On the Potential of Adaptive Predictors and their Transfer between Different Devices for both Mitigation and Prevention of Disruptions

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Closed-World Learning

Traditional supervised Machine Learning is based on the *closed-world assumption:*

- All the classes in the test and final applications must have been seen in the training (with suitable number of examples).
- The systems under study must be stationary. The i.i.d. assumption (data independent and identically distributed) means that the results are valid only if the pdf of the data are the same for the training set, the test set and the final application.
- Large amounts of data required for the training, obsolescence etc

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Open-World Machine Learning

Motivations *for open-world learning:*

- Plasmas are not necessarily stationary physical objects (*adaptive learning*).
- It would be advantageous to transfer knowledge from one device to another (*transfer learning*).

In Tokamaks there are two main historical effects which violate the stationarity assumption: a) Evolution of the experimental programme between discharges b) Memory effects during shots.

Transfer Learning could be very important particularly at the beginning of operation of new devices.

Adaptive/Transfer Learning

The most powerful approach for learning in non stationary conditions is *adaptive learning*: predictors are updated when appropriate to track the evolution of the phenomena to be predicted. Two main types of adaptation have been implemented to reflect the different time scales involved during and between discharges.

a) Updates of the training sets and modification of the decision functions between discharges

b) Trajectory learning during discharges.

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Outline

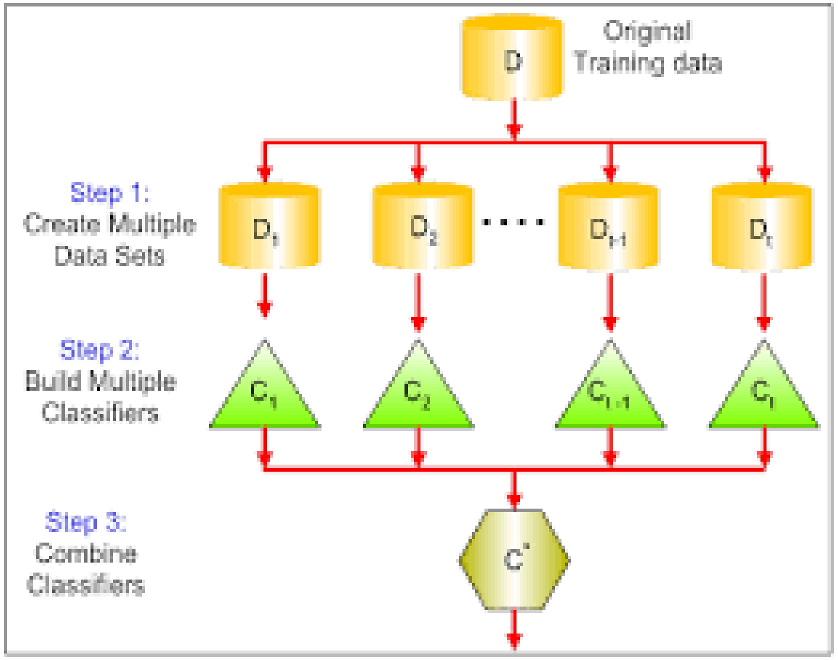
- Overview of Ensemble Classifiers
- Strategies of Adaptive Learning for prediction in non stationary conditions
- Results for AUG (mitigation and prevention)
- Transfer to JET (mitigation and prevention)
- Conclusions and future lines of investigation

Weak Learning and Ensembles of classifiers

Many classifiers are not very stable; small changes in the training set can result in major differences in the final trees and therefore in the final classification.

- A 'weak' learner (either classifier or predictor) is just a machine learning tool, which might not have excellent performance but is computationally not too demanding.
- The relatively limited computational resources required allow training various versions of such weak learners which can then be pooled together to create a "strong" **ensemble classifier**.

The trick is to increase diversity by training with slightly different sets.



The basic classifiers used as weak learners are CART trees.

