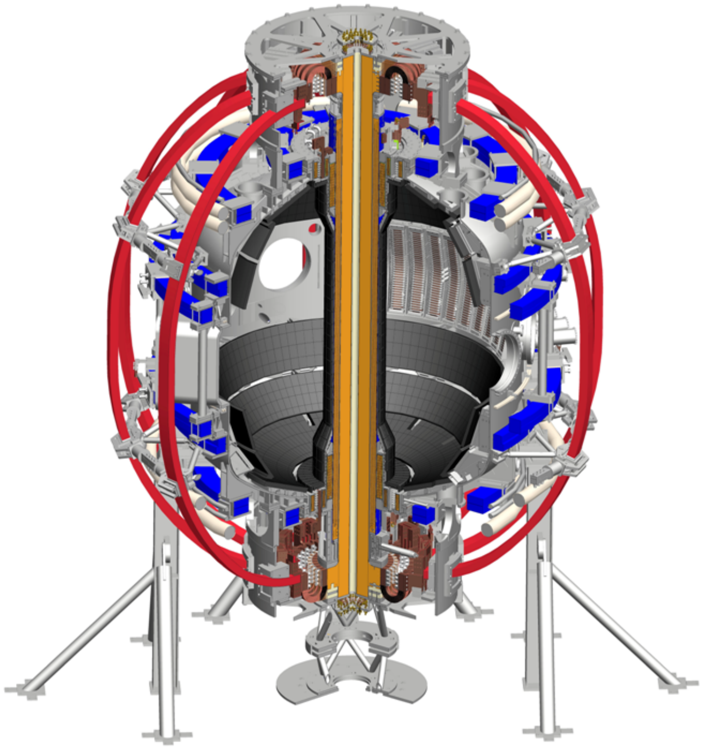
Machine learning activities in experimental fusion science



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U. Wisconsin-Madison (@PPPL)

PPPL SULI seminar
July 12, 2018

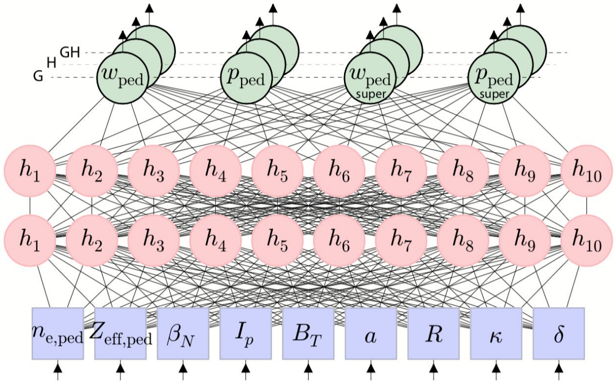
Areas of ML applications in fusion science

1. Reduced models derived from neural networks
2. Machine control and disruption avoidance
3. Automated mode classification

Nearly all of the slides in this presentation are taken from other presentations.
Hyperlink references are listed at the end.

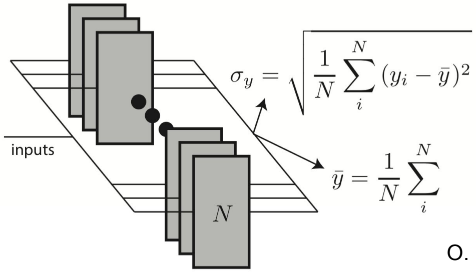
1. REDUCED MODELS DERIVED FROM NEURAL NETWORKS

EPED1-NN can reproduce same pedestal structure of EPED1 model



Ensemble of NNs used to estimate the error in NN models prediction

- random NN initialization
- each NN trained on random subset of the training DB



Approach used for other similar problems

- well established theories
- scalar inputs/outputs
- no time history
- different dB filling techniques

- EPED1-NN
- TGLF-NN
- NEO-NN

Built database of ~20,000 EPED1 runs (2 million CPU hours)

DIII-D: 3,000 runs

KSTAR: 700 runs

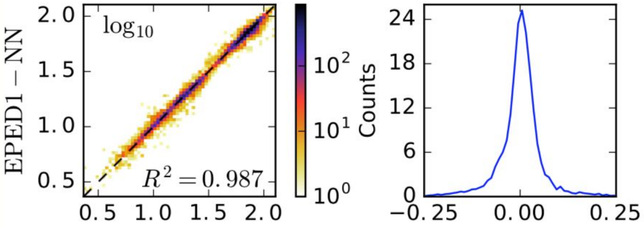
JET: 200 runs

ITER: 15,000 runs

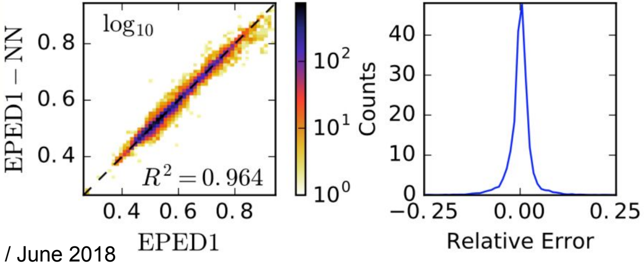
CFETR: 1,200 runs

$\times 10^9$ **speedup**

Pedestal height p_{ped} [kPa]

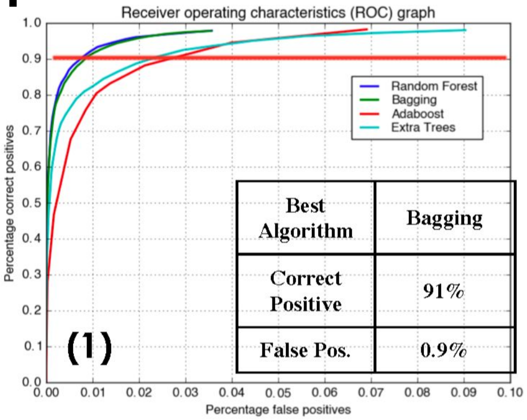


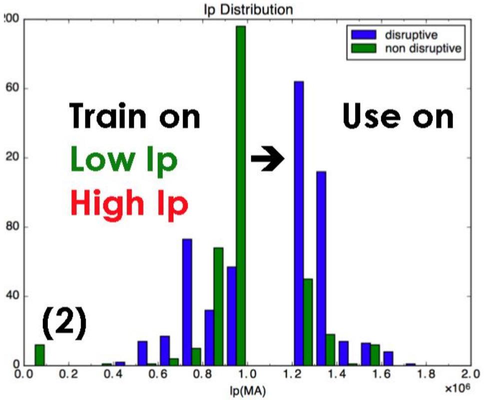
Pedestal width w_{ped} [$\Delta\%\psi$]

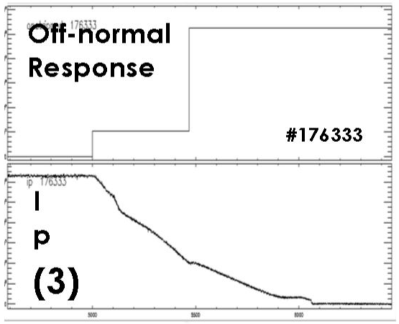


2. MACHINE CONTROL AND DISRUPTION AVOIDANCE

Tested different algorythms - Generalization at different IP - Rumpdown control







Compared 4 ML Algorithms for Disruption Prediction at DIII-D

Best Algorithm (90% (95%) Correct Positive with <1% (2%) False Positive)

ITER can safely disrupt at Low Ip but not at high Ip

Train ML Algorithm at low Ip (based on safe disruptions) and use on high Ip

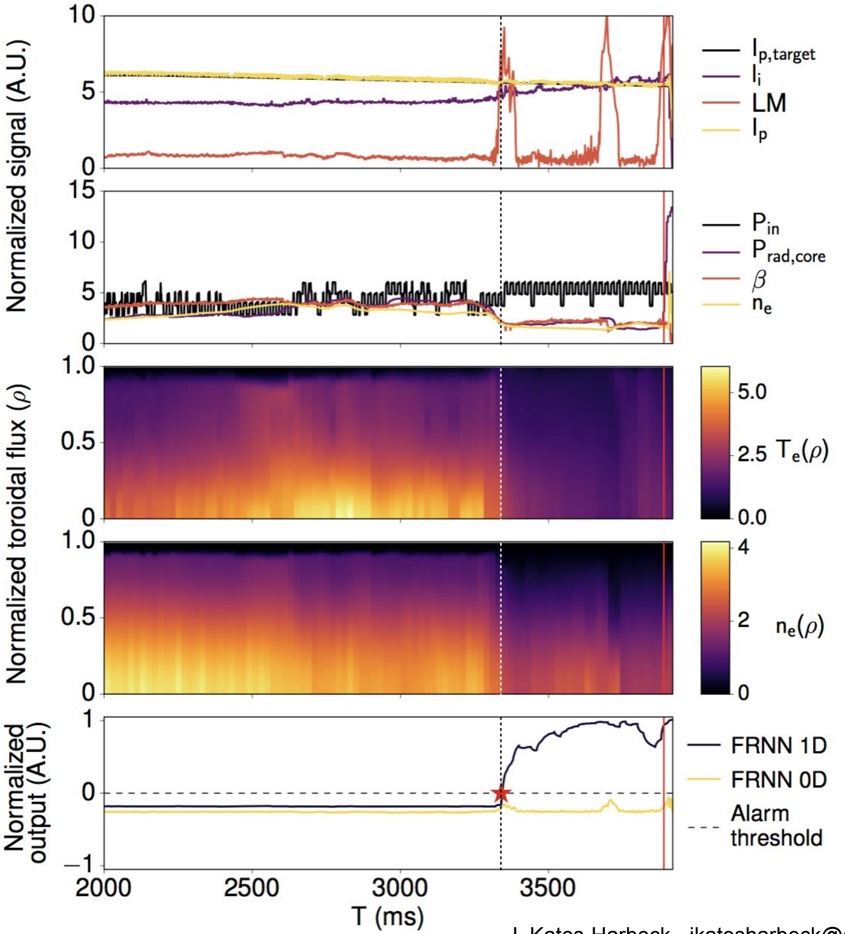
Tested the idea on DIII-D: Best Algorithm - ***AdaBoost (90% CP with 2% FP)***

Applied the ML Algorithm in real-time Control of DIII-D:

When the "disruptivity' increase above a threshold: Go to safe rampdown

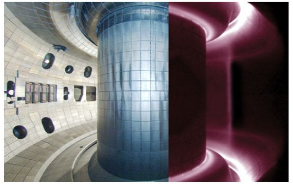
Kolemen Group: K. Kleijwegt, Y. Fu

Deep RNN can generalize better

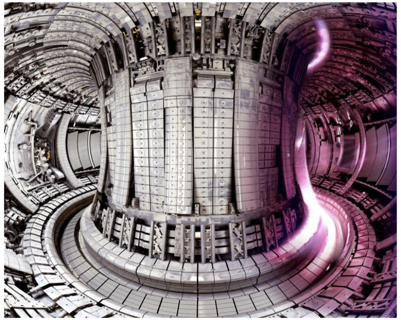


Deep RNN can learn invariant representation of input features and generalize better:

- Make full use of **high dimensional** data (e.g. profiles) and **time-varying** features
- **Transfer learning:** accuracy increase when a small number (~5) of JET disruptions are added to the test set.
- Accuracy of cross-device prediction and **comparable to shallow learning on single device**



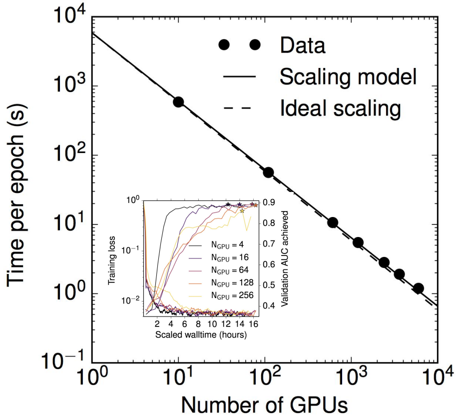
Train (DIII-D)

