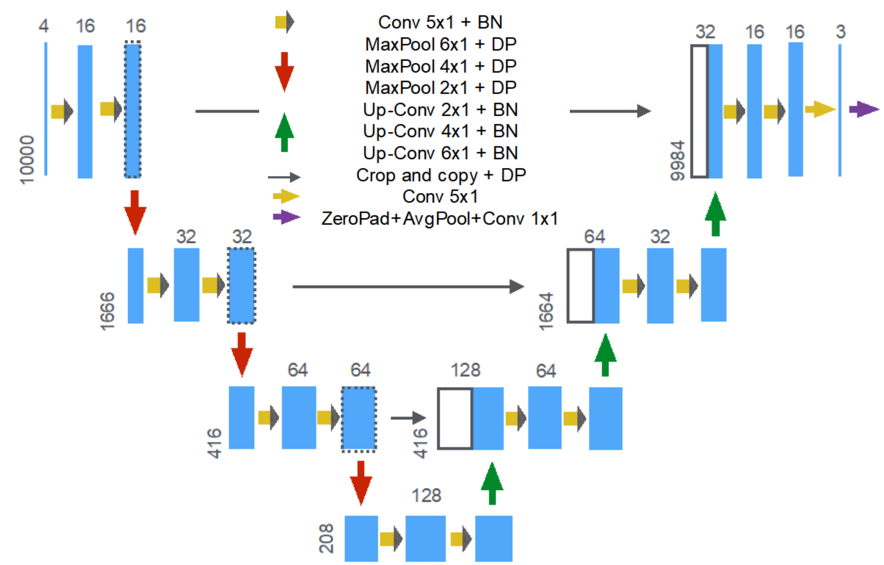
- Model not constrained to have same **source/target resolutions**.
- Decoder was extended with an **attention** layer to capture **larger context** of long input sequences.



REF: [Matos et al NF 2021]

➢ UTIME MODEL:

- **Multi-scale convolutional structure** of UTime allows to capture **patterns at different scales** present in the plasma.
- UTime processes the whole signal at once (offline) with the ability to see at **large context**.



REF: [Marceca et al NEURIPS 2020]

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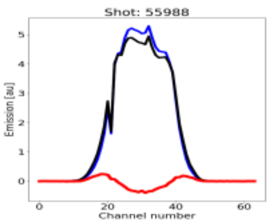
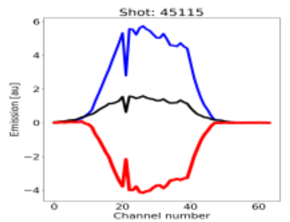
Unsupervised Clustering of fast transient MHD events

TPIV – ML project

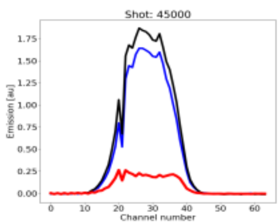
➢ UNSUPERVISED CLUSTERING OF SAWTOOTH AND THERMAL QUENCH CRASHES



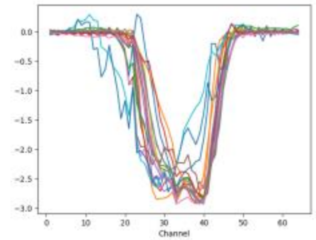
(a) Sawtooth crash



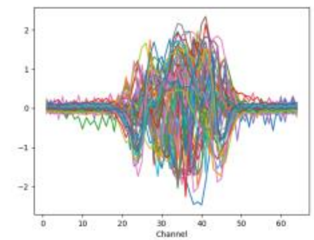
(b) Minor disruption



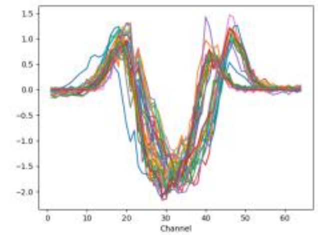
(c) Normal operation



(a) Minor disruptions profiles



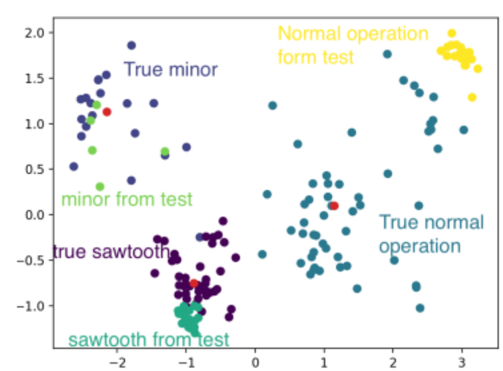
(b) Normal operation profiles



c) Sawtooth profiles

➢ UNSUPERVISED CLUSTERING

- **spline fitting** of difference between «post» and «pre» crash profiles;
- Clustering with ***GMM** of spline coefficients -> classification*