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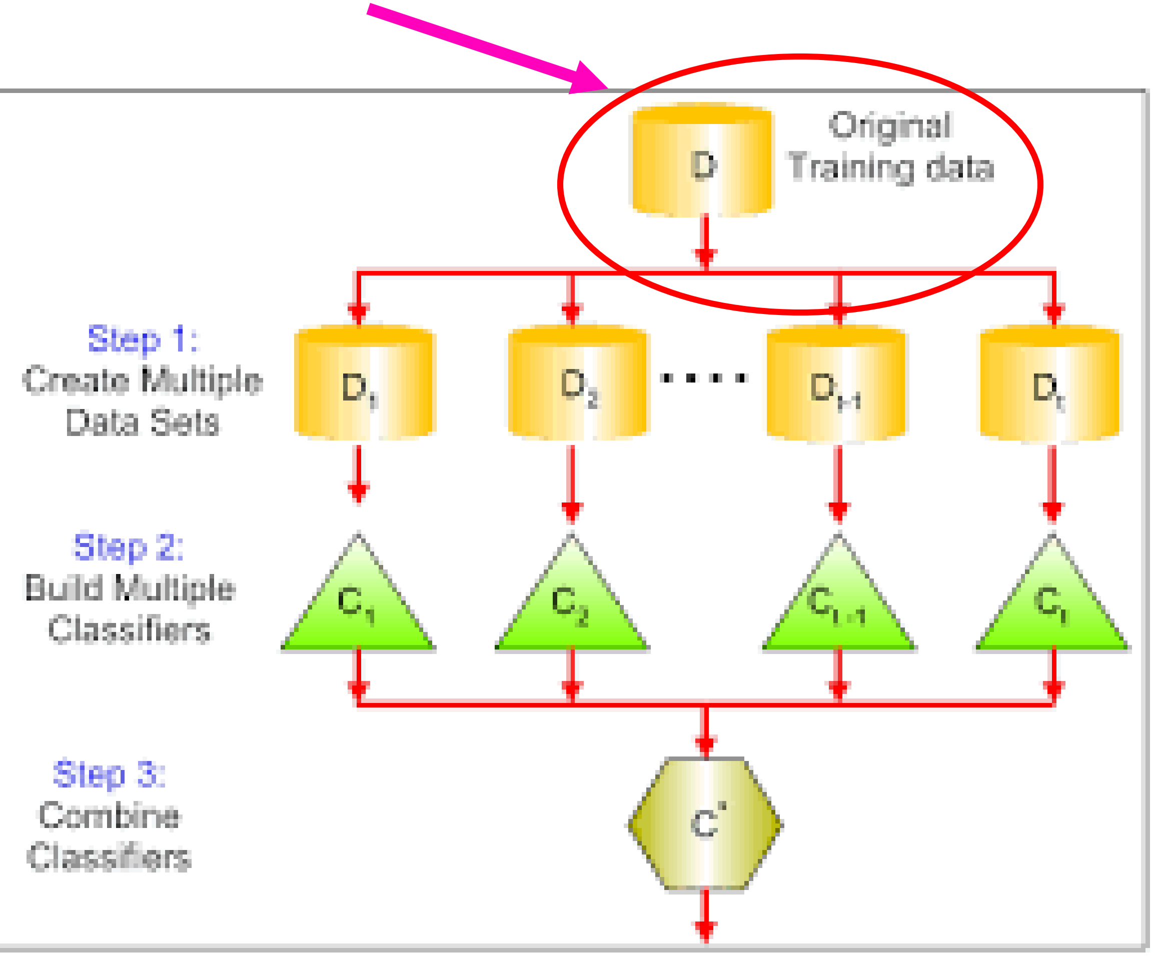
Between discharges: updating the Training Set

The *training set* is updated according to two different criteria.



- When there is a error in the prediction (for example a missed or a tardy alarm).
- To implement de-learning: old examples are discarded when they become obsolete and therefore misleading.

