Exploratory Machine Learning studies for disruption prediction on DIII-D

by

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the successful avoidance of disruption events is extremely relevant for fusion devices and in particular for ITER

- the problem complexity has motivated the recent efforts for development of **data-driven predictors** and **Machine Learning** studies to successfully **predict** disruption events with **sufficient warning time**

- SQL databases created, gathering time series of relevant plasma parameters: tables available on **DIII-D**, EAST and C-Mod (**cross-device analysis**)
  - more than 40 available parameters, ~500k samples per parameter
  - both disrupted and non-disrupted discharges, focus on 2015 campaigns for now

- **exploratory studies** to gain insights on the DIII-D dataset before addressing the problem of a disruption-warning algorithm
  - binary and multi-class classification analysis through Machine Learning algorithms
  - variable importance ranking
  - accuracy metrics and comparison between different applications

we chose a subset of features and samples for ML applications to the DIII-D database for disruption prediction

10 features out of ~40 available parameters

mainly **dimensionless** or
machine-independent parameters

li	Ip_error_fraction	Vloop
q95	radiated_fraction	n1amp
beta_p	dWmhd_dt	
n/nG	Te_HWHM	

focus on **flattop disruptions: 195** flattop **disruptions** complemented by an analogous number of discharges that did not disrupt, possibly extracted from the same experiments (similar operational space) ⟹ **392 discharges**

~70,000 samples for each of the **10** chosen **input variables**

reliable knowledge base capable of highlighting the underlying physics :

- validated signals and EFIT reconstructions
- avoided intentional disruptions
- avoided hardware-related disruptions by specifically checking for feedback control on plasma current or UFOs events

a plethora of ML algorithms is available in literature – already tested on other devices for disruption prediction

- ML supervised and unsupervised algorithms, mainly developed at JET and also studied in real-time environment, **“black box”** approach:
  - Artificial Neural Networks[1-2], multi-tiered Support Vector Machines[3], Manifolds and Generative Topographic Maps[4]

[1] G. Pautasso et al. Nuclear Fusion 42 (2002) 100-108

[2] B. Cannas et al. Nuclear Fusion 44 (2004) 68-76

[3] J. Vega et al. Fusion Engineering and Design 88 (2013)

[4] B. Cannas et al. Nuclear Fusion 57 (2013) 093023

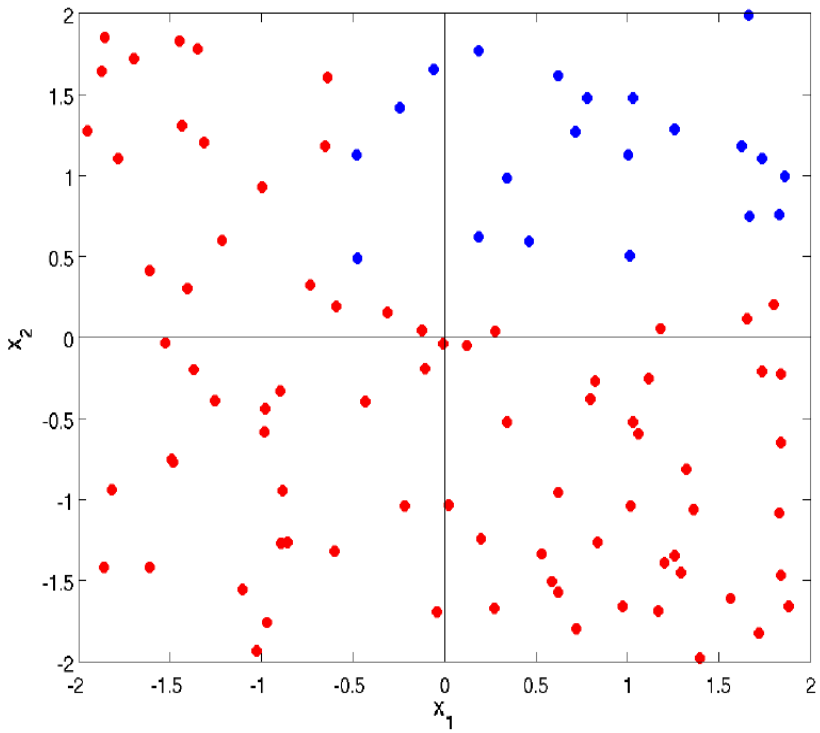
- to better understand the dataset: **“white box”** approach
  - inner components and logic are available for inspection
  - importance of individual features can be determined

- **Random Forests**[5]: a large collection of randomized de-correlated **decision trees** that can be used to solve both **classification** and regression problems

[5] L. Breiman, “Random Forests”, Machine Learning, 45(1), 5-32, 2001

decision trees are hierarchical data structures implementing the *divide-and-conquer* strategy: 2D classification example

- **CART** (Classification and Regression Trees) algorithms repeatedly partition the input space, implementing a test function at each split (node), to build a tree whose nodes are as pure as possible
- 2 features (x_1, x_2) and 2 classes (**red**, **blue**)



the algorithm selects a splitting value to partition the dataset, by **minimizing** an **impurity** measure:

$$\mathcal{I}'_m = -\sum_{j=1}^{n} \frac{N_{mj}}{N_m} \sum_{i=1}^{K} p^i_{mj} \log_2 p^i_{mj}$$

E. Alpaydin, "Introduction to Machine Learning", 2nd edition, MIT Press

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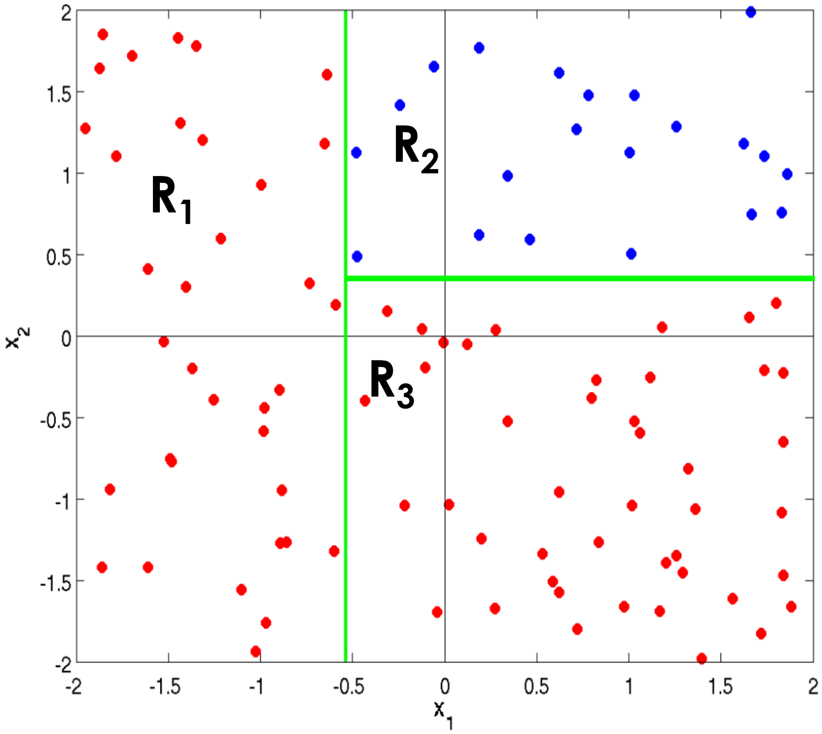

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all the subdivided regions are **pure** red or blue data

- a **set of rules** is defined and can be visualized as a **tree structure**

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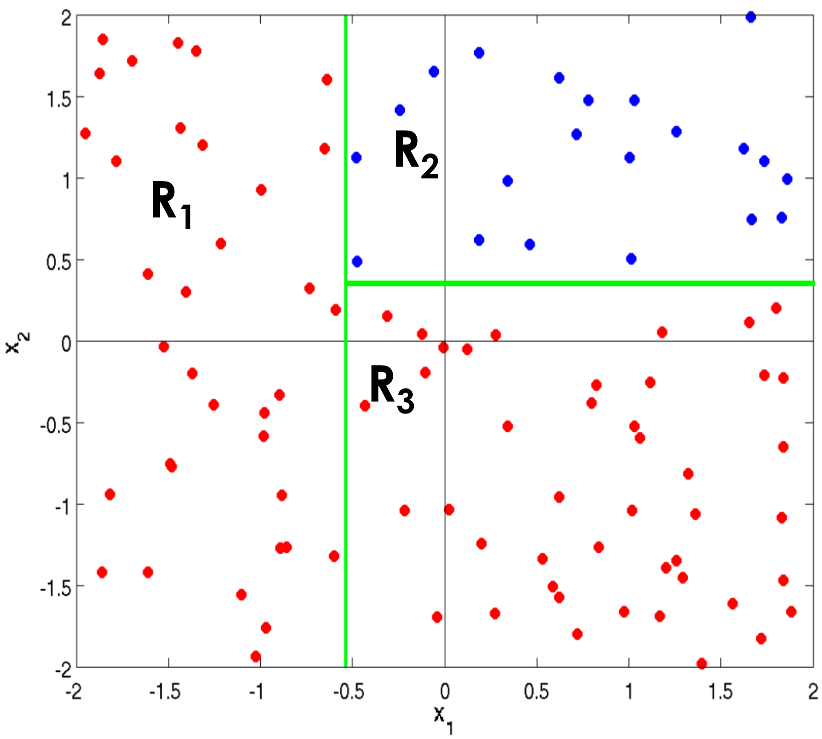