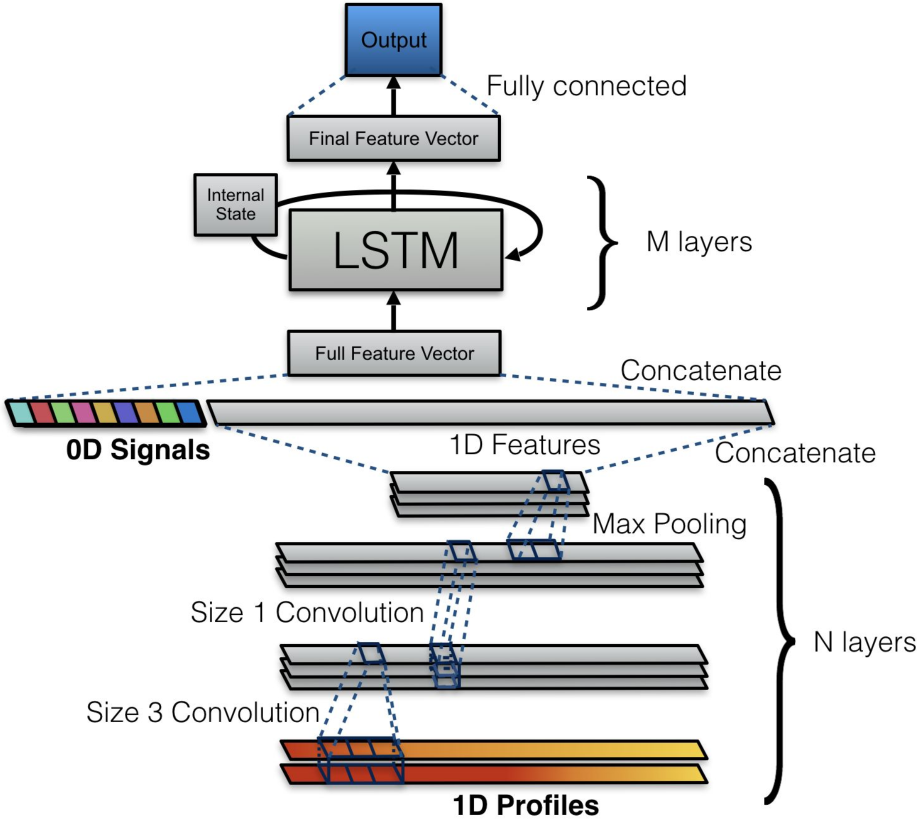


Test (JET)

Disruption Prediction via deep Recurrent Neural Network - FRNN

- FRNN model:
  - **Convolutional layers** to learn features from 1D data (profiles)
  - **LSTM** to learn temporal patterns
- Plug other **ML models**
  - (SVM, MLP, RF, GBT, etc.)
- **HPC** to accelerate training and hyperparameter tuning





JET Disruption Data

# Shots	Disruptive	Nondisruptive	Totals
Carbon Wall	324	4029	4353
Beryllium Wall (ILW)	185	1036	1221
Totals	509	5065	5574

Sample 7 Signals of zero-D time traces (07)	Data Size (GB)
Plasma Current	1.8
Mode Lock Amplitude	1.8
Plasma Density	7.8
Radiated Power	30.0
Total Input Power	3.0
d/dt Stored Diamagnetic Energy	2.9
Plasma Internal Inductance	3.0

JET produces ~ Terabyte (TB) of data per day

~55 GB data collected from each JET shot

➔***Well over 350 TB total amount with multi-dimensional data yet to be analyzed***

Deep Recurrent Neural Networks (RNNs): Basic Description

- "Deep"
  - **Hierarchical representation** of complex data, building up salient features automatically
  - Obviating the need for hand tuning, feature engineering, and feature selection
- "Recurrent"
  - Natural notion of time and memory → i.e., at every time-step, the output depends on
    - Last Internal state "s(t-1)" ***Recurrence!***
    - Current input x(t)
  - The internal state can act as memory and accumulate information of what has happened in the past

Internal State ("memory/ context")

$$s_t = A(W_{in}x_t + W_{recurrent}s_{t-1} + b)$$

$$h_t = W_{out}s_t$$

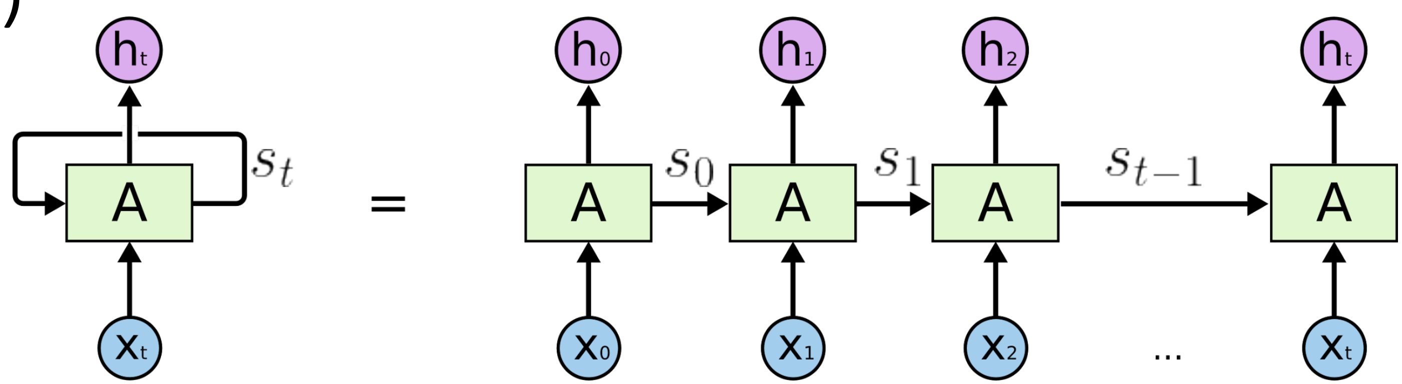
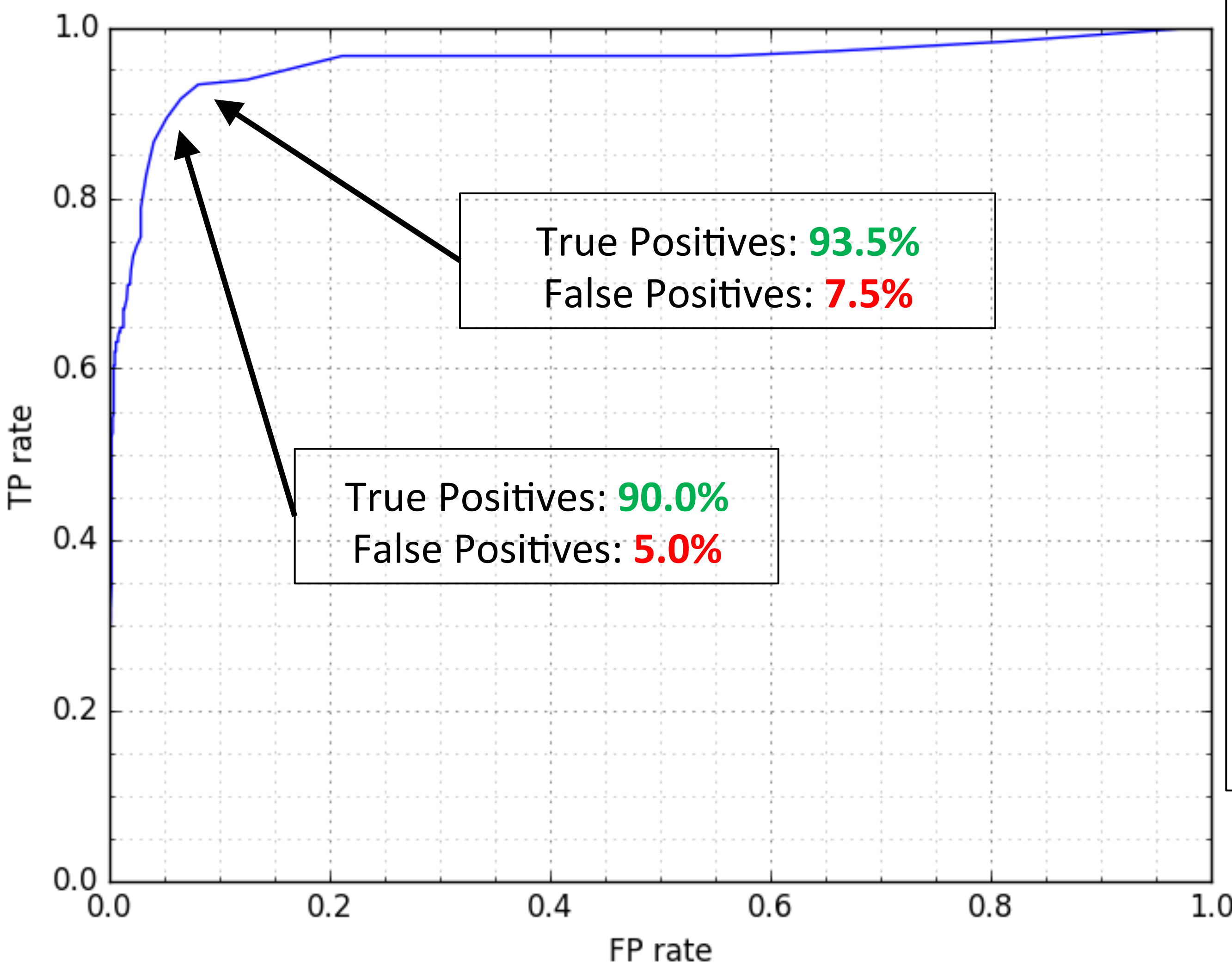


Image adapted from: colah.github.io

FRNN ("Fusion Recurrent Neural Net") Code Performance (ROC Plot)

Performance Tradeoff: Tune True Positives (good: correctly caught disruption) **vs. False Positives** (bad: safe shot incorrectly labeled disruptive).