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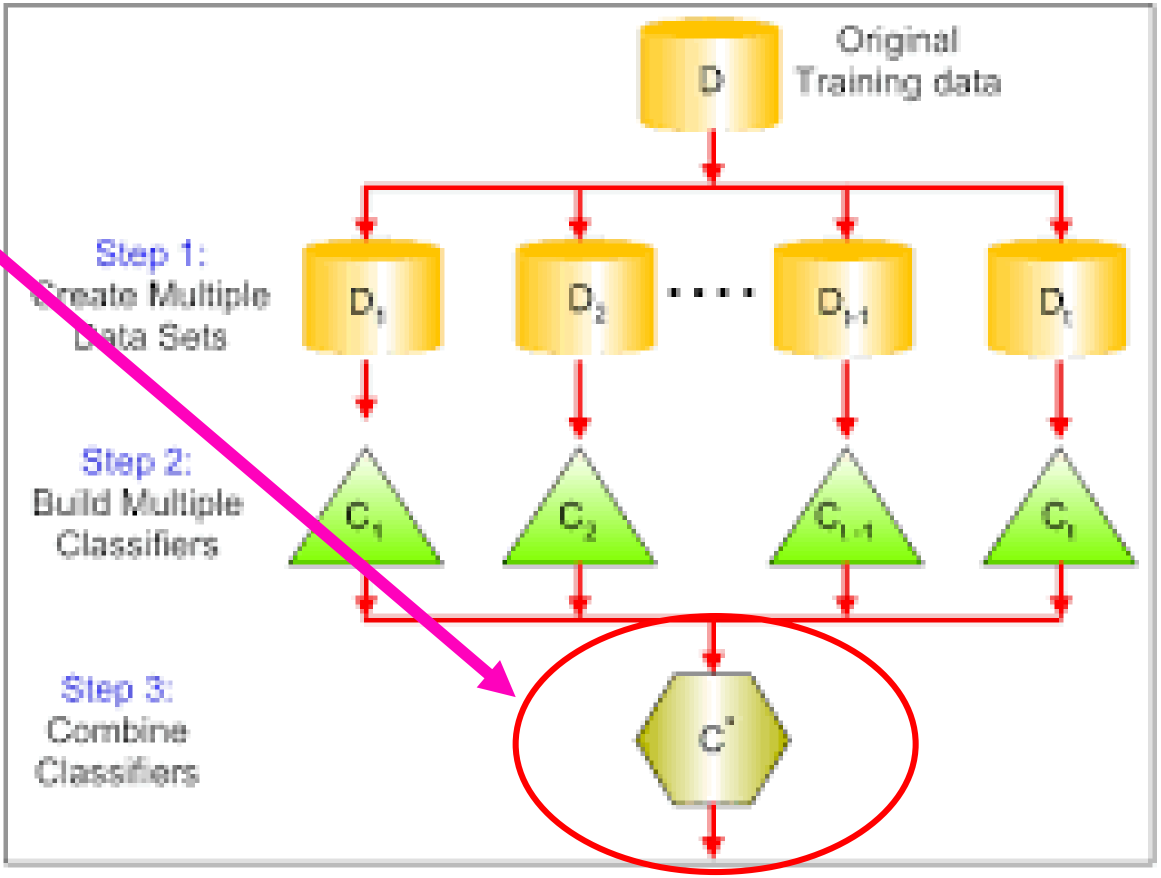
Between discharges: updating the decision function

The ensembles are pooled and the final output is obtained with a *decision function*