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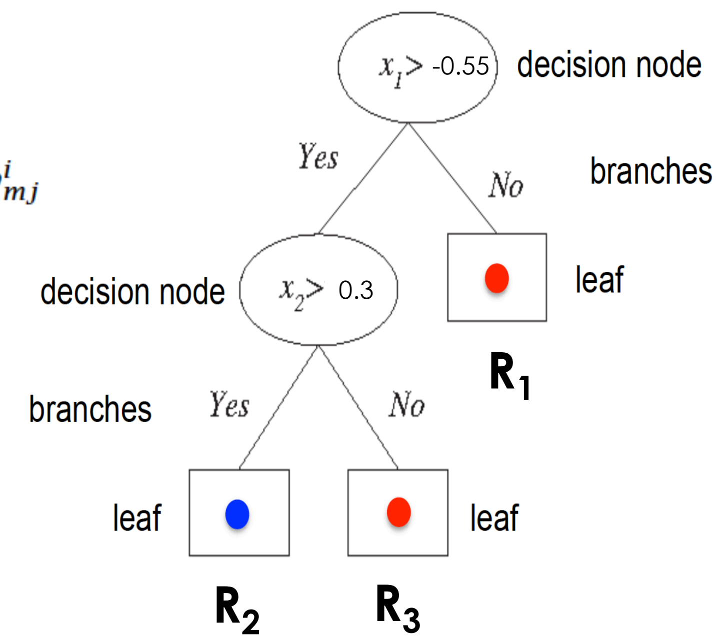

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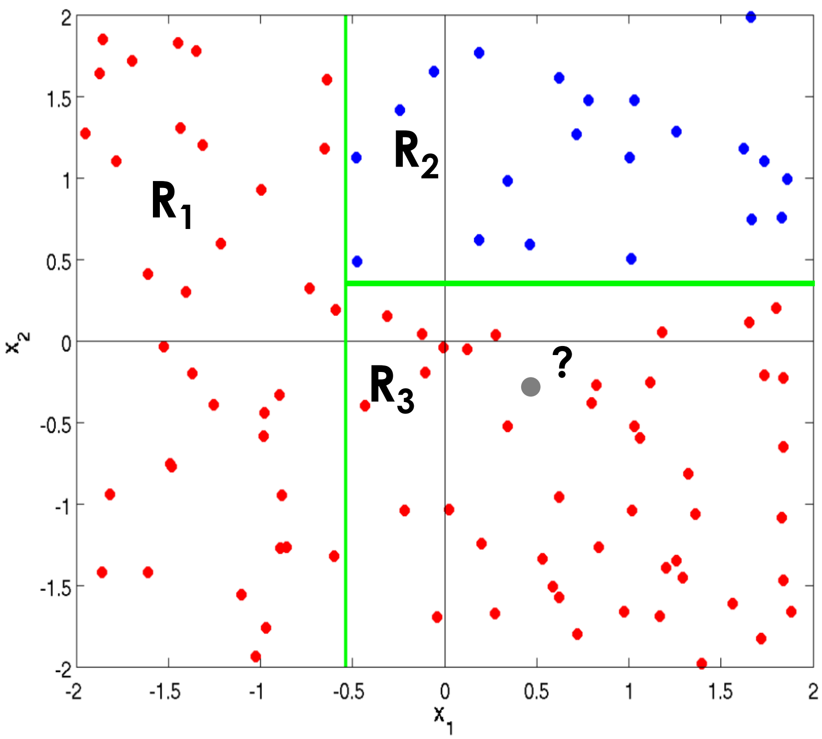

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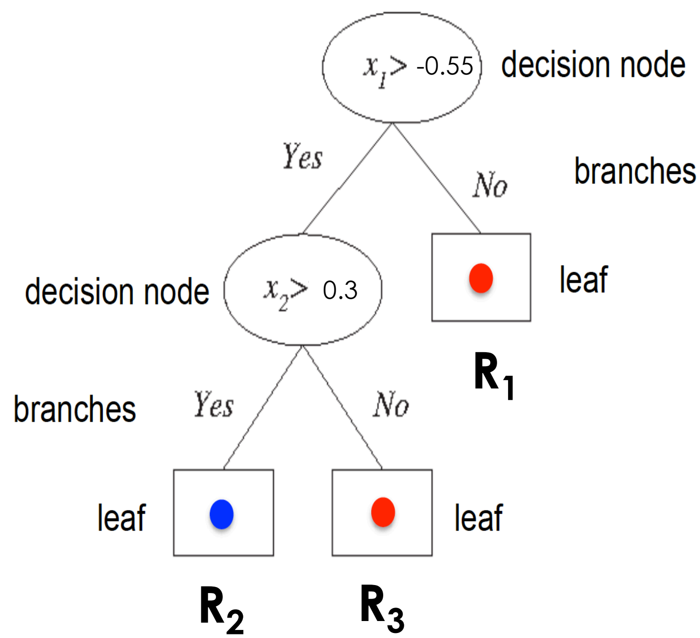
all the subdivided regions are **pure** red or blue data

- this **set of rules** is used to classify a new, unseen (test) sample



recursive binary trees have a key feature: interpretability, but they tend to overfit – pruning needed

- decision trees have advantages and limitations, as well as other ML algorithms - **Random Forests** seems a promising algorithm

for classification purposes:	RF	Tree	Neural Nets	SVMs
no overfitting	good	poor	poor	fair
intrinsic feature selection and robustness to outliers	good	good	poor	poor
parameter tuning	good	good	poor	poor
non-parametric models (no a-priori assumptions)	good	good	poor	poor
interpretability	fair	good	fair	fair
natural handling of mixed type data	good	good	poor	poor
prediction accuracy	good	poor	good	good
time handling	poor	poor	good	fair

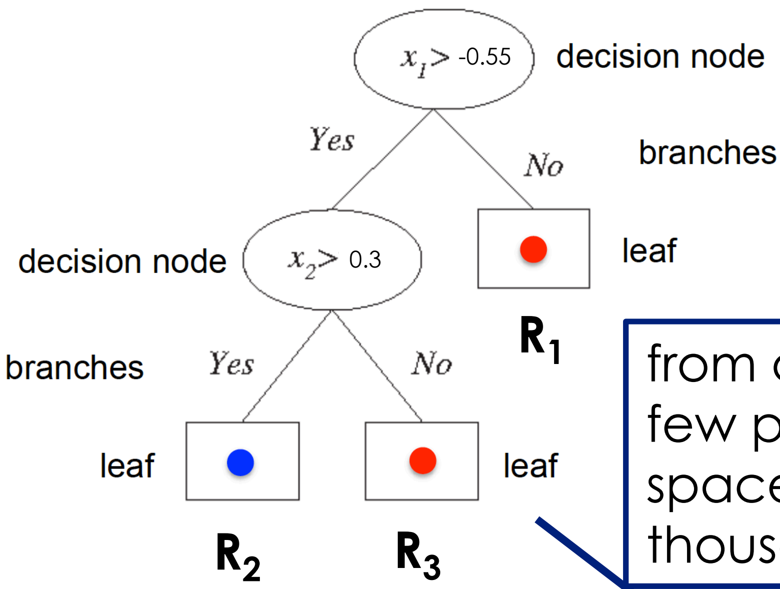
● good ● fair ● poor

Random Forests is an ensemble method, leveraging bootstrapping and averaging techniques (*bagging*)

main steps of the algorithm:

- grow many trees (e.g., 500 trees) on **bootstrap samples** of the original training set
  - random sampling with replacement from the training set
- trees are fully grown - **minimize bias** (no pruning needed)
- **reduce variance** of noisy but unbiased (fully grown) trees by **averaging** (regression) or **majority voting** (classification) for the final decisions on test samples
- very **fast**, highly **parallelized** algorithm

binary classification problem:
labeling a time slice as disrupted/non-disrupted

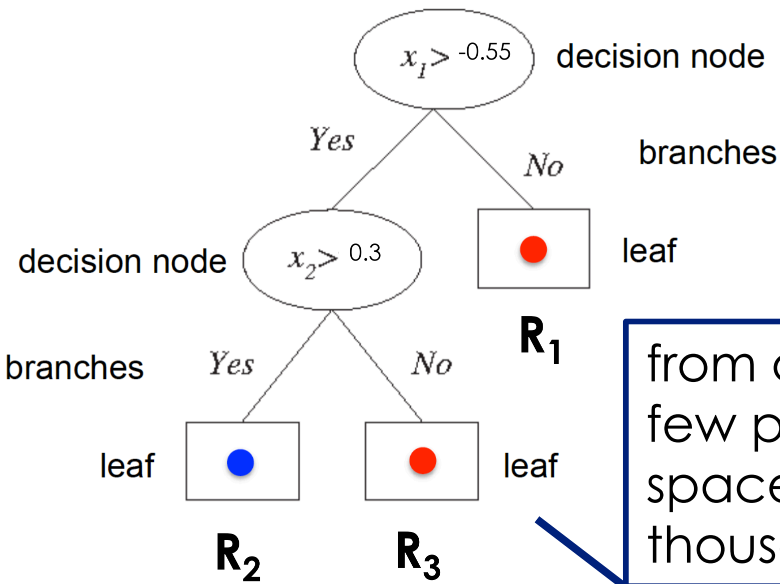


$(x_1, x_2) \rightarrow$

li	**Ip_error_fraction**	**Vloop**
q95	**radiated_fraction**	**n1amp**
beta_p	**dWmhd_dt**	
n/nG	**Te_HWHM**	

from a 2D space with few points to a 10D space with many thousands of points

binary classification problem: disrupted/non-disrupted
graphical depiction of a single tree in a Random Forests