RNN Data:

- Testing **1200 shots** from Jet ILW campaigns (C28-C30)
- **All shots used**, no signal filtering or removal of shots

Jet SVM* work:

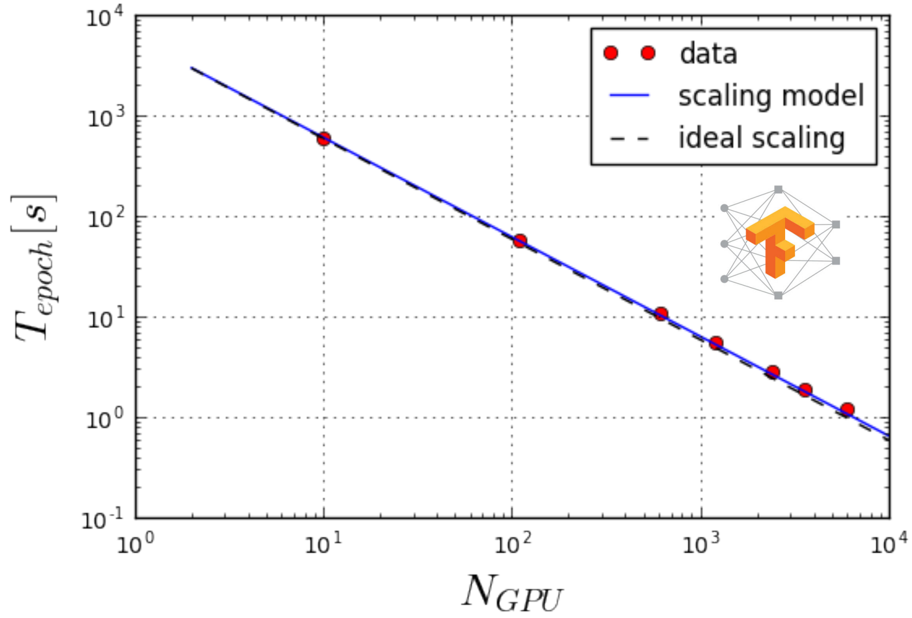
- **990 shots** from same campaigns
- **Filtering** of signals, **ad hoc removal of shots** with abnormal signals
- **TP 80 to 90%, FP 5%**

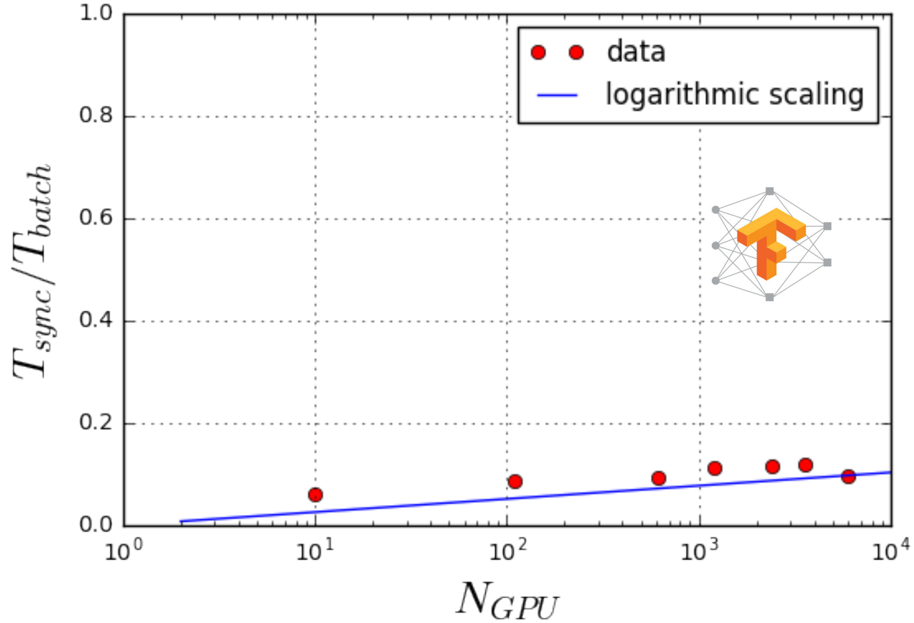
*Vega, Jesús, et al. "Results of the JET real-time disruption predictor in the ITER-like wall campaigns." *Fusion Engineering and Design* 88.6 (2013): 1228-1231.

FRNN Scaling Results on GPU's

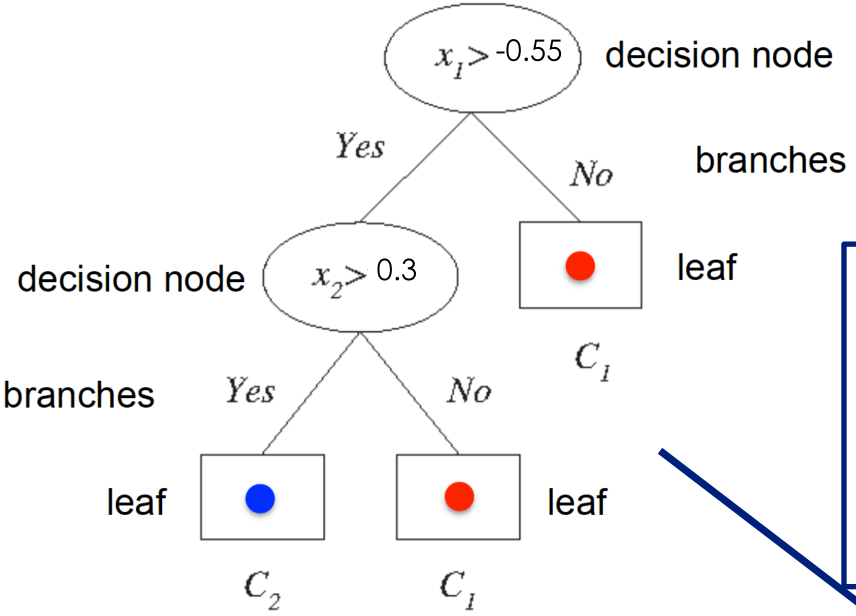
- Tests on OLCF Titan CRAY supercomputer
  - ***OLCF DD AWARD**: Enabled Scaling Studies on Titan currently up to 6000 GPU's*
  - Total ~ 18.7K Tesla K20X Kepler GPUs

Tensorflow+MPI





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

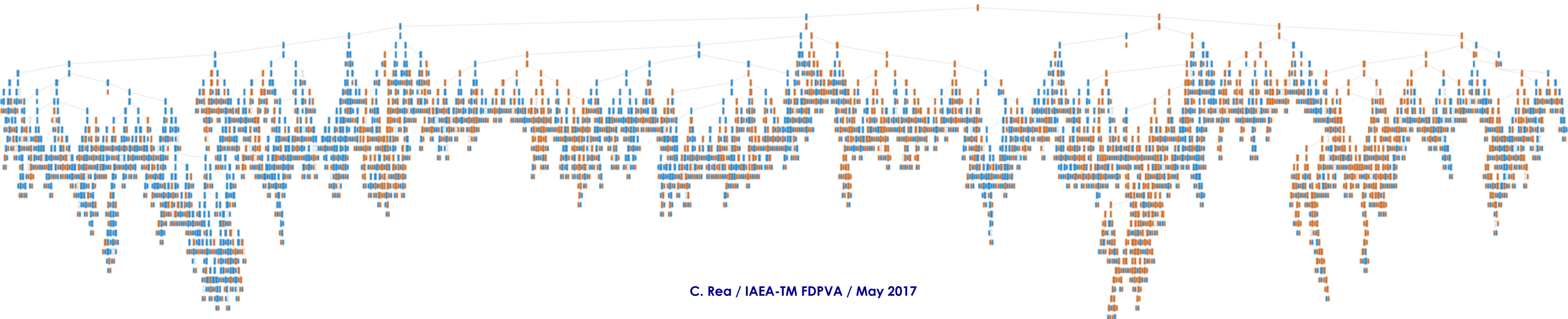


(x_1, x_2) →

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

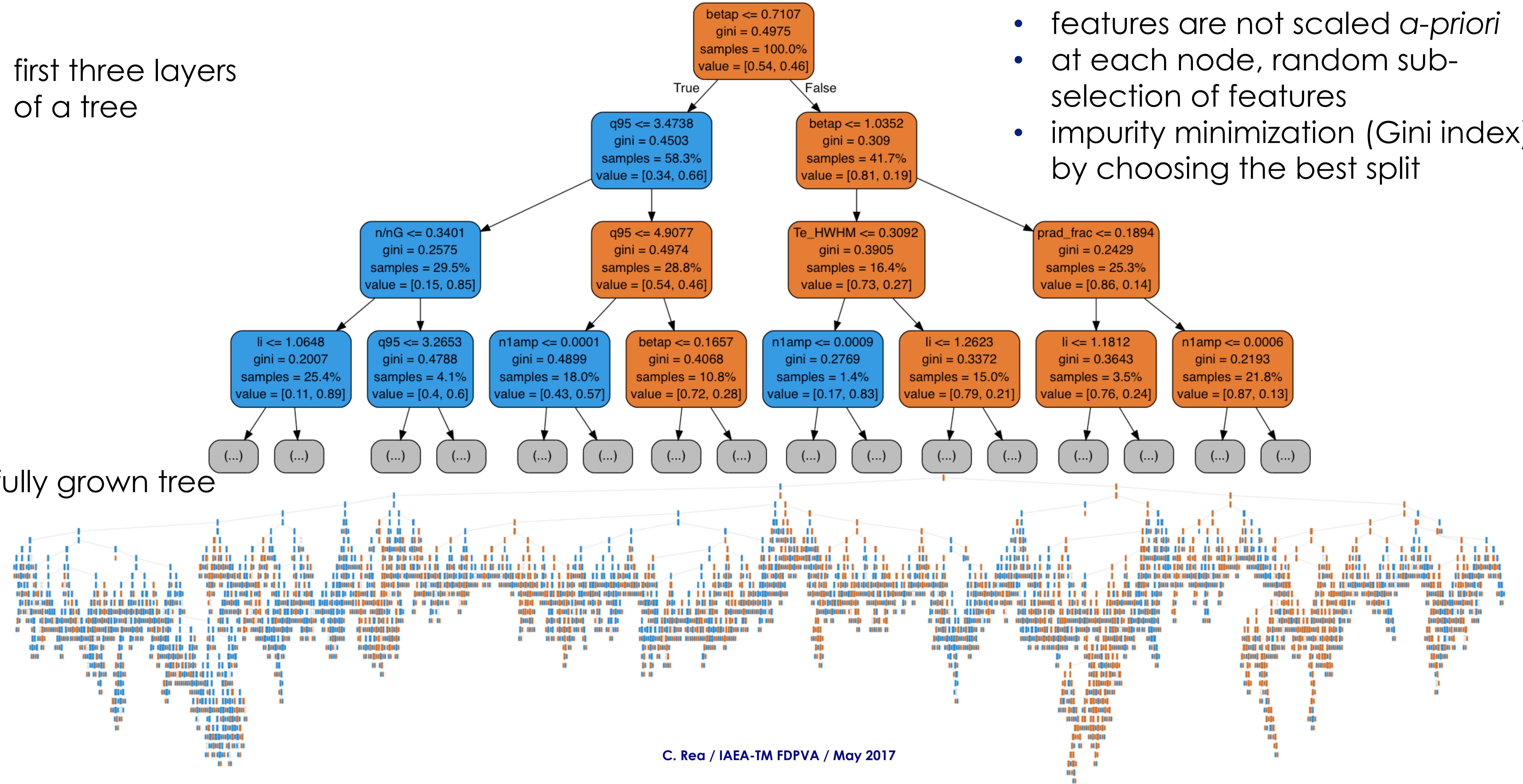
from a 2D space with few points to a 10D space with many thousands of points