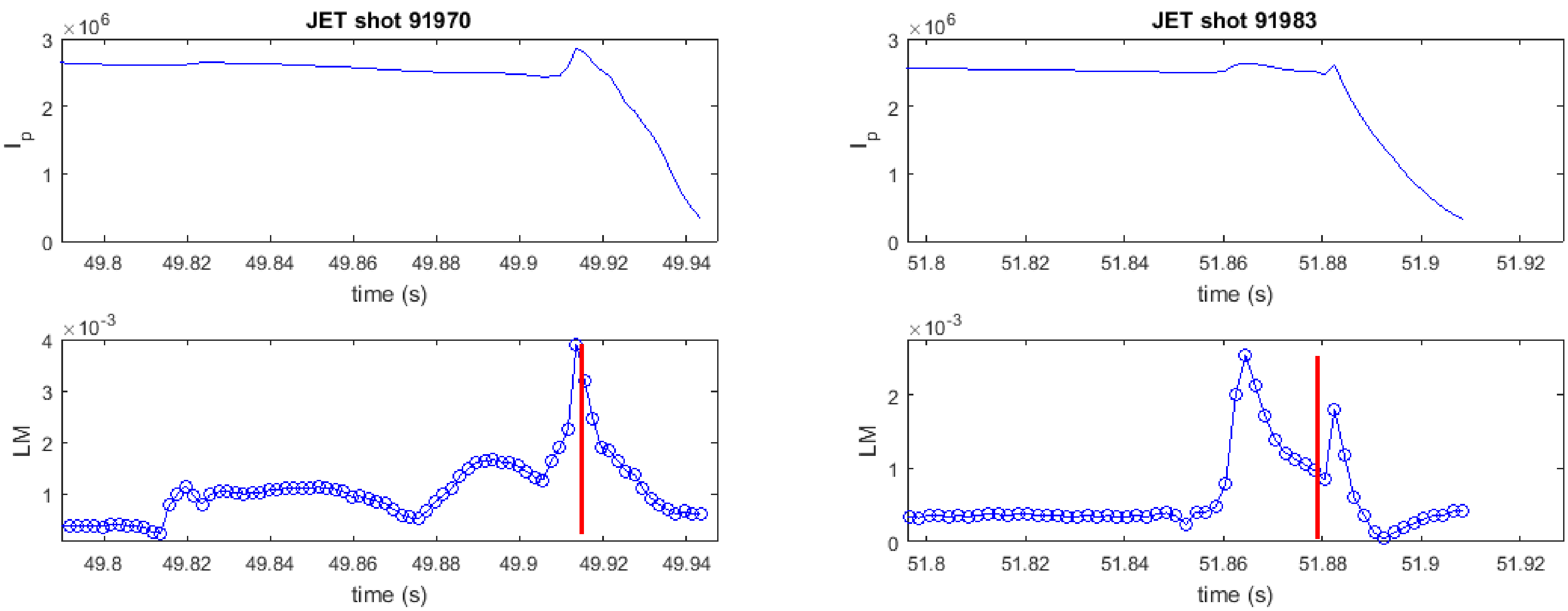
Various decision functions are run in parallel and the one with the best results so far is used to generate the alarm.



At this stage one can optimise *de-learning*, the rejection of old and therefore misleading examples.

During a disxcharge: trajectory learning

In ***trajectory learning***, the training sets contains the history of the data (sequence of samples) so that the predictors can learn the system trajectory in the feature space.



Statistically, the trajectory of the ML amplitude can be different depending on the shot.

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Features and time rescaling

For mitigation the inputs used are: normalised locked mode amplitude (and its std deviation), internal inductance.

For prevention a profile factor of bolometry has been added: ratio of divertor versus core lines of sight.

Features are dimensionless or normalized: no need to modify them

For mitigation a time dilation of a factor of 4 has has been derived “a priori” by heuristic comparison of the two machine electromagnetic circuits (from 1.5 to 6 ms).

For prevention a time dilation of a factor of 100 has been derived by observing the dynamics of impurity transport of the two devices (from 10 to 1000 ms).