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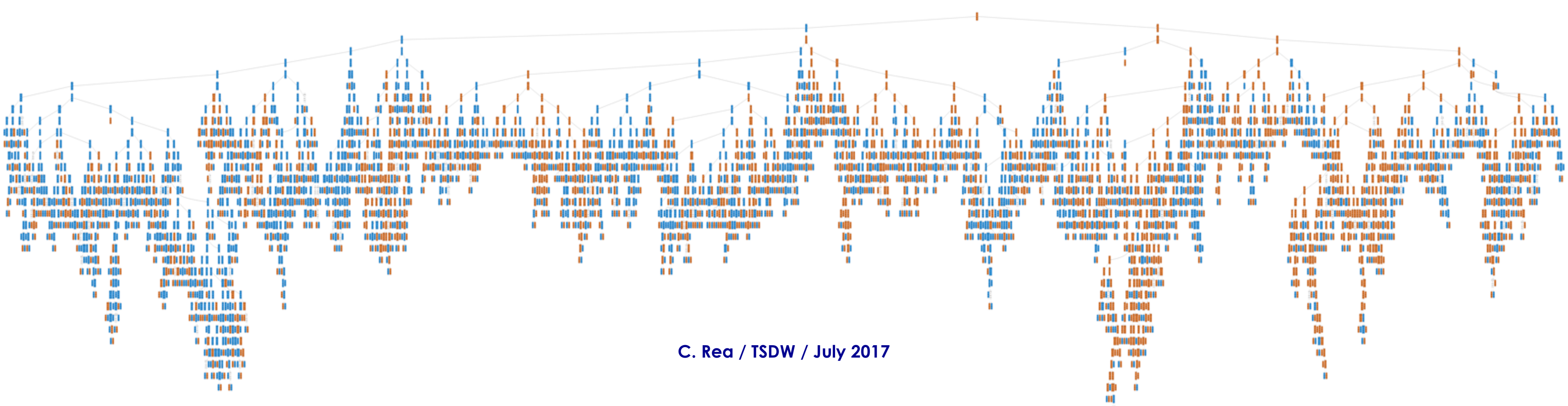
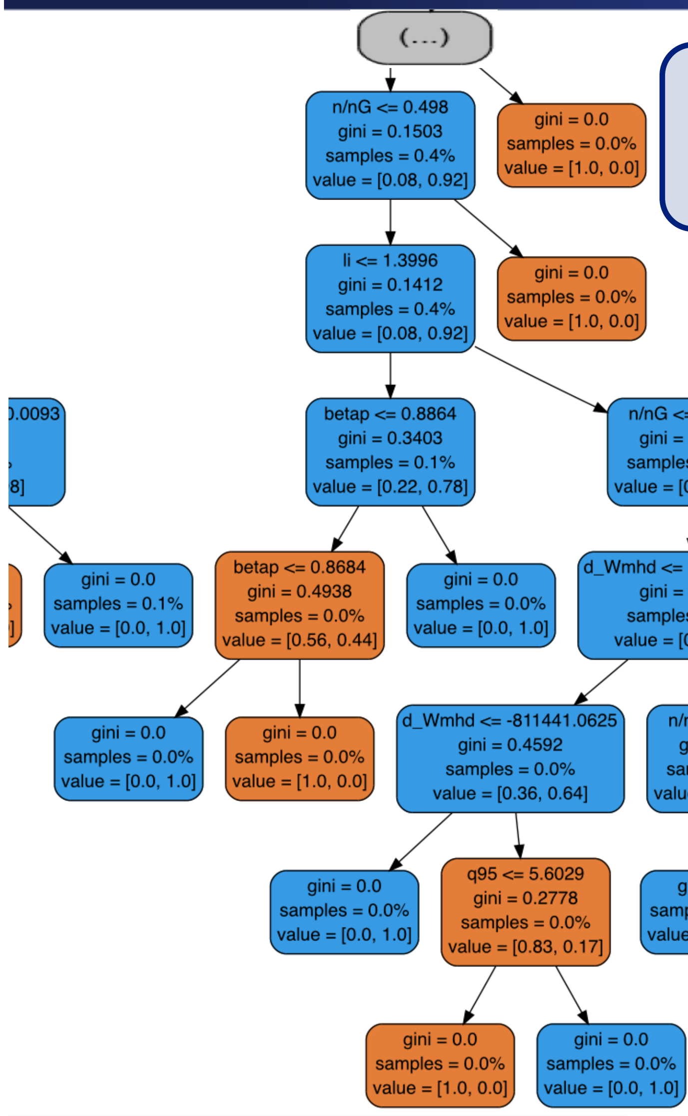
from a 2D space with few points to a 10D space with many thousands of points

10 variables
~ 70,000 time slices
394 discharges
195 flattop disruptions
500 decision trees



binary classification problem: disrupted/non-disrupted
no time dependency – 10D feature vectors



original dataset split in **training** and **test** subsets

500 trees built on **training data** to define a set of rules

- features are **not scaled a-priori;**
- at each node, **random sub-selection** of features;
- impurity minimization by choosing the **best split;**

set of rules is used to decide if new, unseen samples in our **test set**, belong to one of the two classes

confusion matrix is used as an accuracy metrics to assess the model's capability to discriminate between class labels

binary classification -
no time dependency -
15ms **black window**
before disruption event

non-disrupted **disrupted**

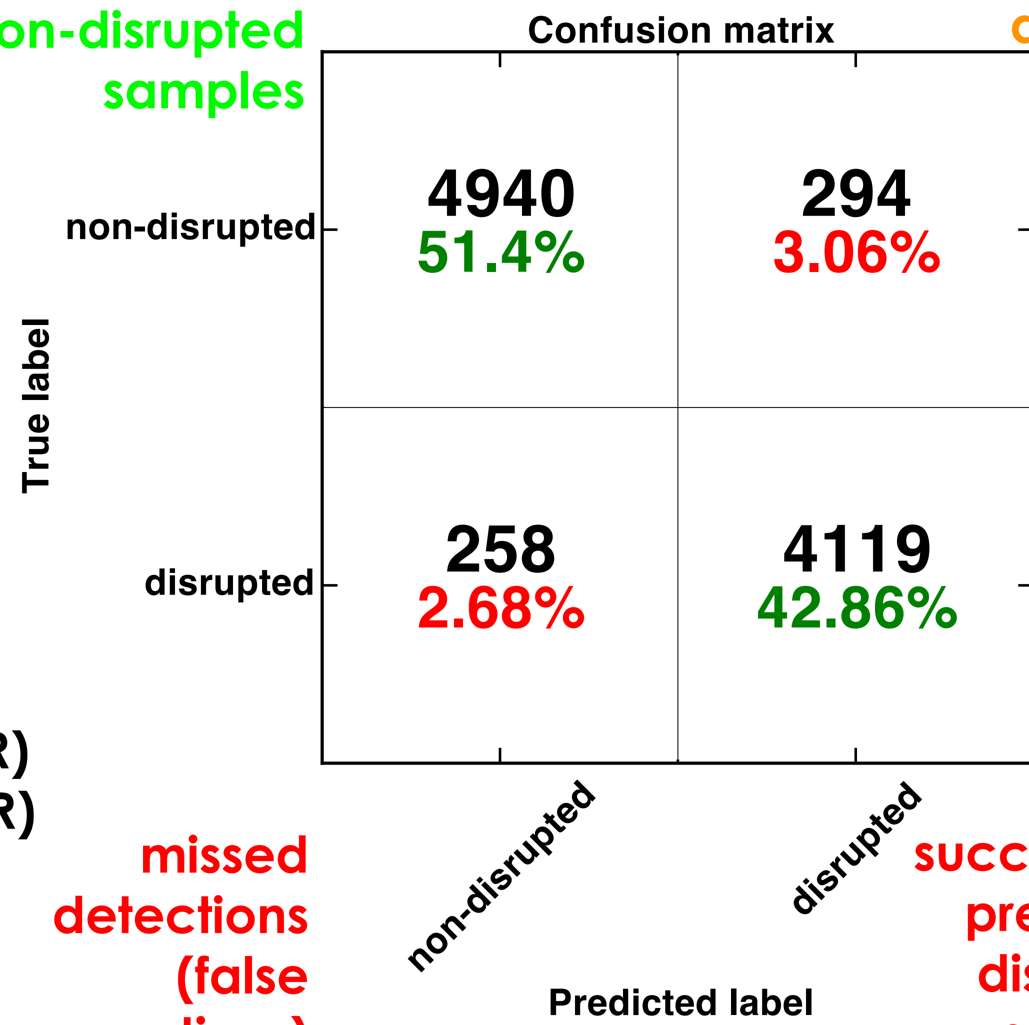
confusion matrix is used as an accuracy metrics to assess the model's capability to discriminate between class labels

binary classification - no time dependency - 15ms **black window** before disruption event

non-disrupted **disrupted**

successfully predicted non-disrupted samples

false positive alarms



missed detections (false negatives)

successfully predicted disrupted samples

class accuracy:

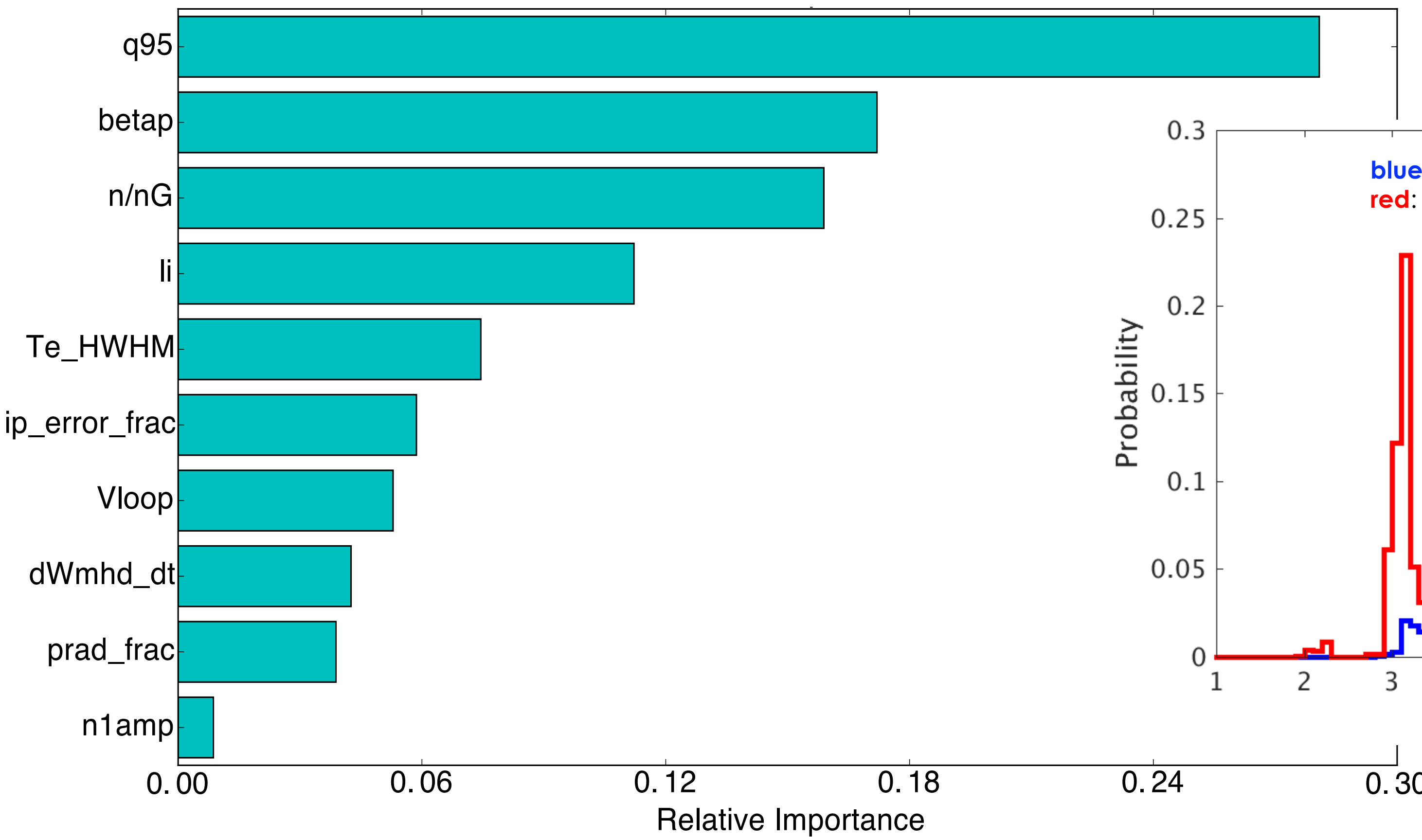
- **disrupted** **94.1% (TPR)**
- **non-disrupted** **94.4% (TNR)**

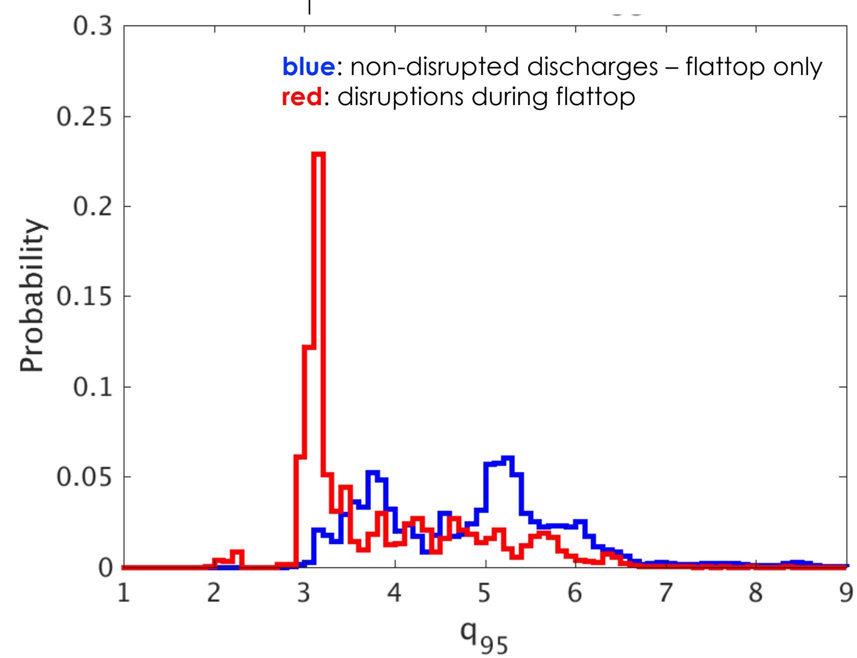
overall accuracy: **~94.3%**

relative importance ranking can be extracted from the Random Forests – 'white box' approach

- relative variable importance wrt label predictability is defined as mean decrease impurity and can give indications on the underlying physics

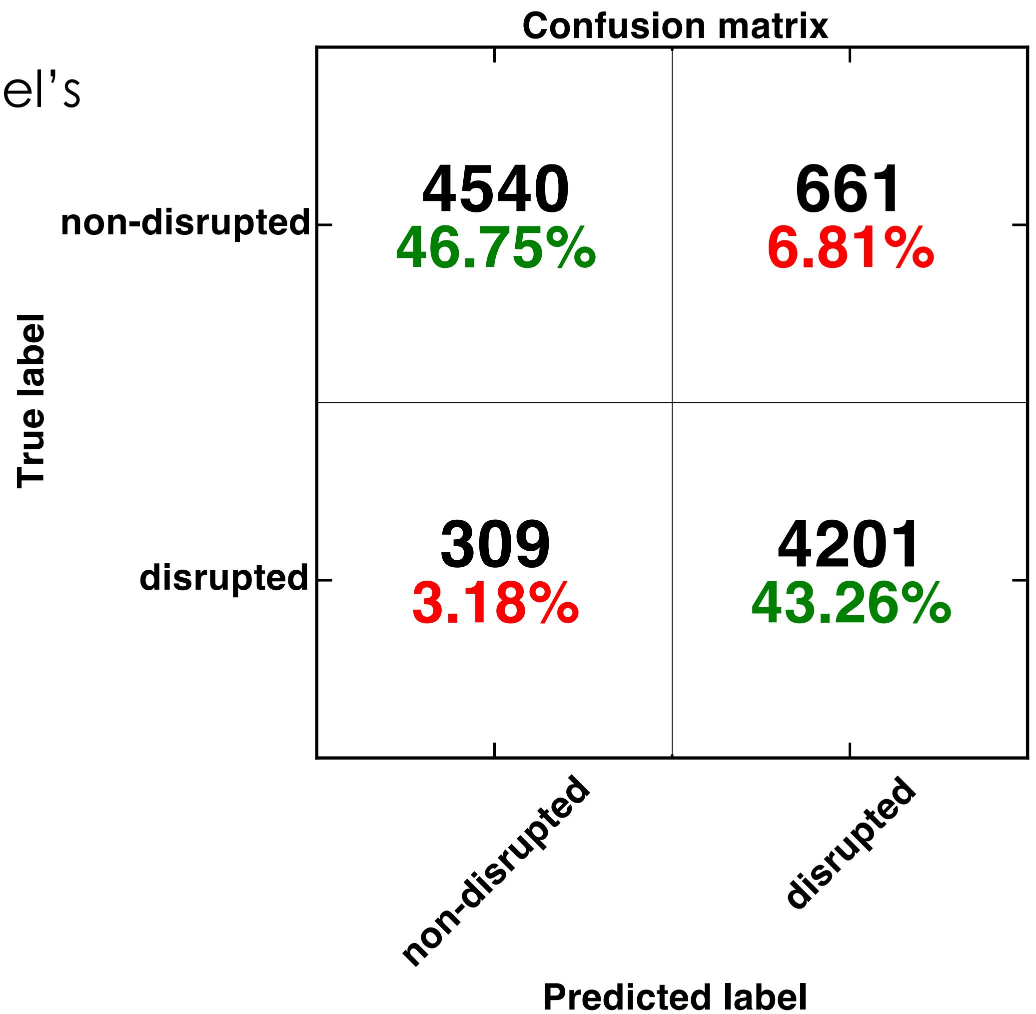
- q95 is the relatively most important variable
  - probability distributions for disrupted and non-disrupted samples show different behaviors





binary classification – train/test split on the basis of the whole discharges and not the individual samples

- information pertaining to the same discharges should not be shared with the training set: how can we assess the model's **generalization** capabilities?
- reliable test set, capable of correctly highlighting the model's **predictive power**



class accuracy:
- **disrupted** 93.1%
- **non-disrupted** 87.3%

overall accuracy: **~90%**

in the multi-class classification, the time dependency is introduced through the definition of different class labels

multi-class classification

- **non-disrupted** : time slices for non disruptive shots
- **far from disr** : time_until_disrupt > 0.35s
- **close to disr** : time_until_disrupt ≤ 0.35s
- …

class accuracy:

- **non-disrupted** **88.6%**
- **far from disr** **84.4%**
- **close to disr** **86.6%**

overall accuracy: **~87%**

Confusion matrix

True label \ Predicted label	non-disrupted	far from disr	close to disr
non-disrupted	4607 47.44%	579 5.96%	15 0.15%
far from disr	326 3.36%	2594 26.71%	152 1.57%
close to disr	71 0.73%	121 1.25%	1246 12.83%