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



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

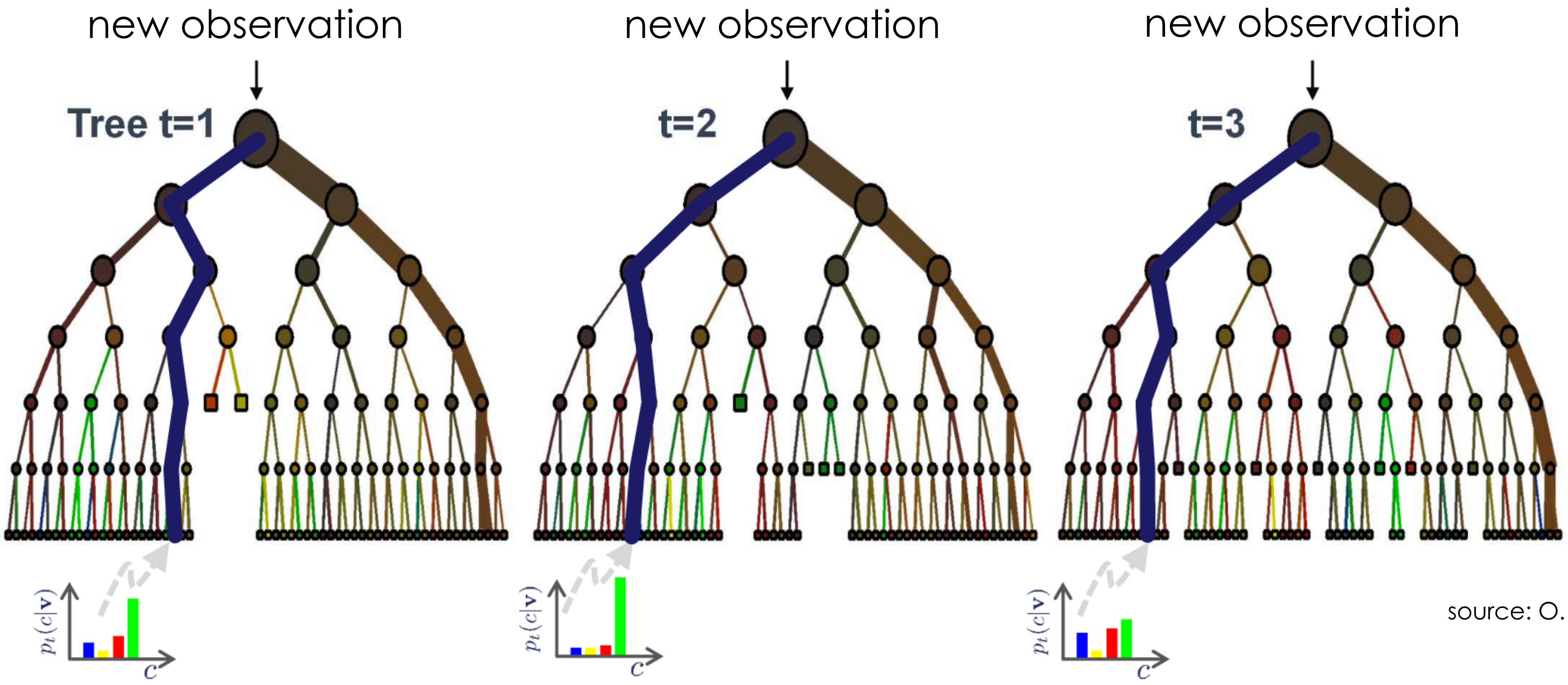
first three layers of a tree



fully grown tree

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

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



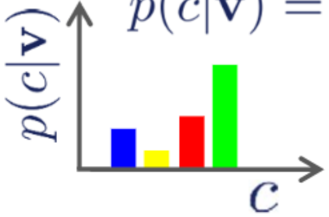
for all the trees in the forest

...

source: O. Dürr, ZHAW School of Engineering

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

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

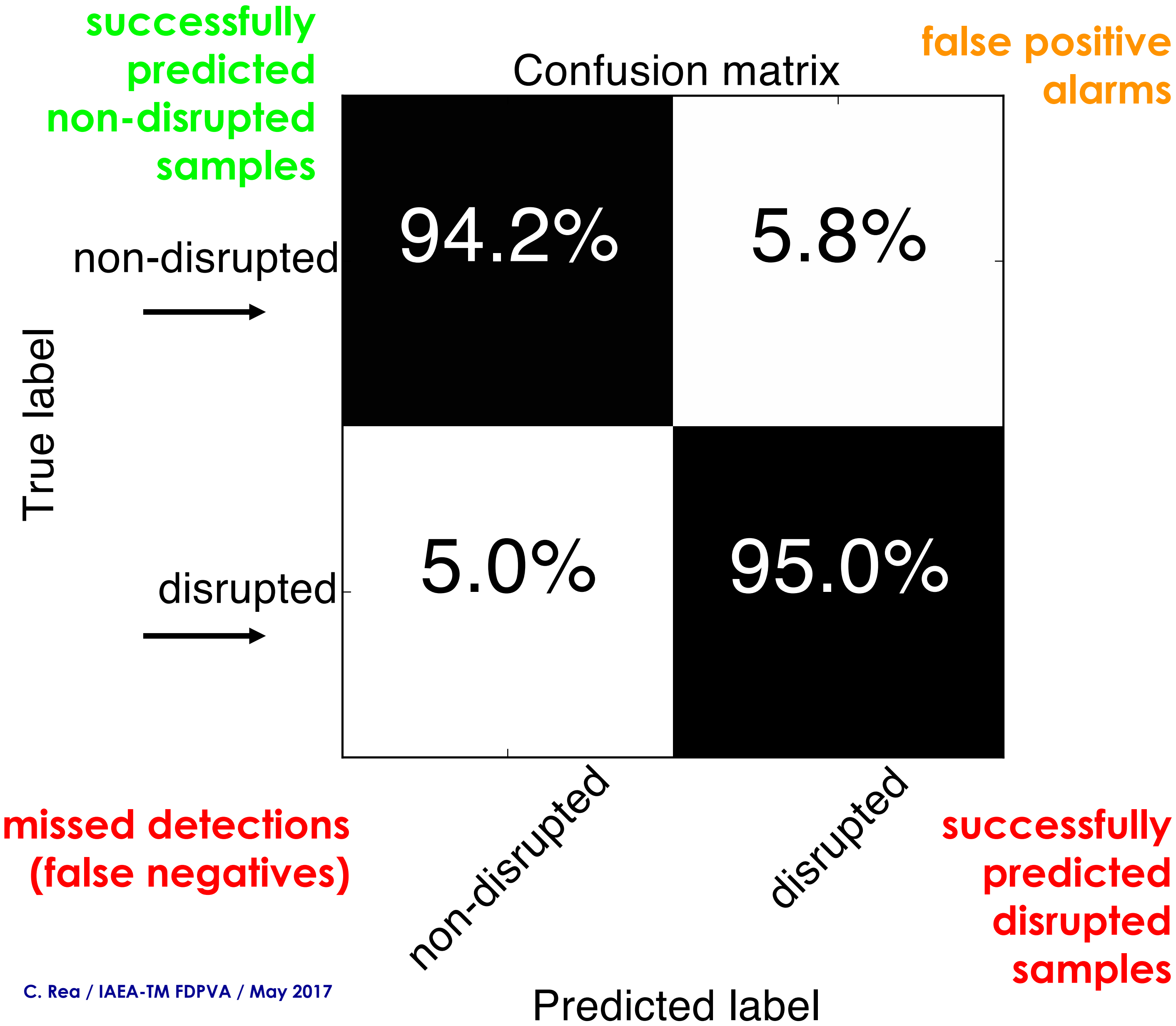


confusion matrix is used as an accuracy metrics to assess the model's capability to discriminate between class labels

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

non-disrupted | disrupted

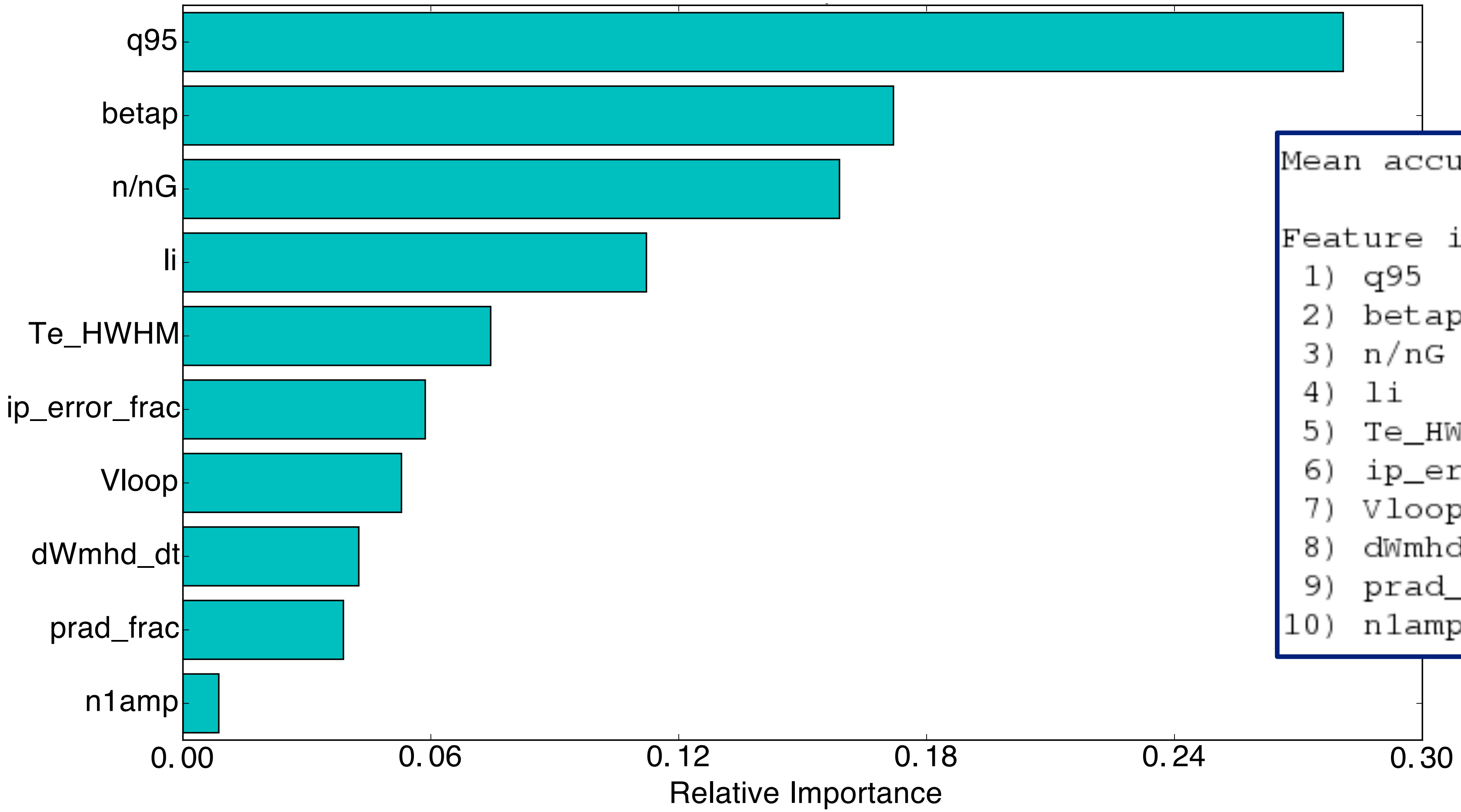
confusion matrix percentages are normalized with respect to each **true class label**



DIII-D NATIONAL FUSION FACILITY

relative importance ranking extracted from the Random Forests – binary classification case – no time dependency

- relative variable importance wrt label predictability is defined as mean decrease impurity
  - possibility to implement the permutation importance metric
- q95 is the relatively most important variable



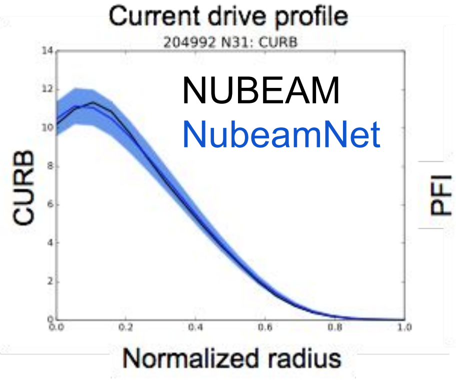

```
Mean accuracy of the model: 0.943

Feature importances:
 1) q95                                   0.280840
 2) betap                                 0.171975
 3) n/nG                                  0.158909
 4) li                                    0.112180
 5) Te_HWHM                               0.074488
 6) ip_error_frac                         0.058647
 7) Vloop                                 0.052894
 8) dWmhd_dt                              0.042557
 9) prad_frac                             0.038838
10) n1amp                                 0.008674
```

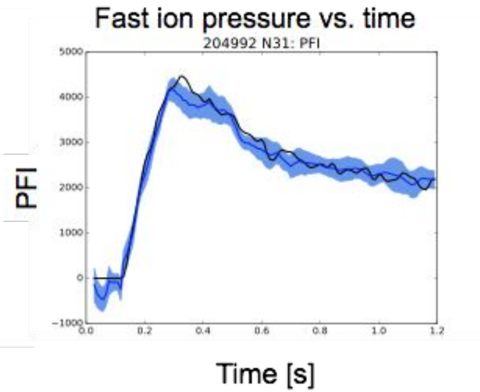
NubeamNet: accelerated neutral beam calculations for scenario optimization and real-time control

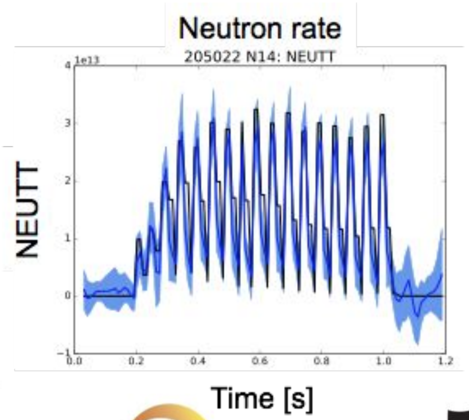
- **Problem:** Scenario development tools and the real-time plasma control system require knowledge of the effect of neutral beams on the plasma for optimization and real-time decision making
    - **NUBEAM** calculates neutral beam heating, current drive, torque, etc., but is a large fraction of the calculation time in the scenario development code TRANSP (>30%) and is not suitable for real-time use. Aiming to reduce calculation time to microseconds (>6 orders of magnitude)
- **Data:** Large database of existing NSTX, NSTX-U, DIII-D, and KSTAR TRANSP runs augmented by scans of important parameters
- **Challenges:**
    - **Profile data:** A few scalar inputs/outputs, but most inputs/outputs are 1D profiles (~20-60 spatial grid points for each quantity).
    - **Beam slowing down time:** adds a dependence on the time history of inputs.