Database AUG and settings

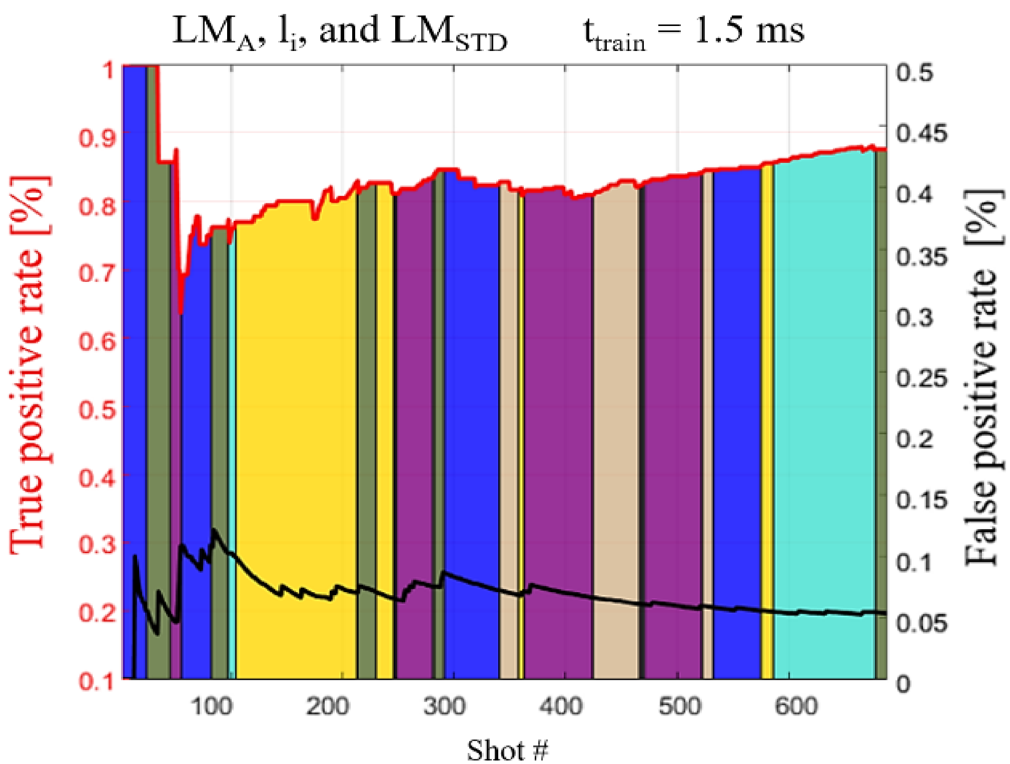
The AUG database analysed comprises 154 disruptive and 535 safe discharges. The interval of discharges ranges of from shot 28007 to shot 30585 (from 2012 to 2014).

The signals have been resampled at 0.1 ms time resolution and all the time slices with plasma current higher than 300 kA have been analysed.

The scan of plasma currents covers the interval from 300 kA to about 1.2 MA.

With regard to the criteria to calculate the statistics of the results, the alarms triggered less than 1 ms from the beginning of the current quench are considered tardy. An alarm is considered early if it is launched more than 1 s before the beginning of the current quench.

Results on AUG for mitigation



Different colours indicate different decision functions. LM$_A$ normalised locked mode amplitude, LM$_{STD}$ locked mode std deviation, li internal inductance

AUG	Success rate	Missed	Early	Tardy	False	Mean [ms]
LM$_A$, LM$_{STD}$ li	87.66% (135/154)	5.84% (9/154)	5.84% (9/154)	0.65% (1/154)	5.70% (31/538)	22.30

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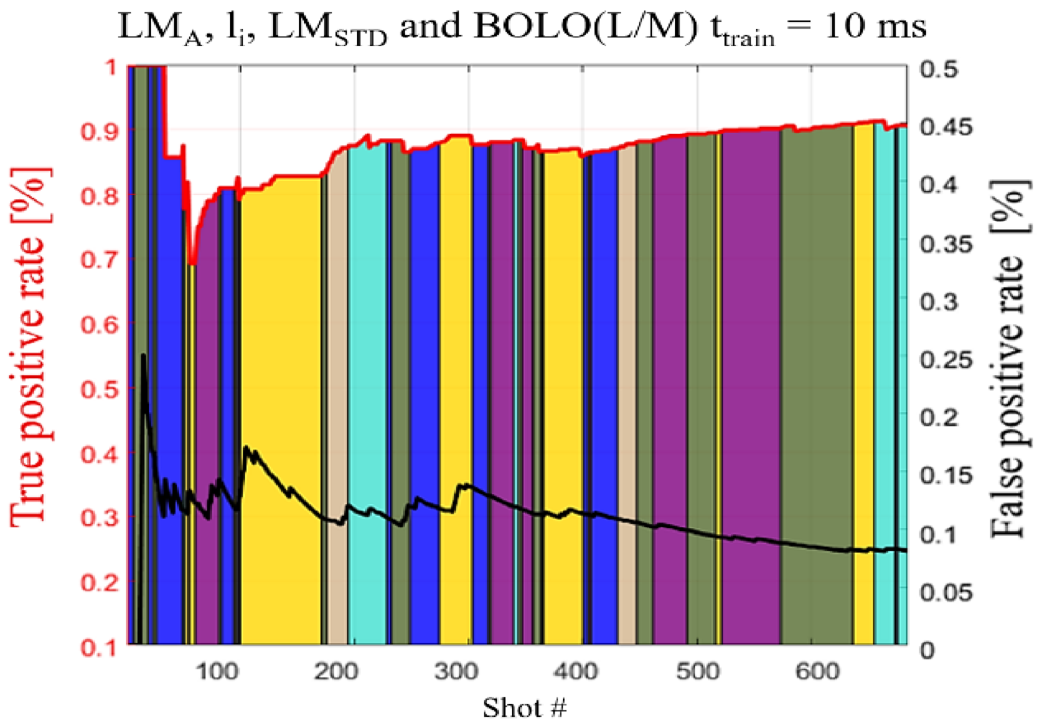
Results on AUG for prevention