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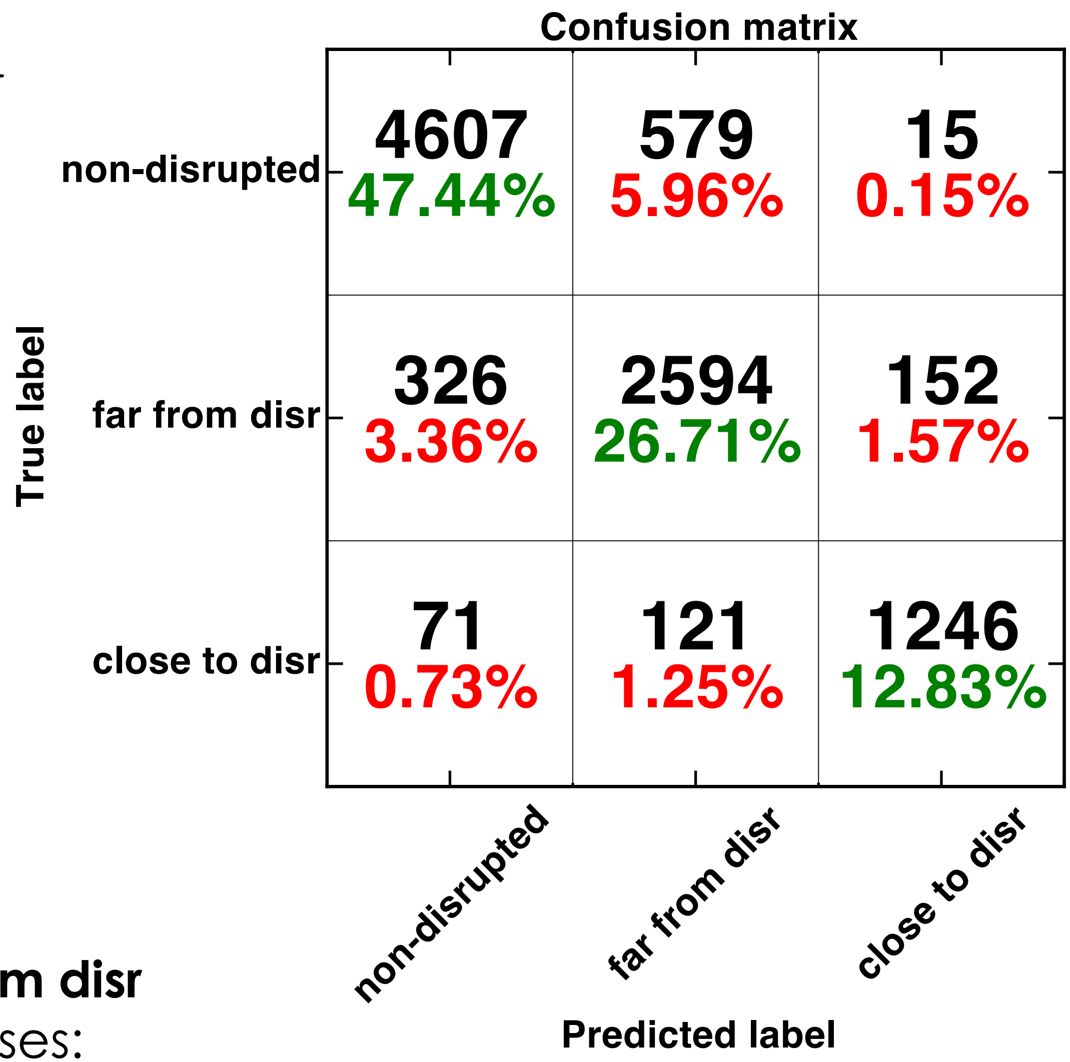
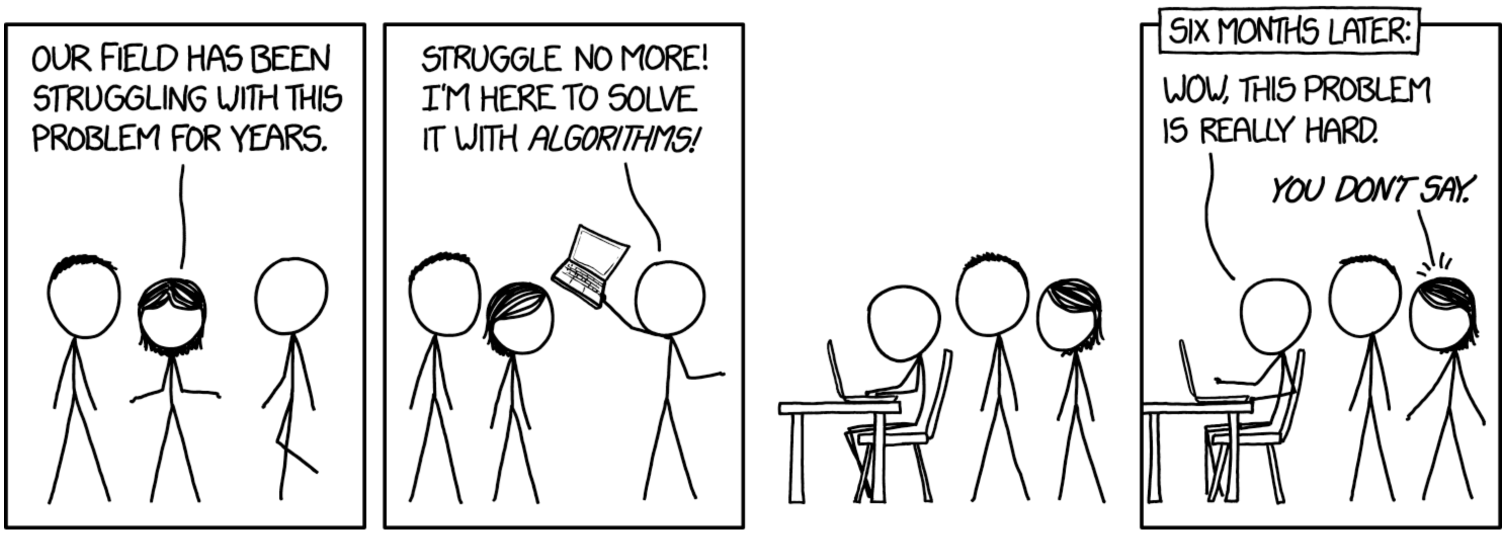
grouping **non-disrupted** and **far from disr** classes, thus defining two new classes: **stable** and **disruptive** (phases), gives an overall accuracy **~96%**



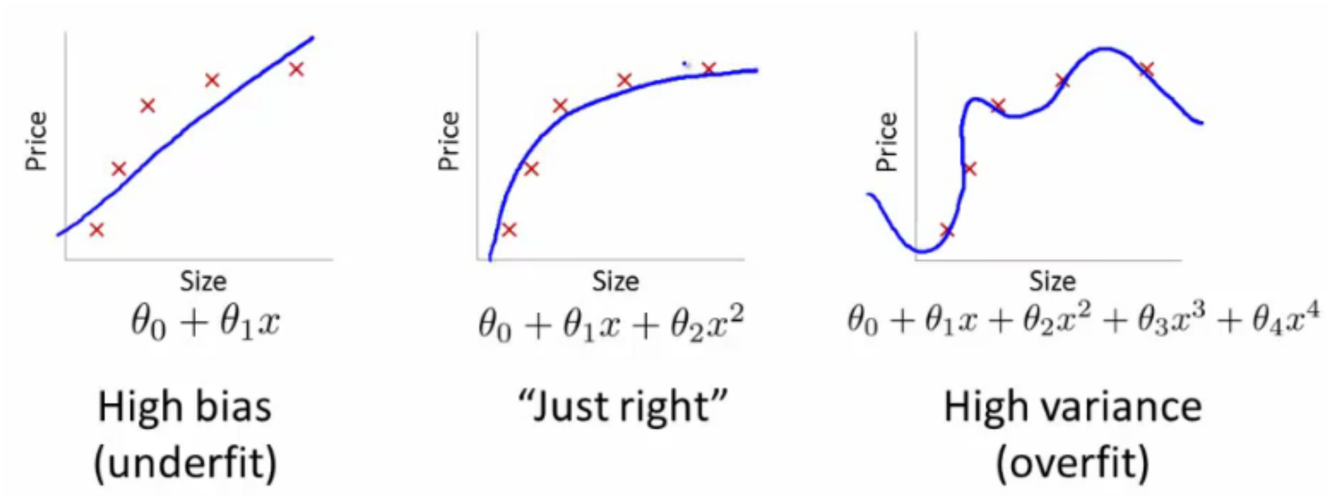
conclusions and future work

- ML **classification** gives promising results, with optimal performances (**Random Forests**) and possibility of gaining insights on the dataset
- address the **disruption-proximity problem**: "how much time until the discharge is going to disrupt" - possibly evaluating different algorithms that could best perform in case of **regression** problems
- **real-time** integration with the PCS
- dimensionless and machine-independent features enable **cross-device analysis**: comparison with EAST and C-Mod data and possible extrapolation to **ITER**