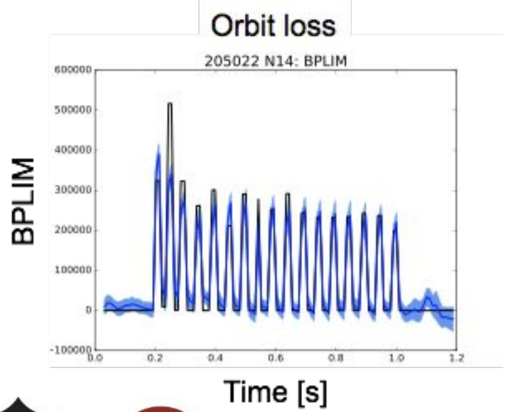
NubeamNet: accelerated neutral beam calculations for scenario optimization and real-time control

- **Solution:** Keep it simple - fully connected NN. To address major challenges:
    - **Profile data**: Principal component analysis of each profile, project data onto reduced set of basis profiles. Avoids need for convolutional neural network to address profile data.
    - **Beam slowing down time:** Augment inputs with low-pass filtered beam powers. Avoids need for recurrent neural network to address time-dependence.
    - Planning to compare to a convolutional+recurrent neural network
    - Implementing in PCS and TRANSP







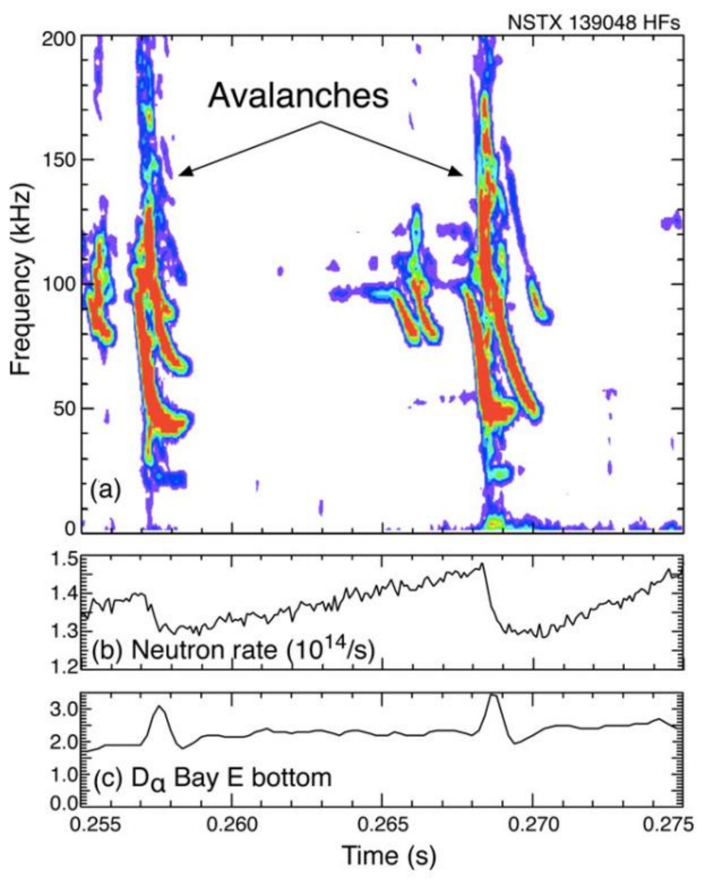


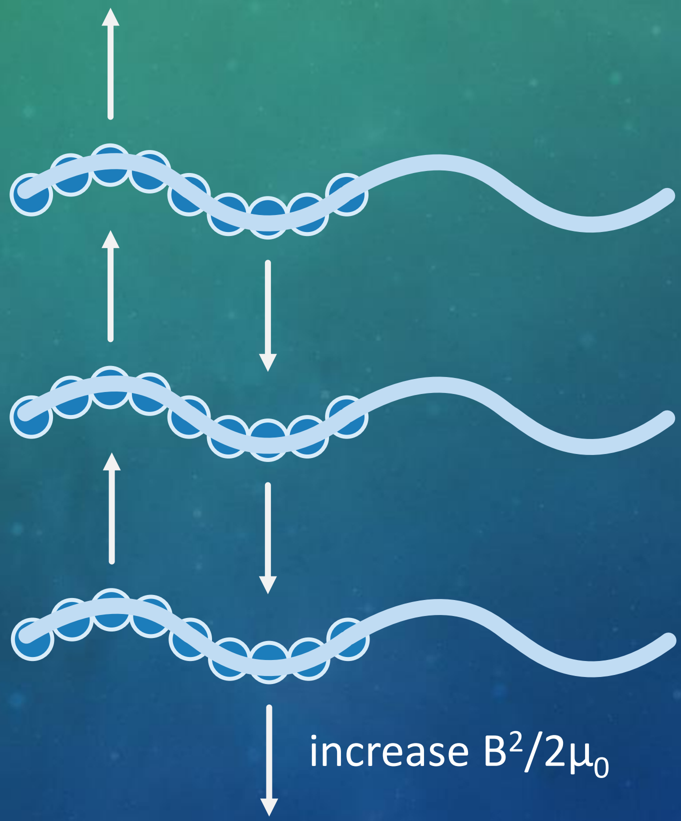
~10us per calculation vs. several seconds

3. AUTOMATED MODE CLASSIFICATION

ALFVÉNIC AVALANCHING

Magnetic fluctuations from NSTX [1]





Alfvén waves
- MHD wave
- **Subject to kinetic instability**
- Compressional branch is analogous to acoustic wave

Fast ion loss correlated with drop in neutron rate during "avalanches"

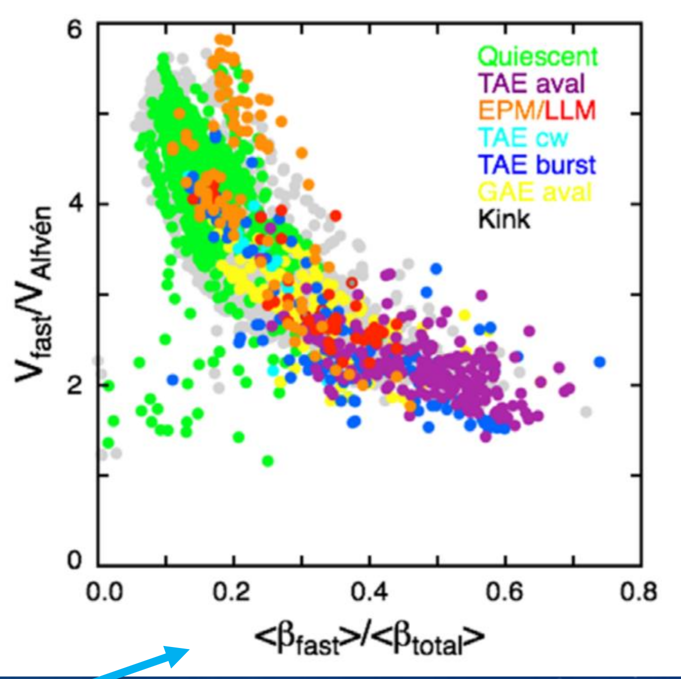
Research questions:
?: What causes mode avalanching?
?: How can we stop it?

[1] E.D. Fredrickson *et al.* 2013 NF **53** 013006

MACHINE LEARNING FOR FUSION APPLICATIONS

- Vast increase in speed for certain tasks
  - Data analysis can be done faster
  - Computational predictions can be extracted faster
  - May prove **vital** for operational performance of a tokamak
- Can we train an AI to recognise and characterise chirping?
  - Potentially feed into overall control system
- Knowledge of correlations between plasma parameters and mode character is **key**
  - i.e. turbulent suppression of mode chirping [3,4]

[2]

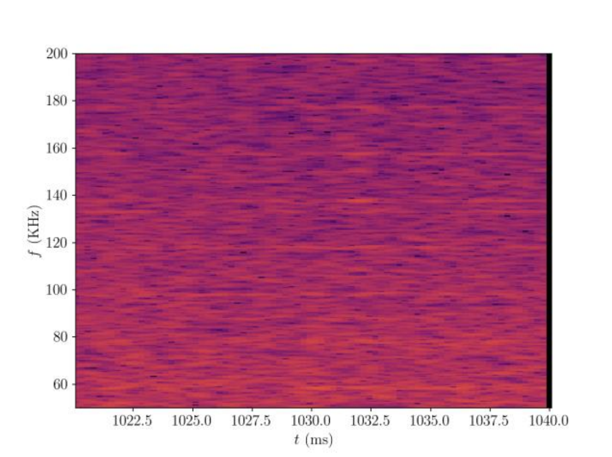


very time consuming to produce

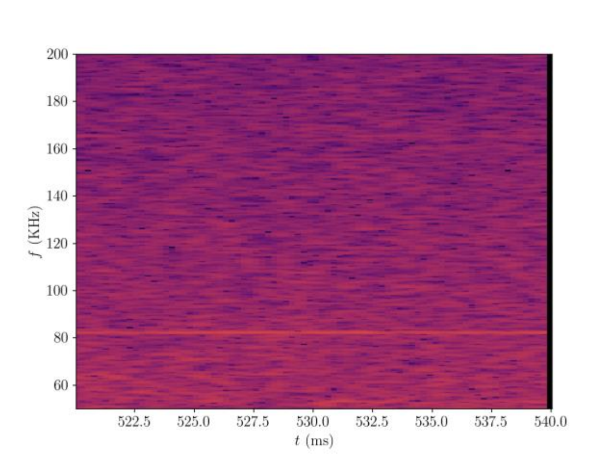
only 2 parameters

[2] E. D. Fredrickson *et al.* 2014 NF **54**, 093007
[3] V. N. Duarte *et al.* 2017 NF **57**, 054001
[4] B. J. Q. Woods *et al.* 2018 NF **58**, 082015