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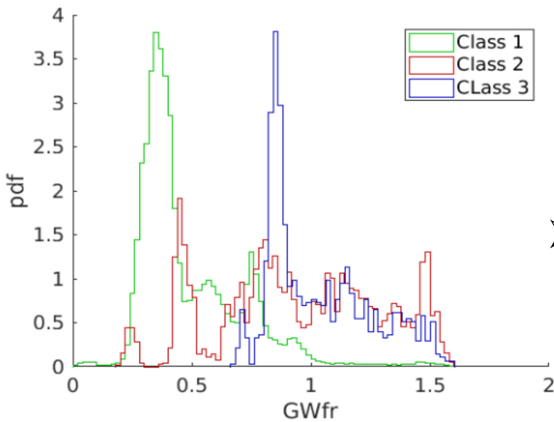
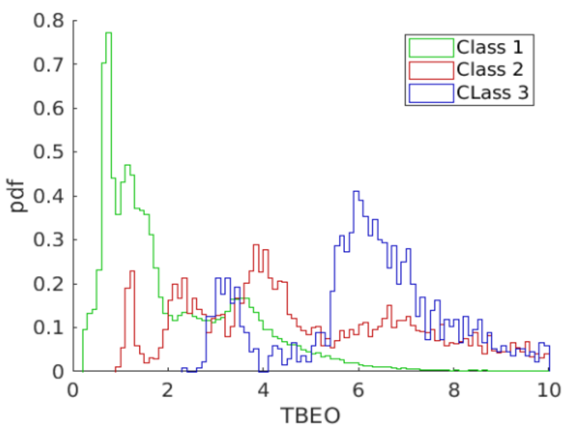
TPIV – ML project

➢ MARFE ONSET PREDICTION VIA SUPERVISED LEARNING



(b)

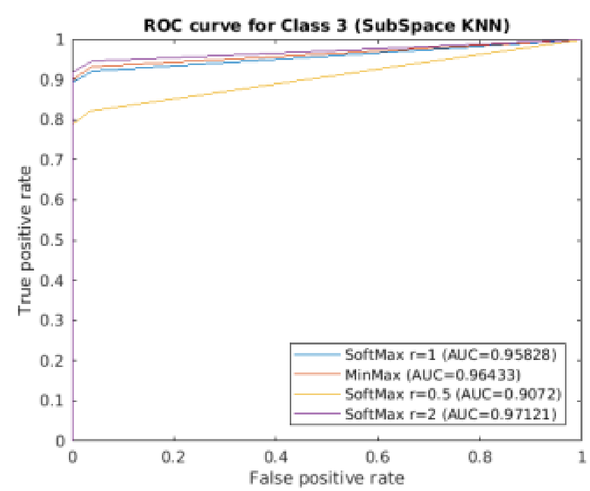


Probability density functions of engineering and physics quantities

➢ **COMPARISON OF SEVERAL CLASSIFICATION ALGORITHMS WITH FOCUS ON ENSEMBLES**

- Labeling of H-mode Density Limit with **MARFE onset** characterization

Hyperparameter	Range
Boosted Tree	
N Learning Cycles	483
Learn Rate	0.9546
Min Leaf Size	46
Max Number Splits	10
SubSpace KNN	
Distance	mahalanobis
Distance Weight	equal
Number of Neighbors	13
N Variables to Sample	9
N Learning Cycles	40
SubSpace Discriminant	
N Variables to Sample	11
N Learning Cycles	30
Delta	1.0124e-06
Gamma	0.0120
Discriminant Type	linear
Gaussian Kernel SVM	
Coding	onevsall
Box Constraint	0.001
Kernel Scale	0.0011
Kernel Function	gaussian



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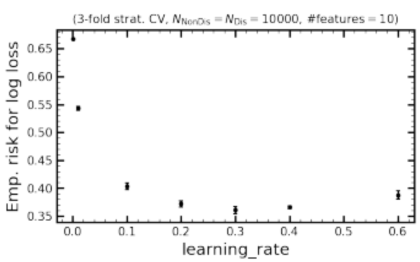
Unsupervised Clustering of fast transient MHD events