Different colours indicate different decision functions. LM_A normalised locked mode amplitude, LM_{STD} locked mode std deviation, li internal inductance, BOLO profile indicator

AUG	Success rate	Missed	Early	Tardy	False	Mean [ms]
LM_A LM_{STD} Bolo L/M	90.73% (137/154)	5.84% (9/154)	3.31% (5/154)	0.00% (0/154)	8.16% (44/539)	43.10

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Database JET with the ILW wall and settings

The DB analyzed covers campaigns C28-C32 (430 disruptions and 1998 safe shots) with 1 ms time resolution and all time slices with Ip > 750 kA.

Tardy alarms: if the alarm is triggered less than 10 ms from the beginning of the current quench.
Early alarms: triggered more than 3 s from the beginning of the current quench.

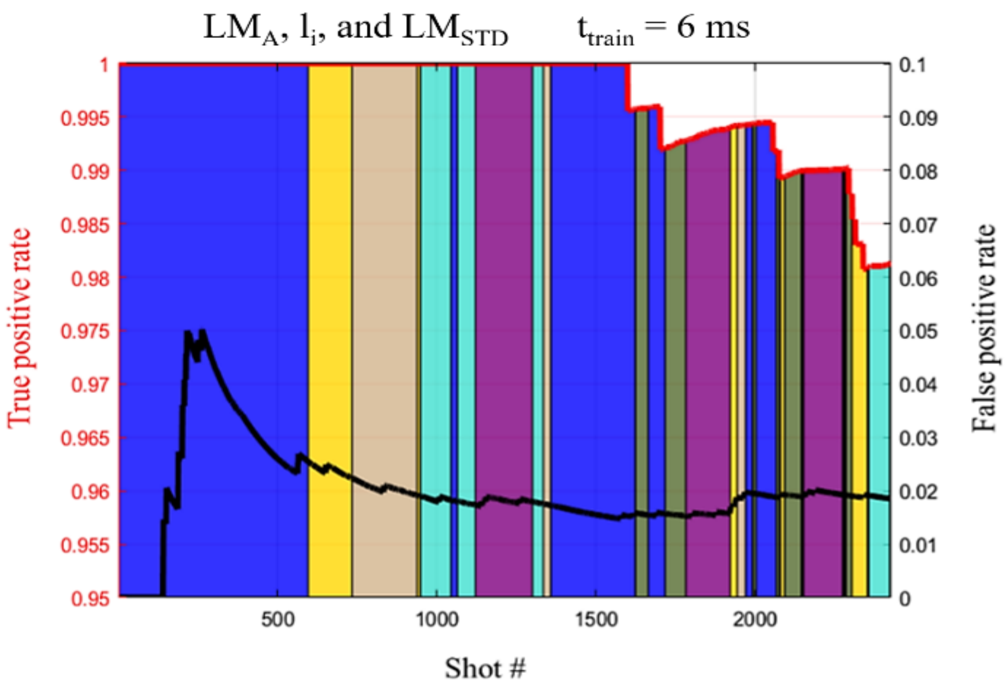
The first model is obtained after the first disruption (from scratch). No selection on the discharges.

No modification of the AUG predictor when transferred to JET: all the parameters of the predictors have been rescaled in time according to the criteria previously described.