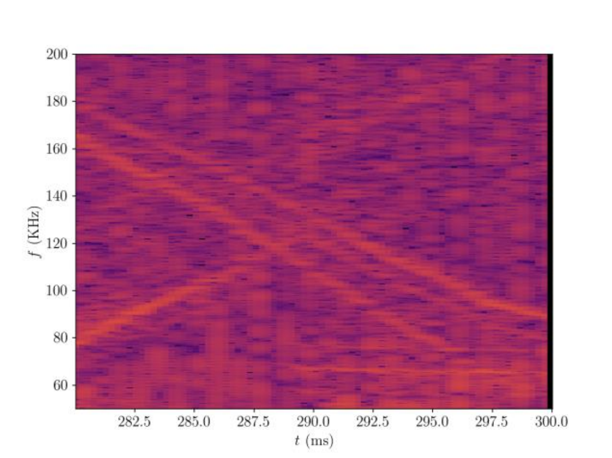
MODE CHARACTER CATEGORIES



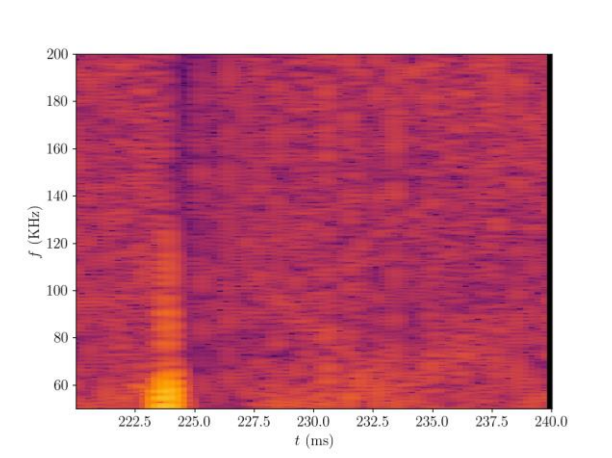
Noise/quiescence



Fixed frequency



Chirping

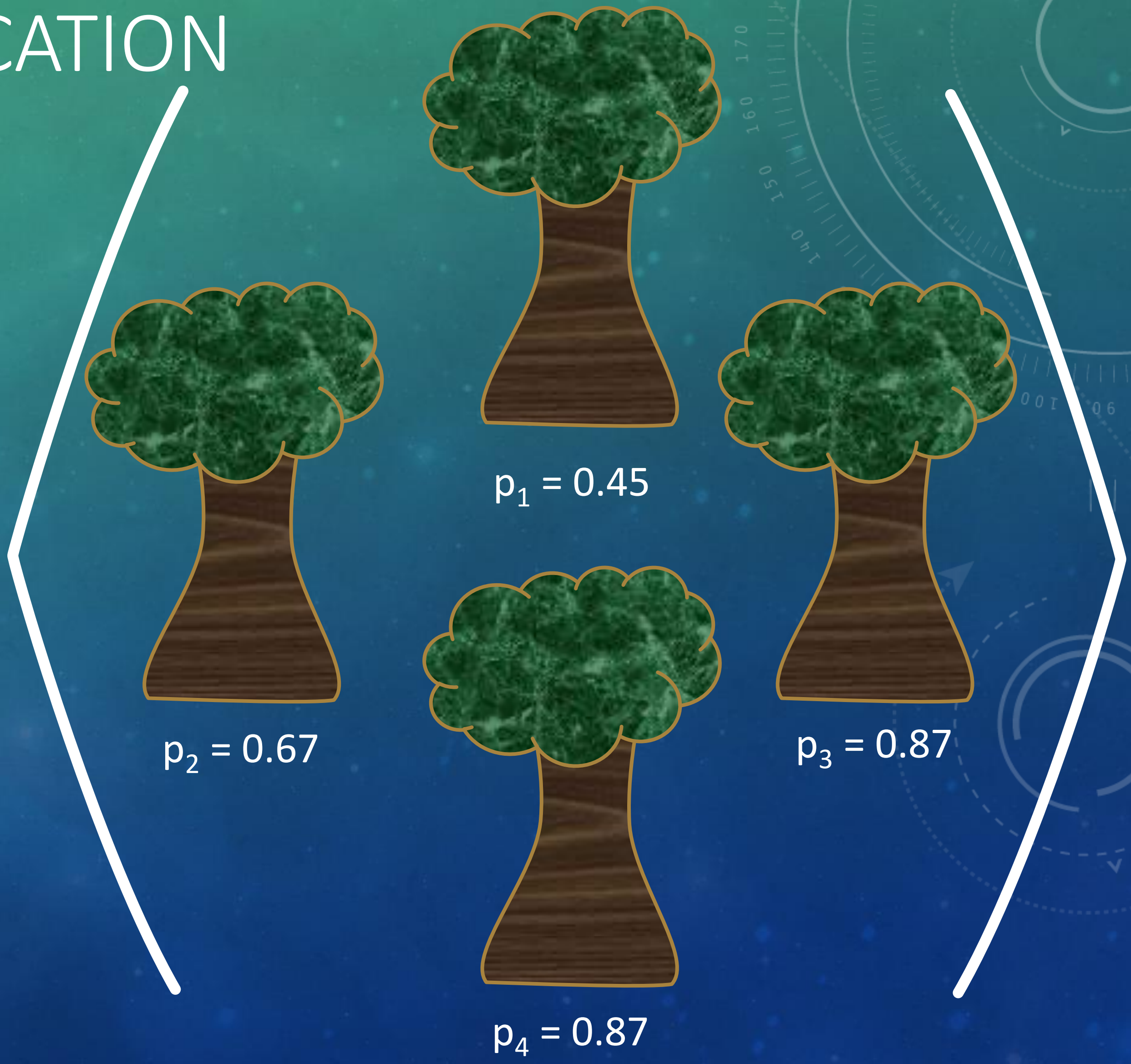


Avalanching

(Shots 127109, 134851)

RANDOM FOREST CLASSIFICATION

- Take an **ensemble** of trees, and take an average classification
- Linear average (mean) yields the mean accuracy
- Non-linear averages (mode, RMS) can yield higher accuracy than the mean
  - If the standard deviation in accuracies is low



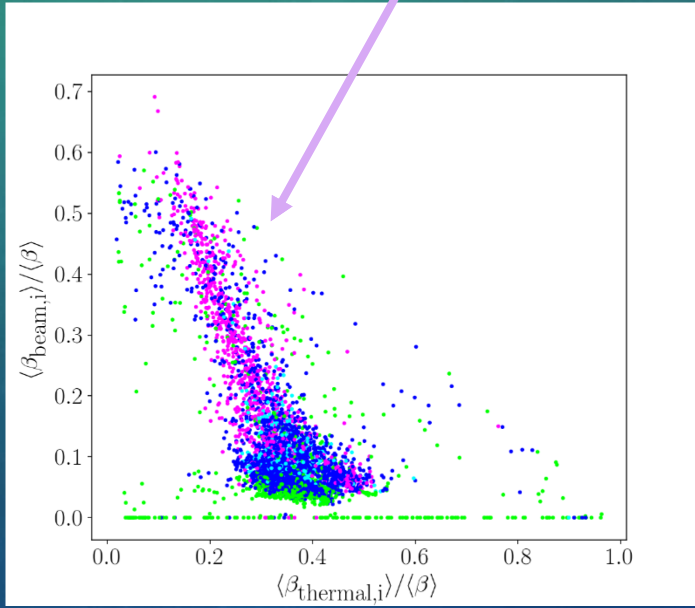
BEAM ION BETA

Measure of fast ion resonant drive

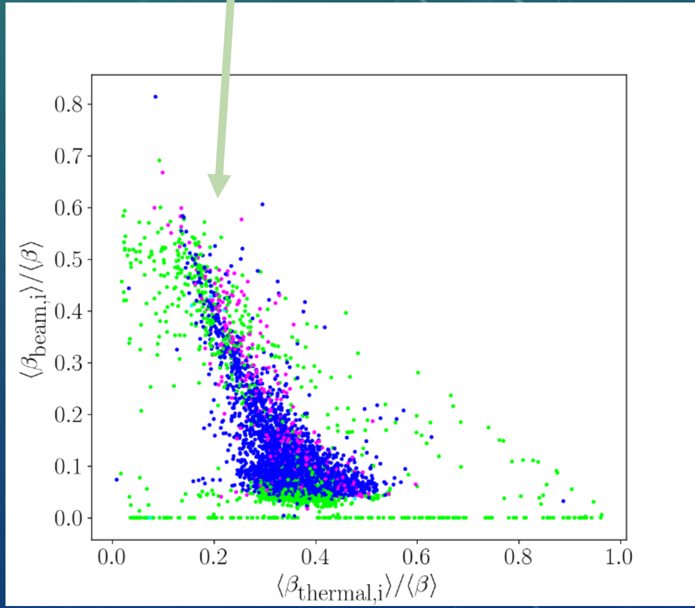
- Low freq. modes:
  - Avalanche at high %
- TAEs:
  - Significantly less avalanching

more avalanching

more quiescence



kink/tearing/fishbones
(1-30 kHz)



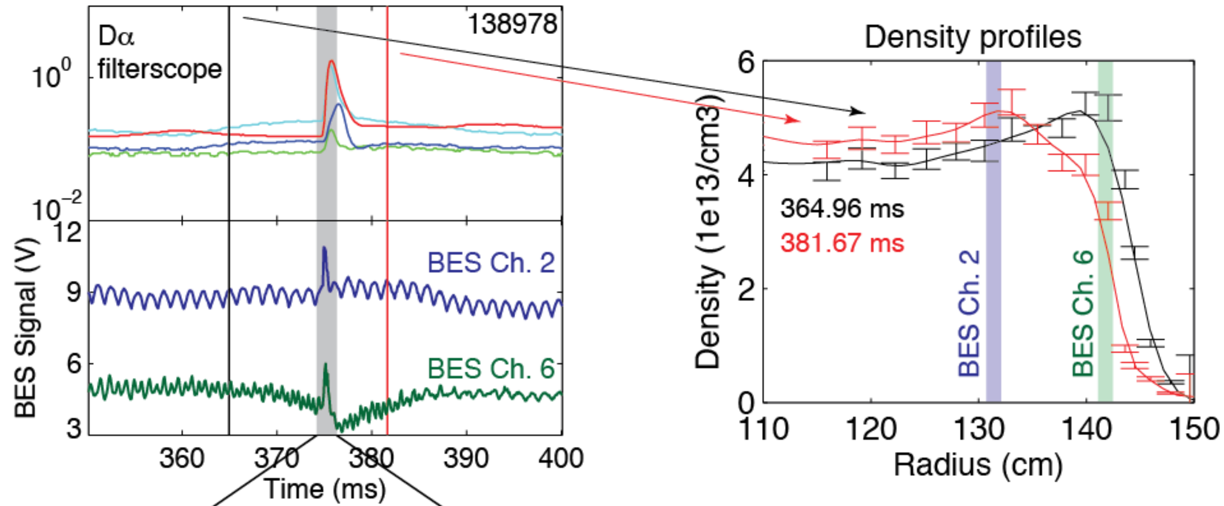
TAEs
(50-200 kHz)

quiescent – fixed freq. – chirping – avalanching

Generally at high beam ion beta, fishbones are very active while TAEs are less active