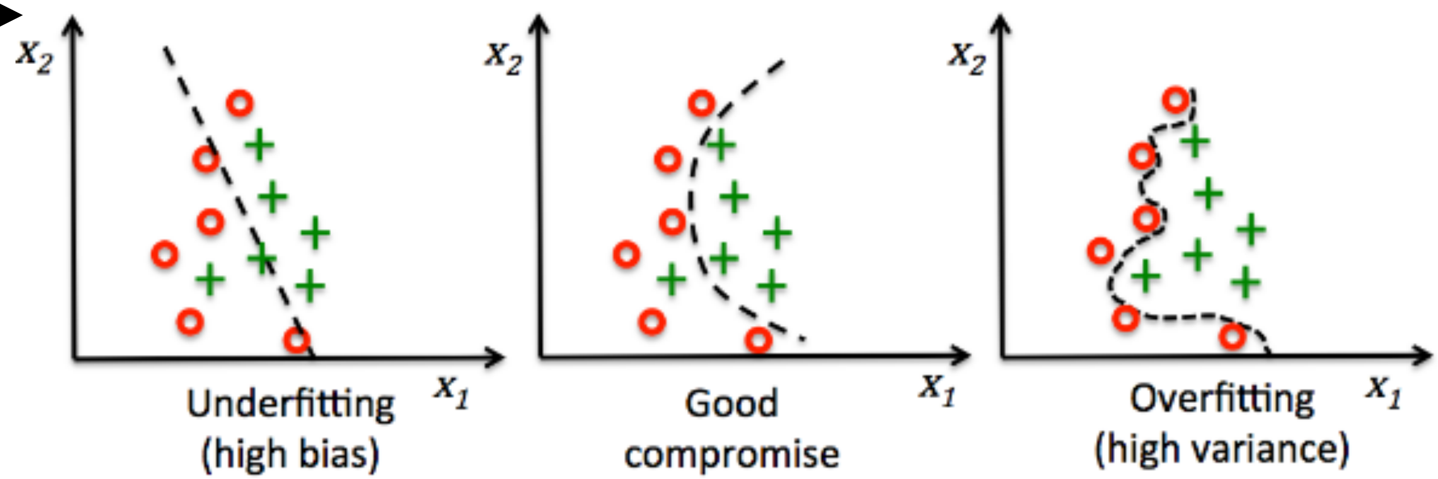
backup slides

bias vs variance aka underfitting vs overfitting



regression case

classification case



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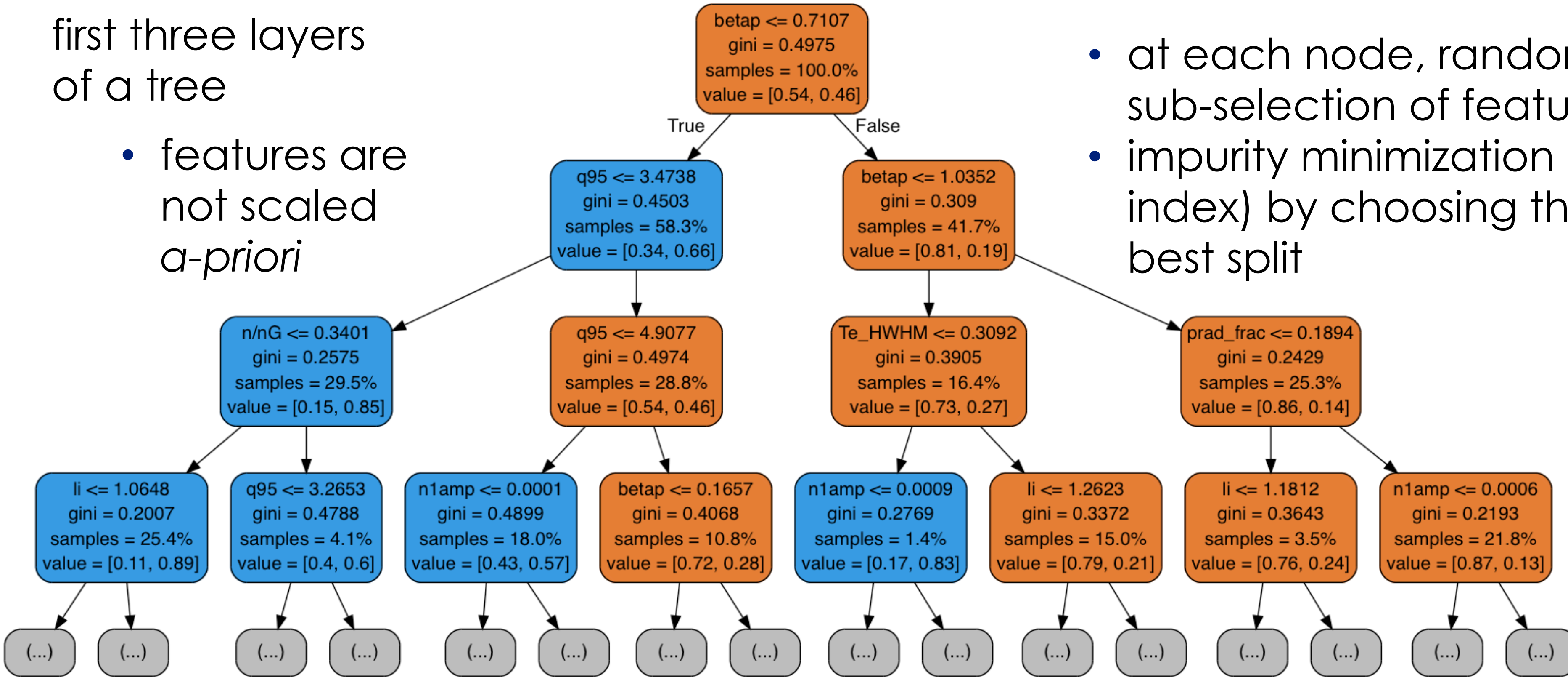
graphical depiction of a single tree in a Random Forests in a classification scheme – disrupted/non-disrupted

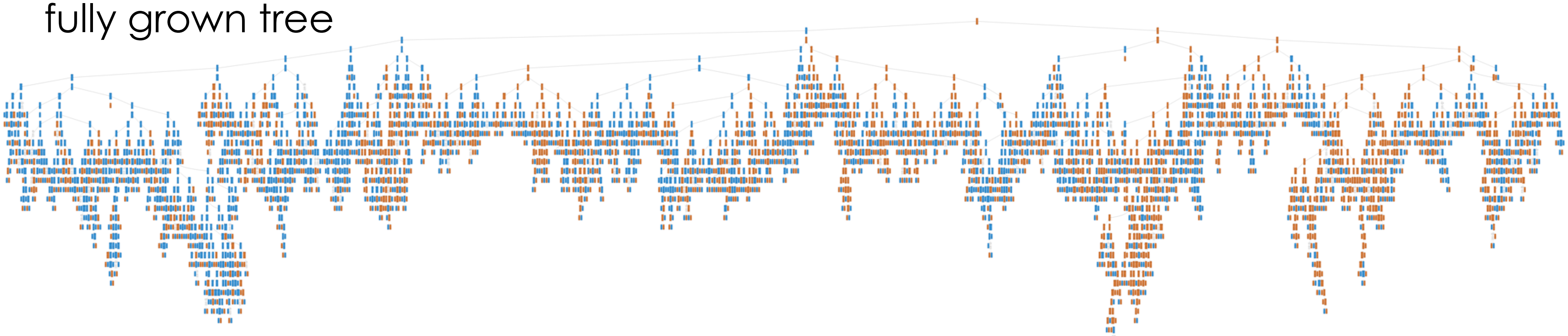
first three layers of a tree

- features are not scaled *a-priori*

- at each node, random sub-selection of features
- impurity minimization (Gini index) by choosing the best split



fully grown tree

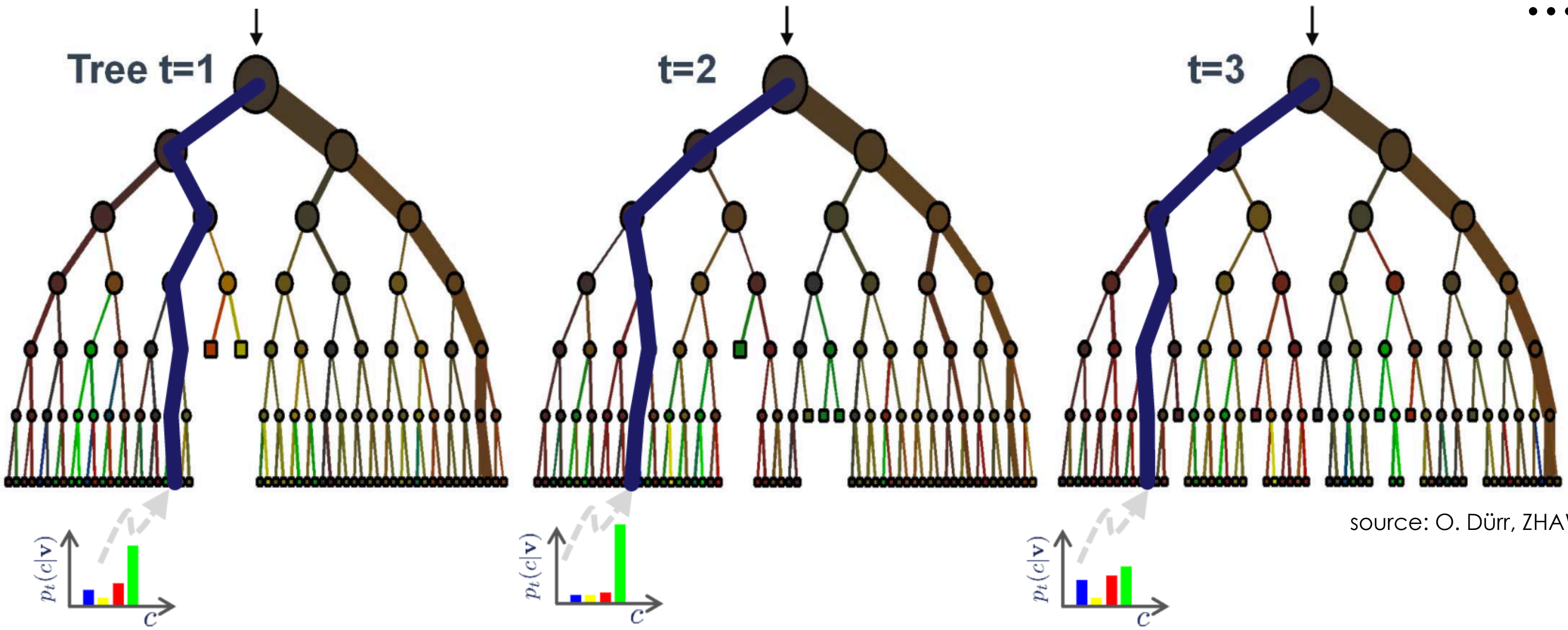


how to classify a new sample belonging to the test subset with a Random Forests and how to assess the classifier’s accuracy