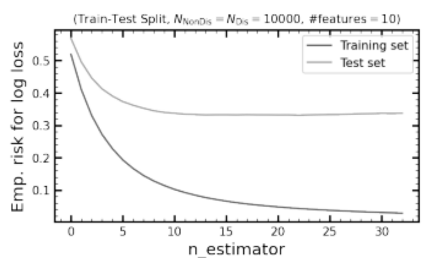
TPIV – ML project

TCV DISRUPTION PREDICTION WITH XGBOOST CLASSIFIER

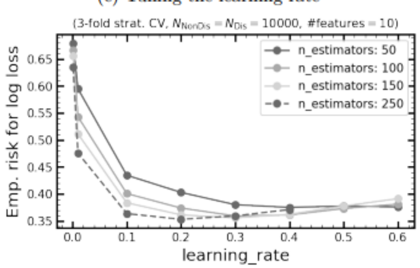
- «BUILT-IN» **HYPERPARAMETER OPTIMIZATION** and feature extraction (over thousands of disruptive & non-disruptive TCV discharges)



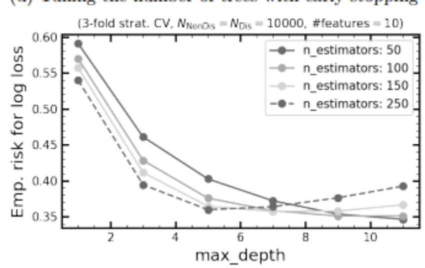
(c) Tuning the learning rate



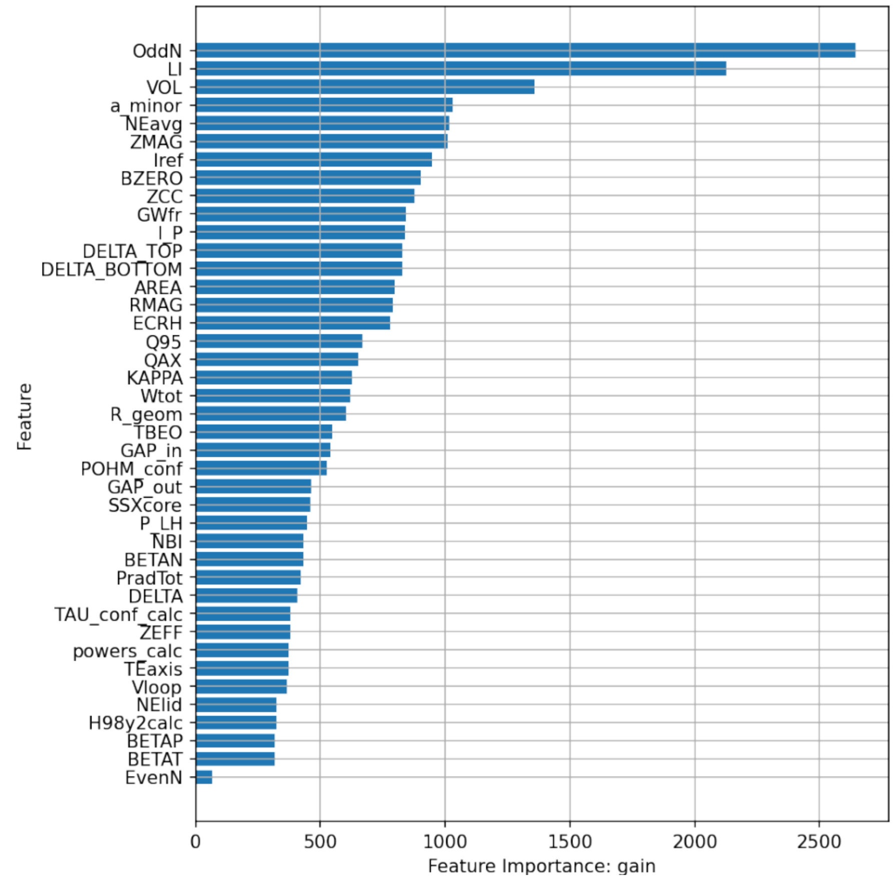
(d) Tuning the number of trees with early stopping



(e) Tuning the number of trees and learning rate



(f) Tuning the number of trees and the tree depth



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Some References on Tokamaks “disruptions prediction” 2

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