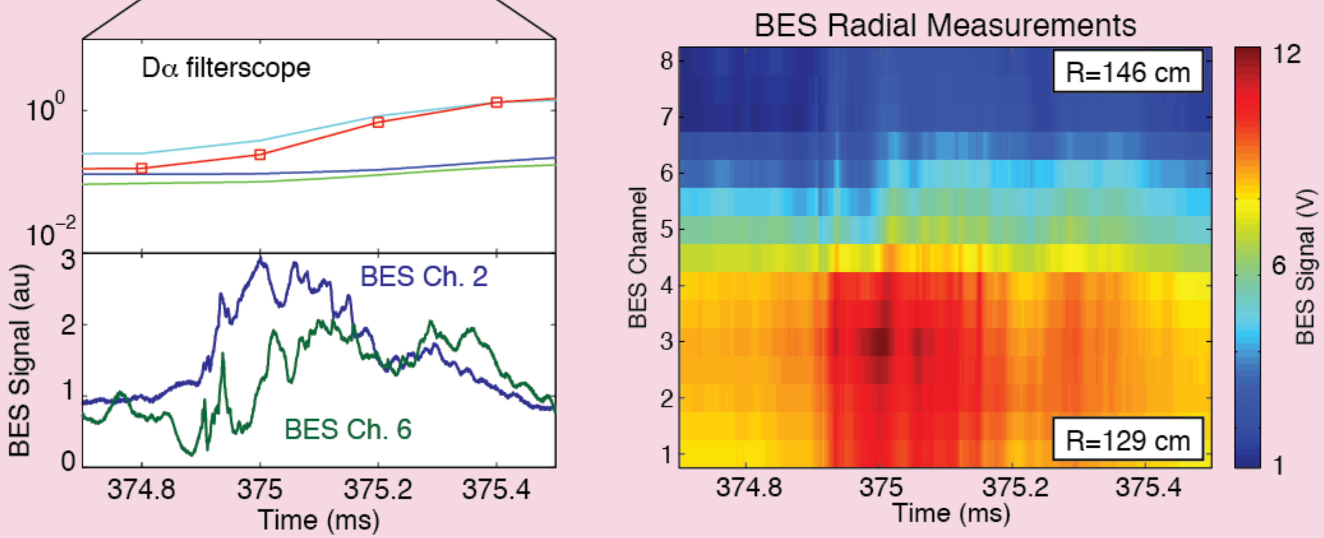
BES measurements capture the Alfven-scale evolution and radial profile of ELM events

Common measurements for ELM characterization do not capture the Alfven-scale evolution of ELM events

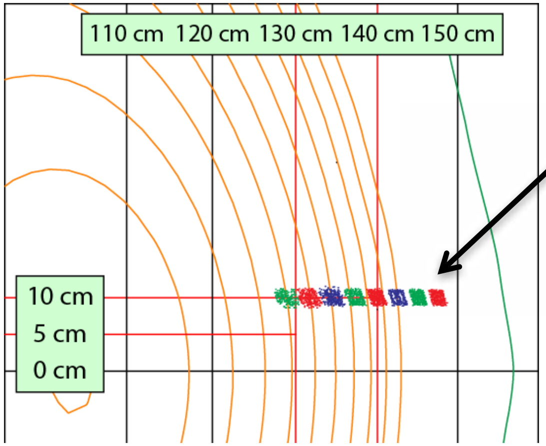


BES captures the Alfven-scale evolution and radial variation of ELM events

$\Delta t/\tau_A \sim 0.1$

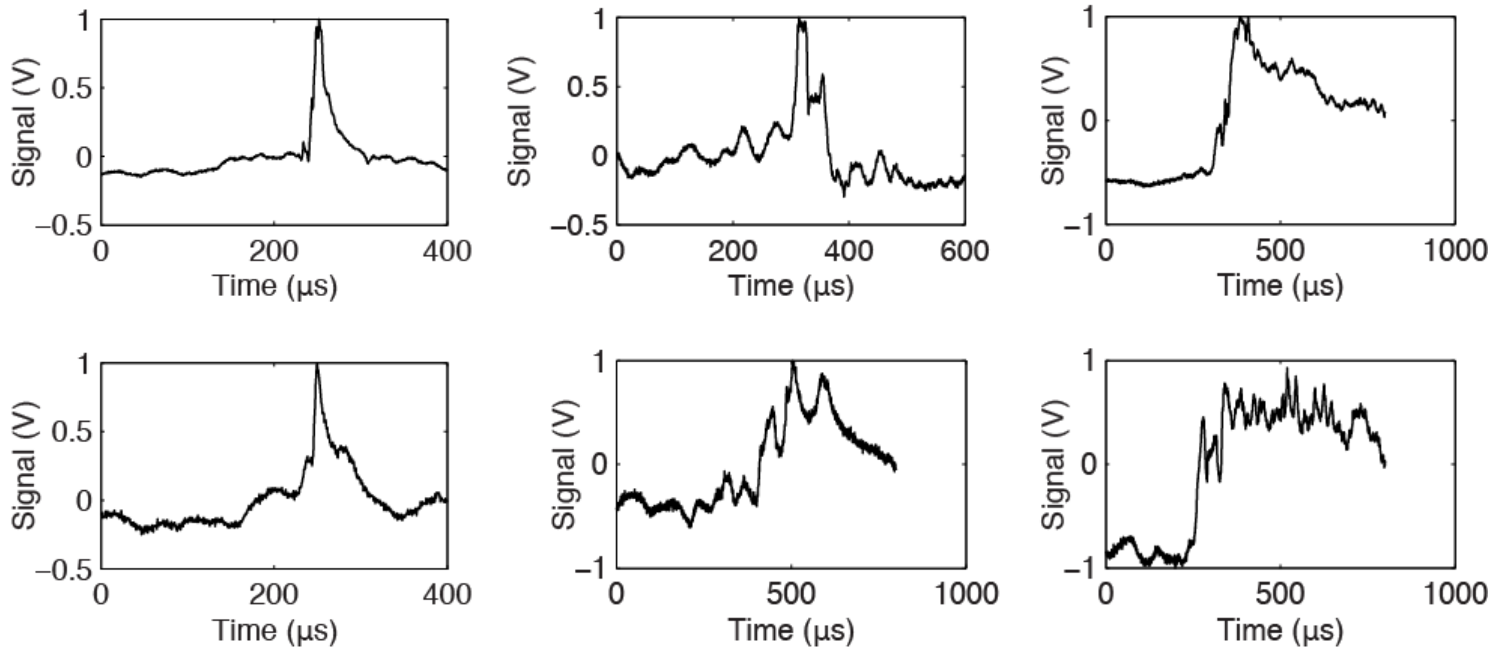


Goal – Identify common evolution patterns (if any) in a database of Type I ELM time-series data



- Database of 51 ELM events measured with BES
  - 8 radial BES channels spanning pedestal region
  - 34 NSTX discharges from 8 run days spanning 4 months
  - 1%-16% stored energy loss and observable pedestal collapse
  - Most likely type I ELMs
  - Time-series from radial measurements condensed into single time-series with principle component analysis

Examples from the ELM database



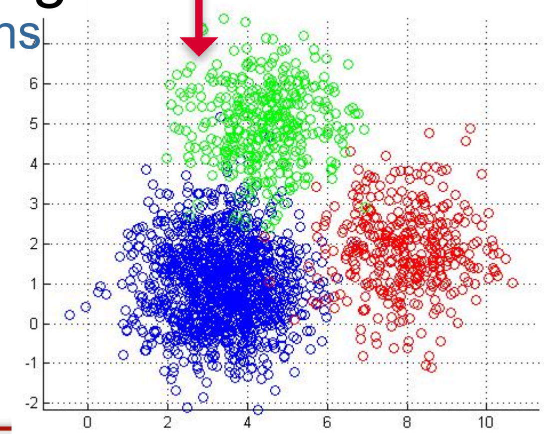
Method – Apply unsupervised machine learning techniques to identify common ELM evolution patterns

- Hierarchical clustering
  - Produces a multi-level hierarchy of objects
  - Popularized in genomics
  - Requires an **similarity metric** to quantify similarity among time-series

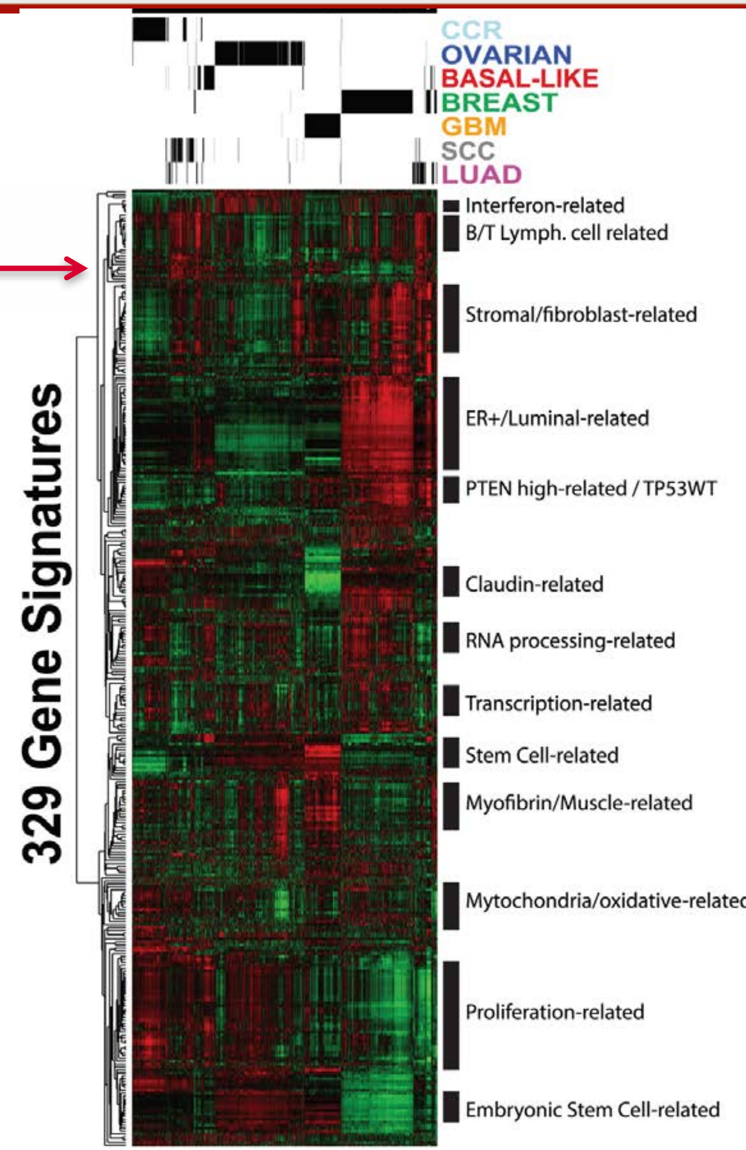
- Time-series similarity metrics
  - Time-lag cross-correlation
  - Euclidean distance
  - Dynamic time warping (DTW)
  - Wavelet decomposition

D. Smith et al, PPCF 58, 045003 (2016)

- K-means clustering
  - Partition observations into k mutually exclusive clusters