new observation　　new observation　　new observation

for all the trees in the forest

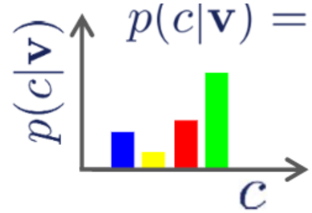
…



source: O. Dürr, ZHAW School of Engineering

final class will be chosen through **majority vote** or by **averaging** the **probabilities**

$$p(c|\mathbf{v}) = \frac{1}{T}\sum_t p_t(c|\mathbf{v})$$



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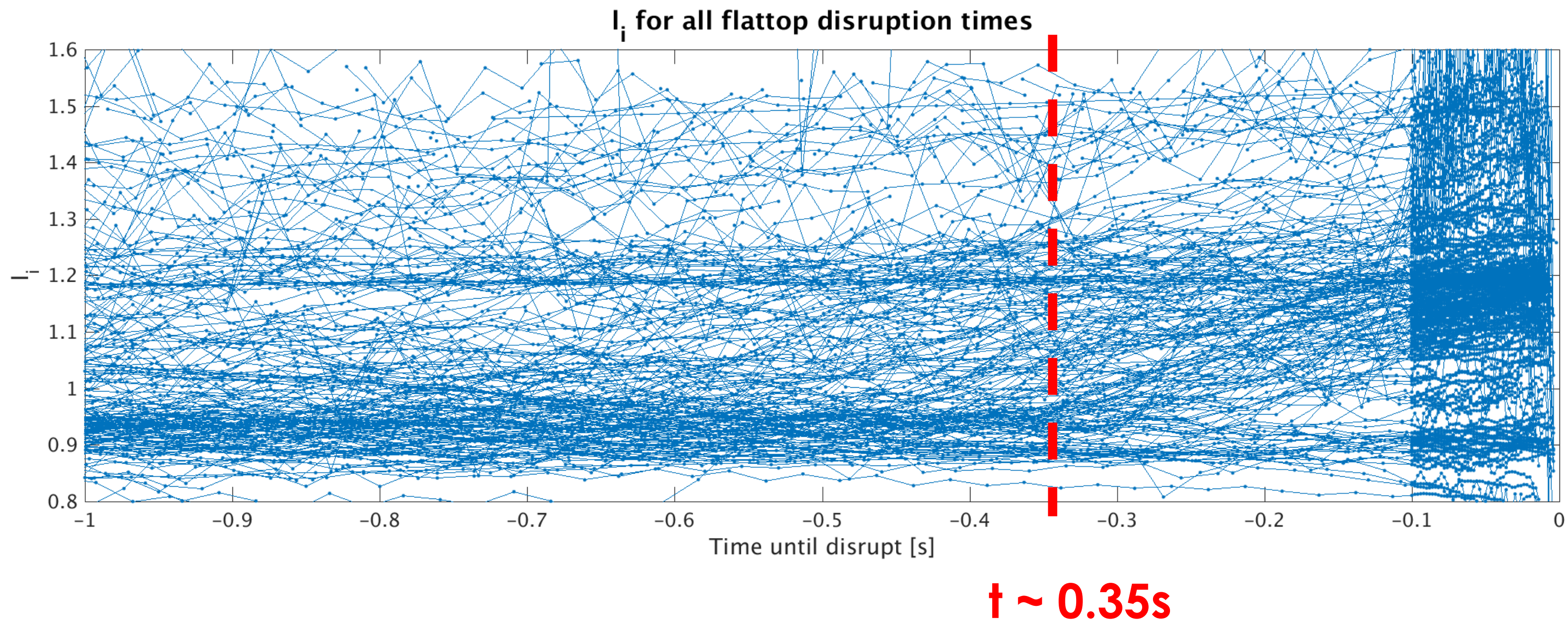
univariate analysis on input parameters leads us to set the proper discrimination threshold in time between classes

- class labels have an induced time dependency for the human eye
- the threshold for the discrimination between the labels **close to disr** and **far from disr** is chosen on the basis of the univariate analysis of individual input parameters:



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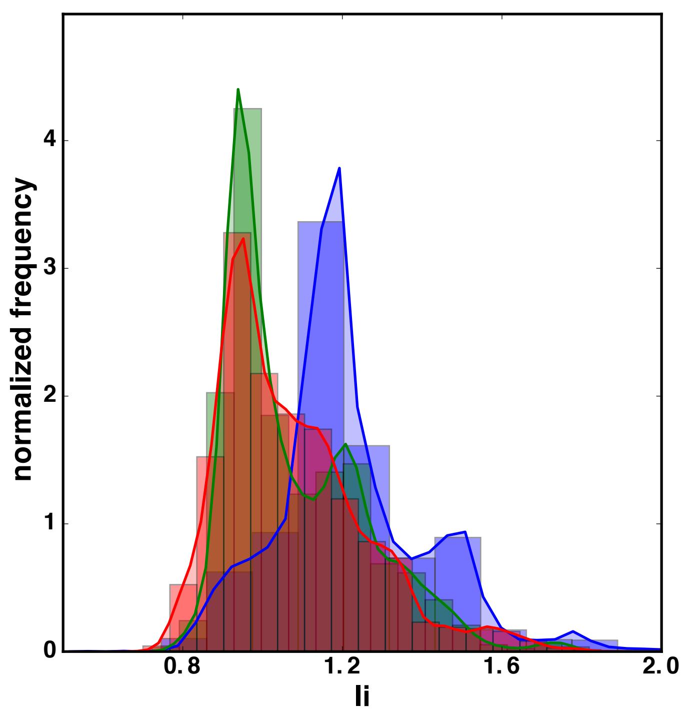
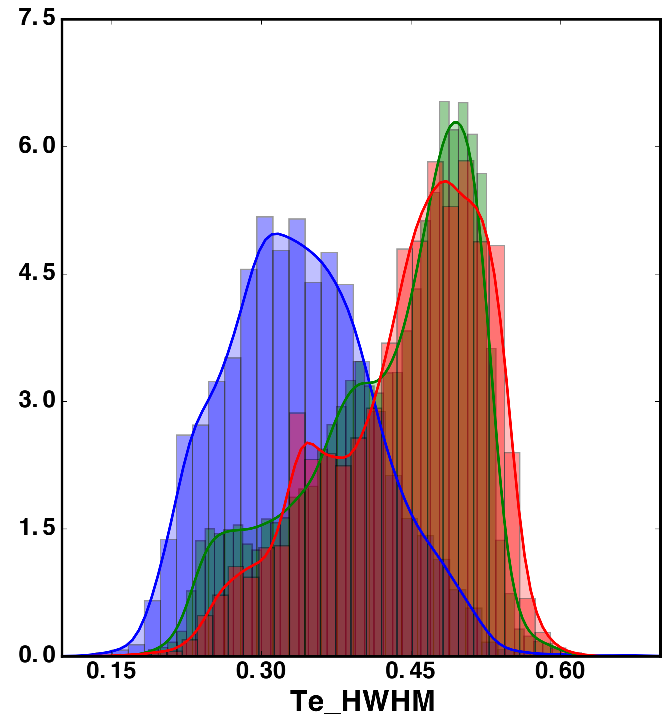
univariate kernel density estimates – color code:

close to disr :
(tud < 0.35s)
far from disr :
(tud > 0.35s)
non-disrupted





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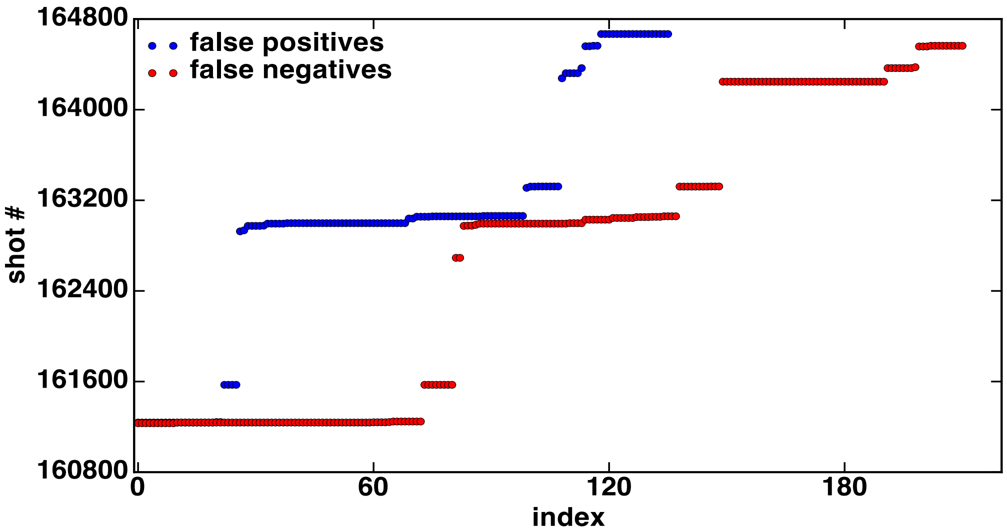
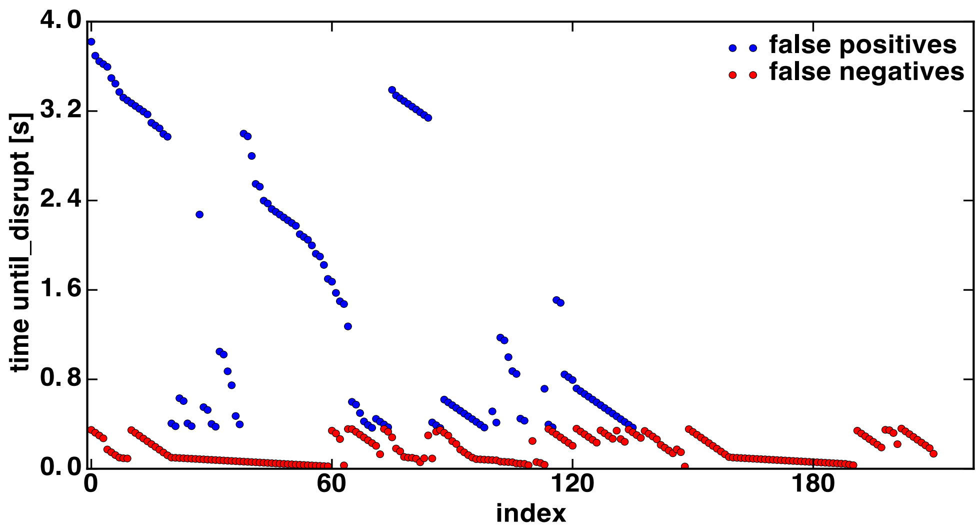
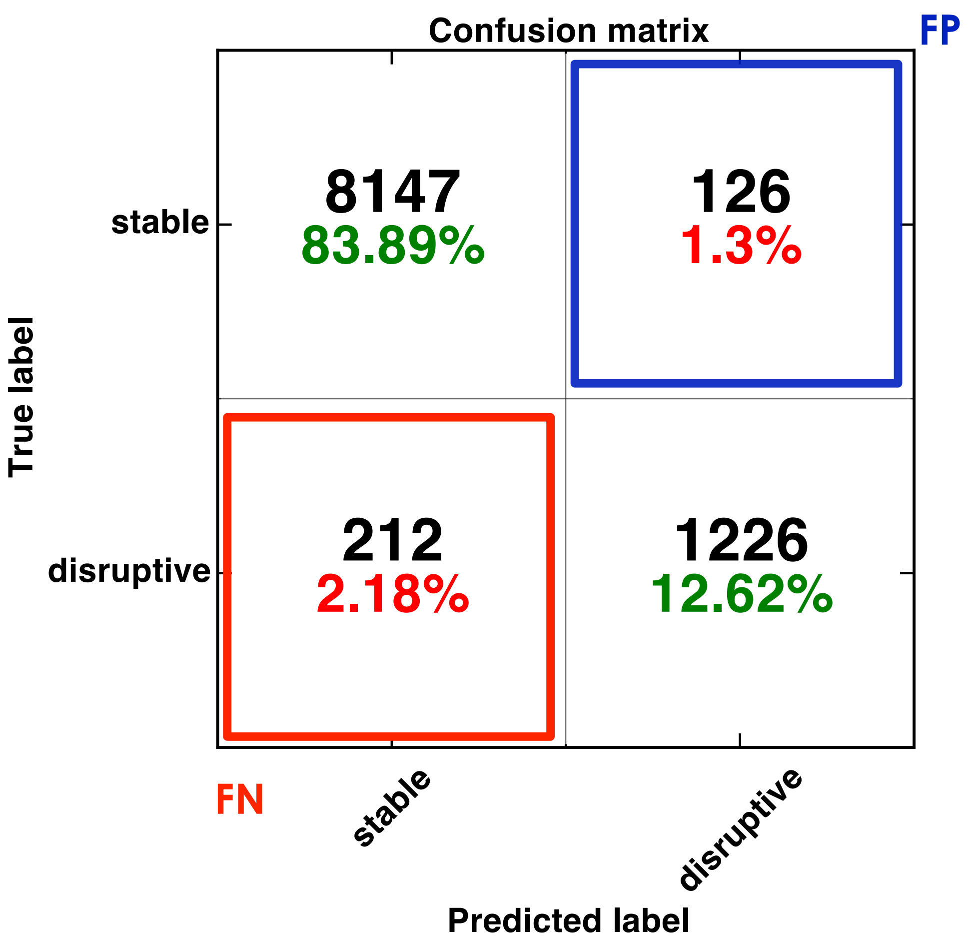
false negatives and false positives distributions reveal a close dependency on a certain number of discharges







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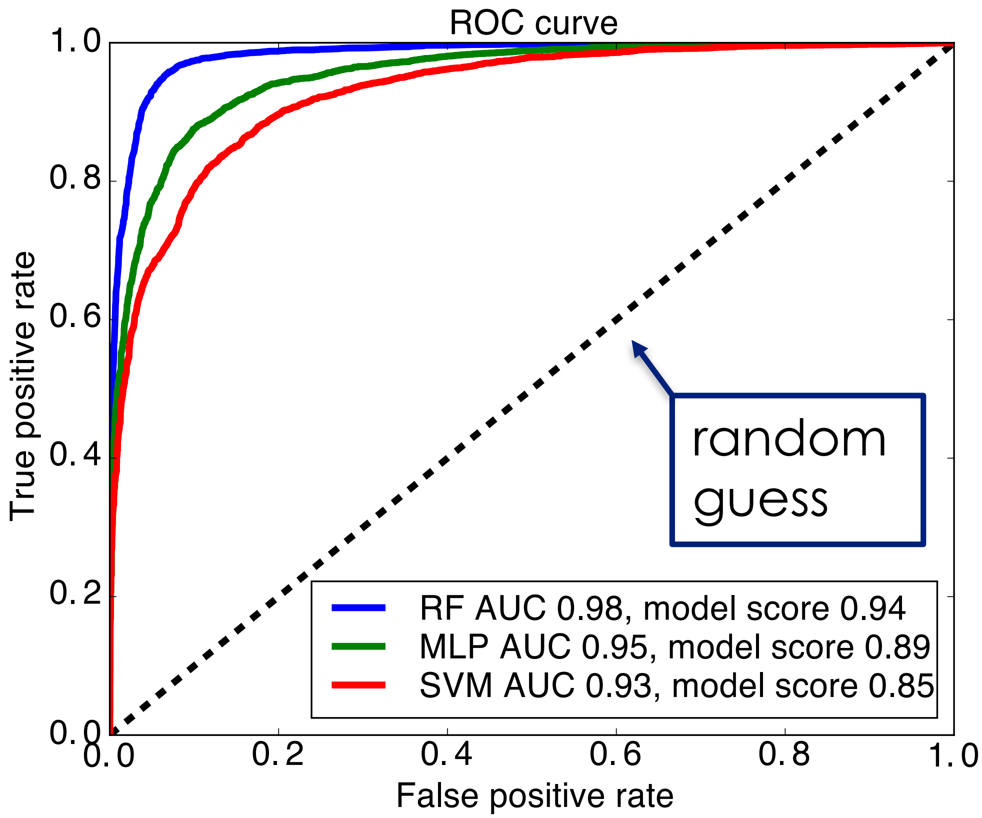
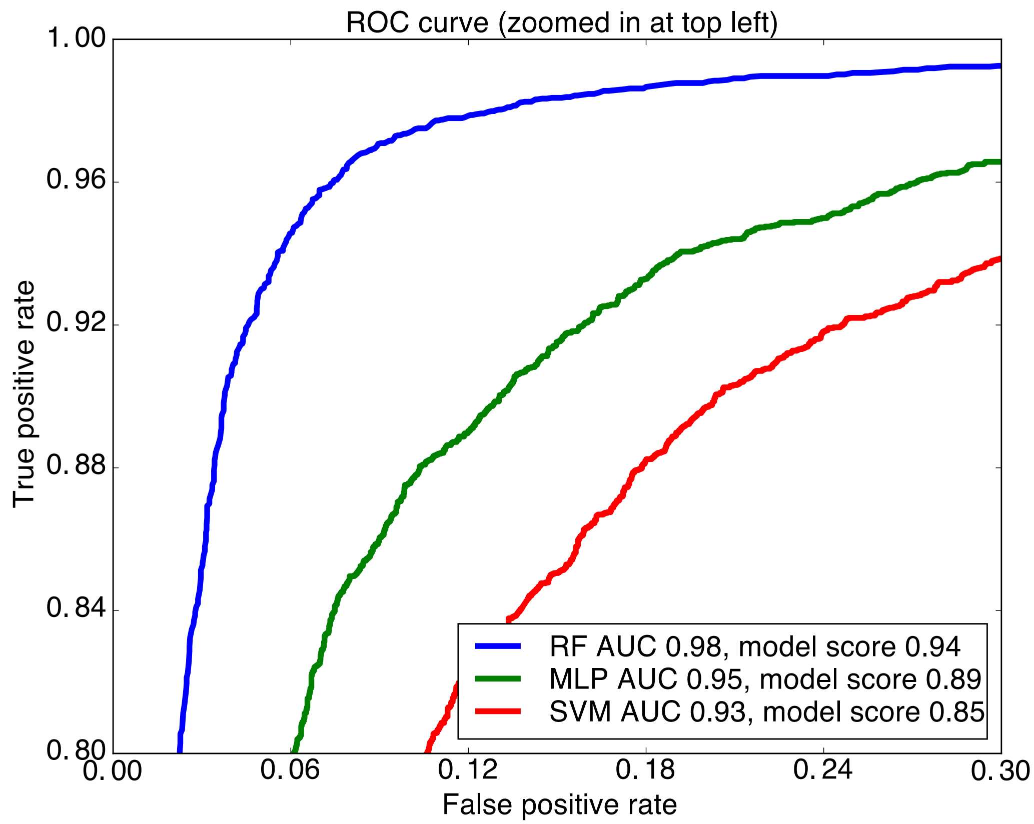
ROCs illustrate relative tradeoff between benefits (true positives) and costs (false positives) of binary classifiers

- **RF** (blue) maximizes the **AUC** (Area Under the Curve) if compared to Multi-Layer Perceptron (**MLP**) or Support Vector Machine (**SVM**)
- RF catches a higher number of correct classification with respect to a lower number of false positives





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