A.Murari et al Adaptive learning for disruption prediction in non-stationary conditions Nuclear Fusion, July 2019, Volume 59, Number 8

Results on JET for mitigation

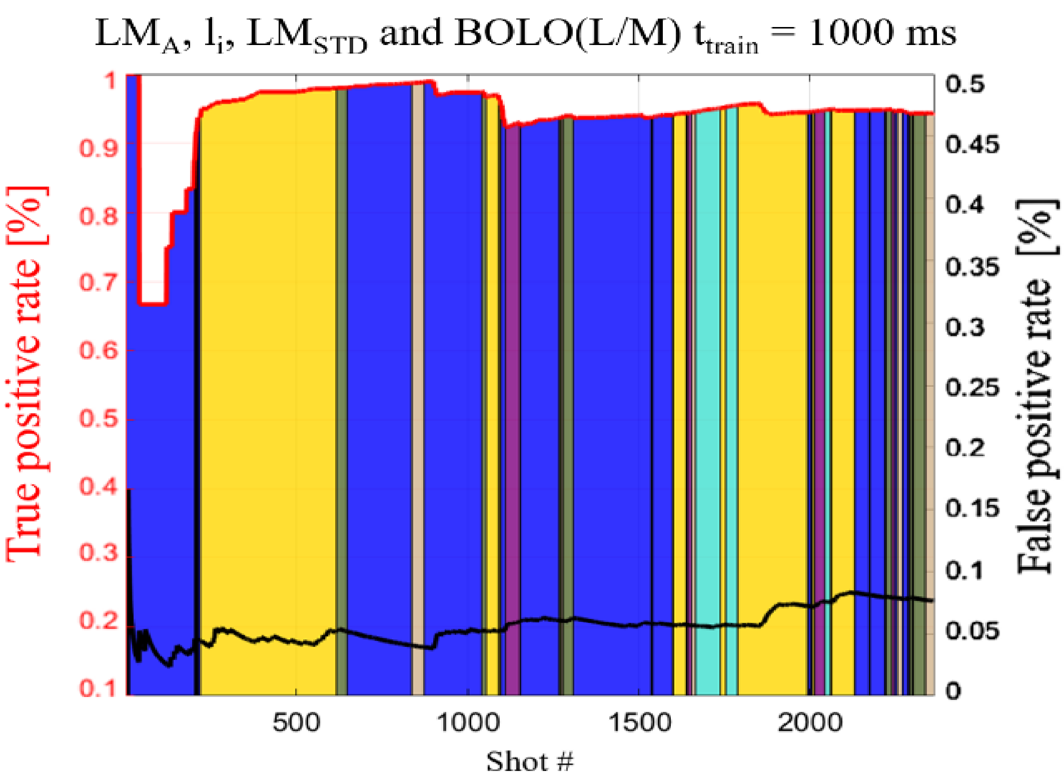
AUG predictors have been applied directly to JET shots without any manipulation (except the time translation)



Different colours indicate different decision functions. LM_A normalised locked mode amplitude, LM_{STD} locked mode std deviation, li internal inductance

JET	Success rate	Missed	Early	Tardy	False	Mean [ms]
LM_A, LM_{STD} , li	98.14% (421/429)	1.4% (6/429)	0% (0/429)	0.47% (2/429)	1.9% (38/1998)	278.3

Results on JET for prevention



Different colours indicate different decision functions. LM_A normalised locked mode amplitude, LM_{STD} locked mode std deviation, li internal inductance, BOLO profile indicator

JET	Success rate	Missed	Early	Tardy	False	Mean [ms]
LM_A, LM_{STD}, li ,Bolo	94.17% (404/429)	1.63% (7/429)	3.73% (16/429)	0.47% (2/429)	7.69% (150/1951)	489.7

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Conclusions

- Adaptive and Transfer Learning are becoming important tasks in Tokamak physics, particularly for disruption prediction.
- The innovative approach of CART Ensembles has proved to be sufficiently flexible to implement complex strategies of adaptive learning and the first example of transfer learning.
- The developed techniques of adaptive/transfer learning have been quite successful in predicting disruptions on JET at the beginning of operation with the new ITER Like Wall after training on AUG.
- The adaptive/transfer learning approach is a good fall-back solution for ITER given the great variations in its operational scenarios
- In the future we intend to apply the same techniques of adaptive learning from scratch and transfer learning to the identification of the disruption types as prerequisite to predicting the time to disruption.

Thanks for Your Attention!

QUESTIONS?

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