Mathworks.com

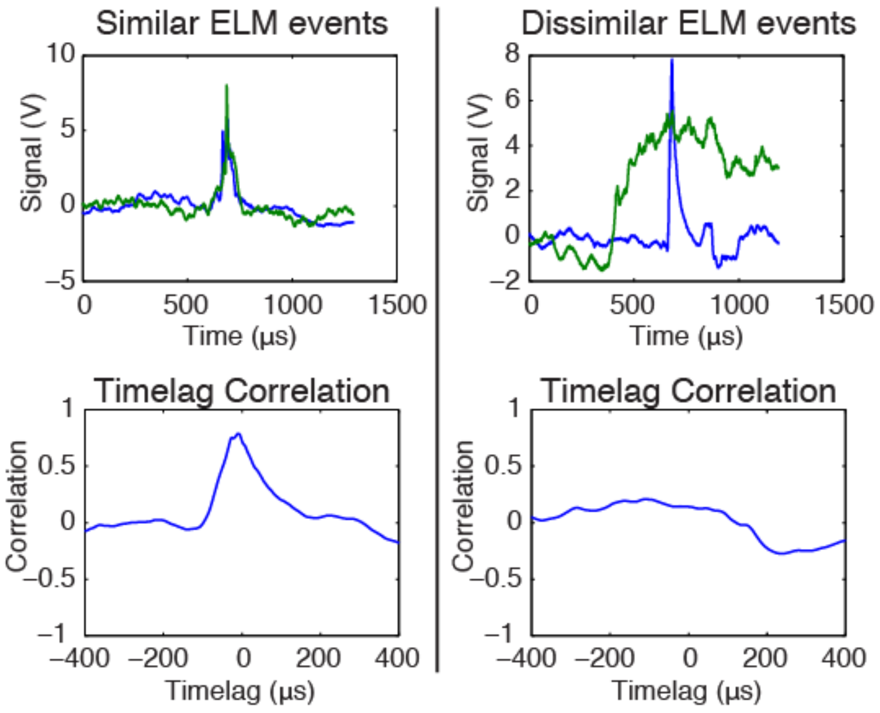


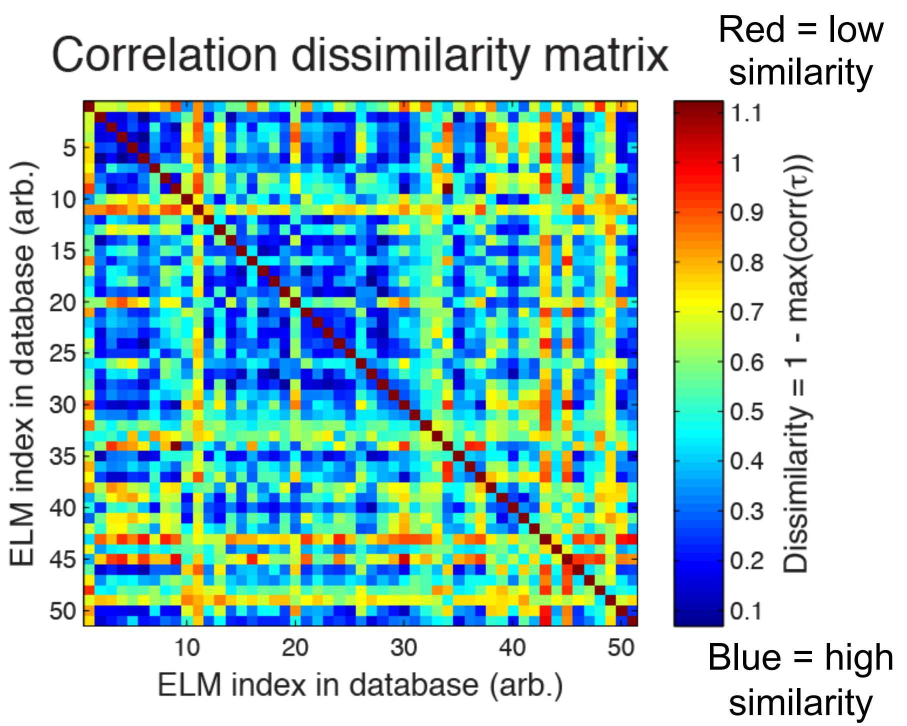
Prat et al, Scientific Reports 3, 3544 (2013)

Hierarchical clustering (I) – Assemble time-lag cross-correlation metrics into a dissimilarity matrix

Time-lag cross-correlation can quantify the similarity of ELM time-series data

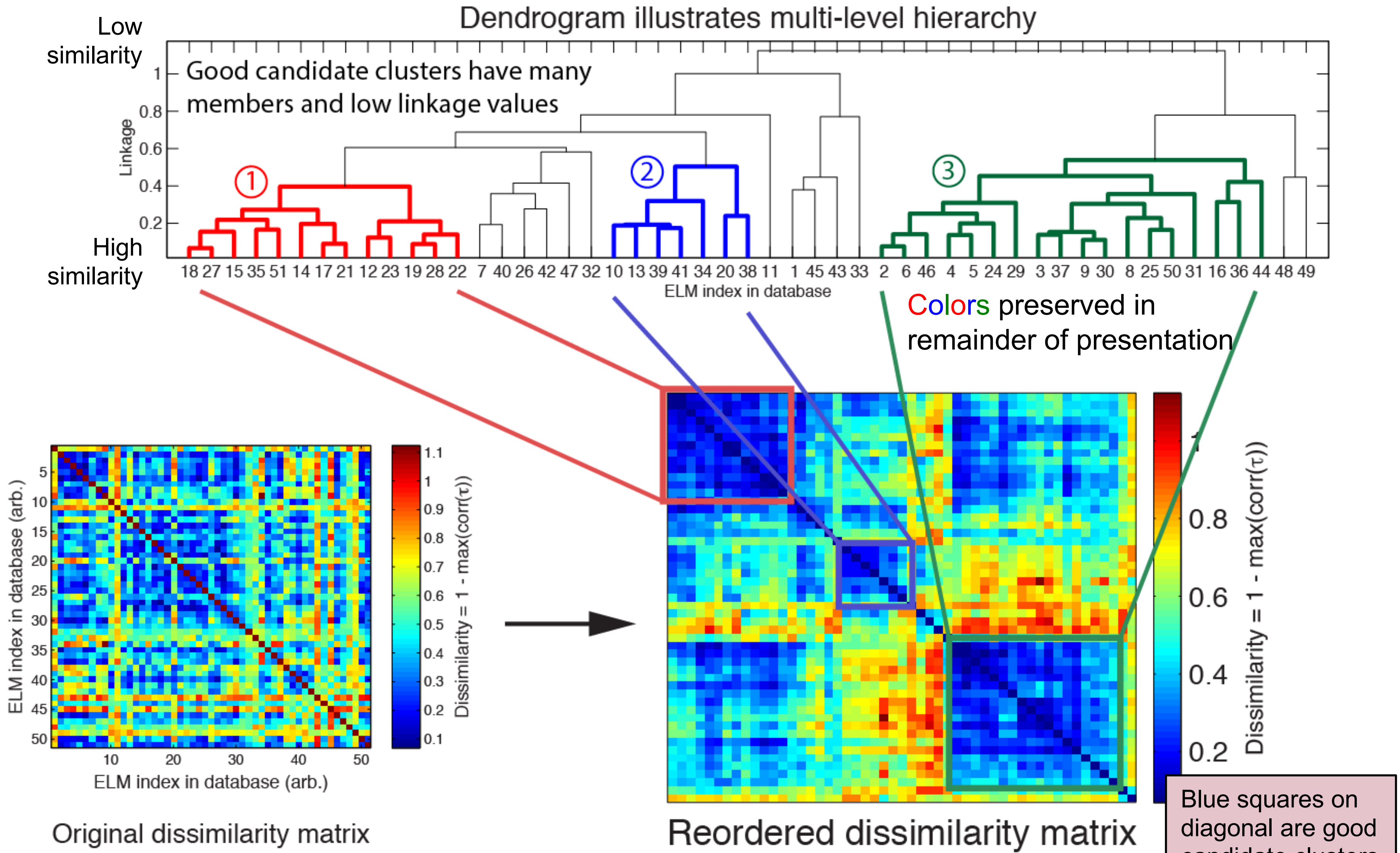
Assemble pair-wise metrics into a dissimilarity matrix





Larger max correlation → more similar

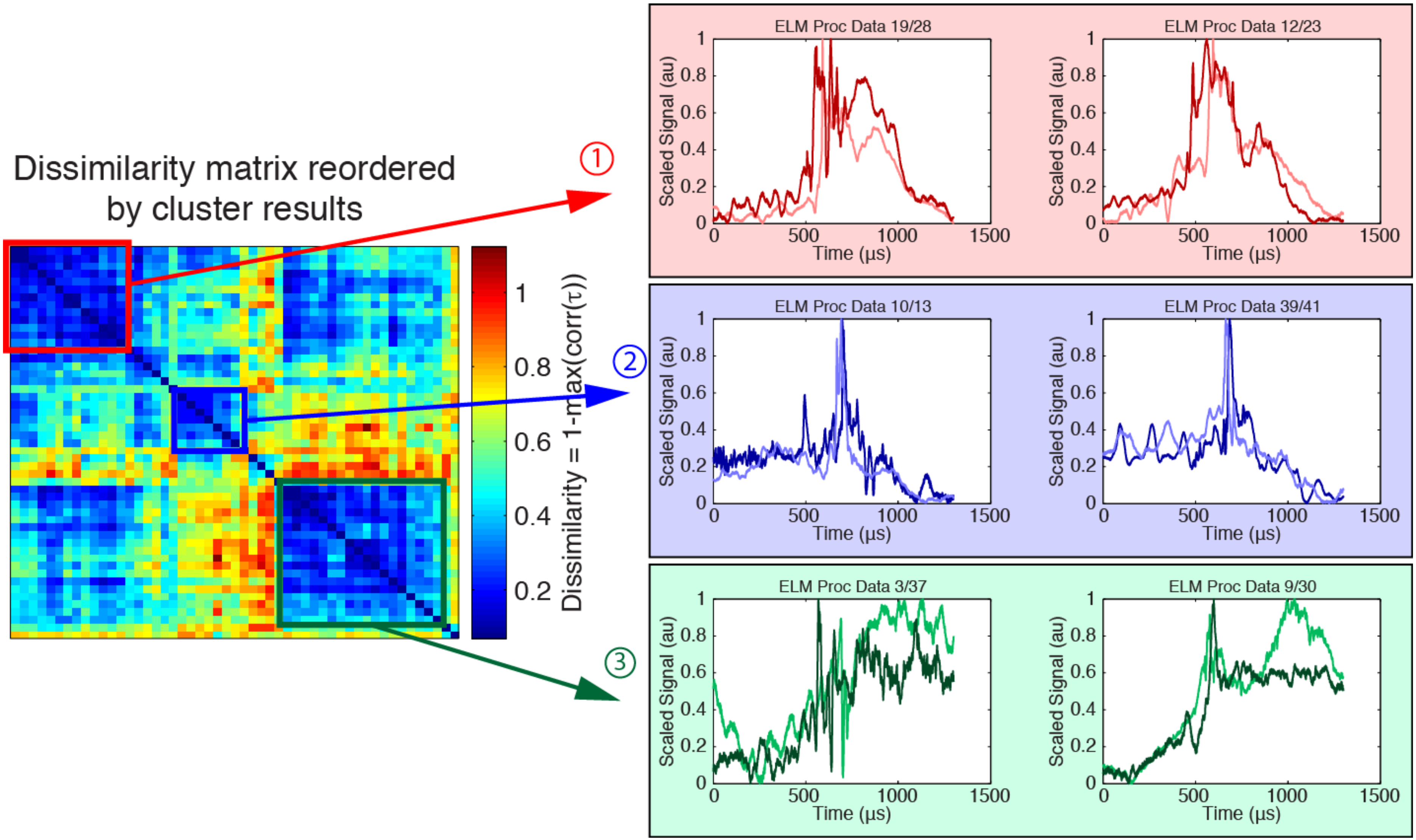
Hierarchical clustering (II) – Apply clustering algorithm to dissimilarity matrix to identify groups of similar ELMs



D. Smith et al, PPCF 58, 045003 (2016)

The identified ELM groups show similar evolution characteristics

Dissimilarity matrix reordered by cluster results



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Fusion/plasma science at U. Wisconsin

- Physics Dept.
  - S. Boldyrev, D. DenHartog, J. Edegal, C. Forest, J. Sarff, P. Terry, E. Zweibel
  - https://www.physics.wisc.edu/research/areas
  - Center for Plasma Theory and Computation https://cptc.wisc.edu/
  - Center for Plasma in the Laboratory and Astrophysics http://plasma.physics.wisc.edu/

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  - R. Fonck, C. Hegna, G. McKee, O. Schmitz, C. Solvenic and many in fusion technology
  - https://www.engr.wisc.edu/department/engineering-physics/research/
  - Pegasus spherical torus https://pegasus.ep.wisc.edu/
  - Fusion Technology Institute http://fti.neep.wisc.edu/
  - Large collaborations at DIII-D, NSTX-U, and W7-X

- Electrical & Computer Engineering Dept.
  - D. Anderson, A. Wendt
  - HSX stellarator https://www.hsx.wisc.edu/