Identification of characteristic ELM evolution patterns with Alfven-scale measurements and unsupervised machine learning analysis

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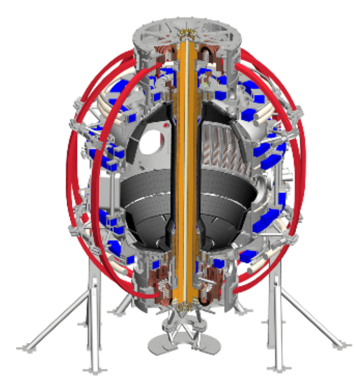
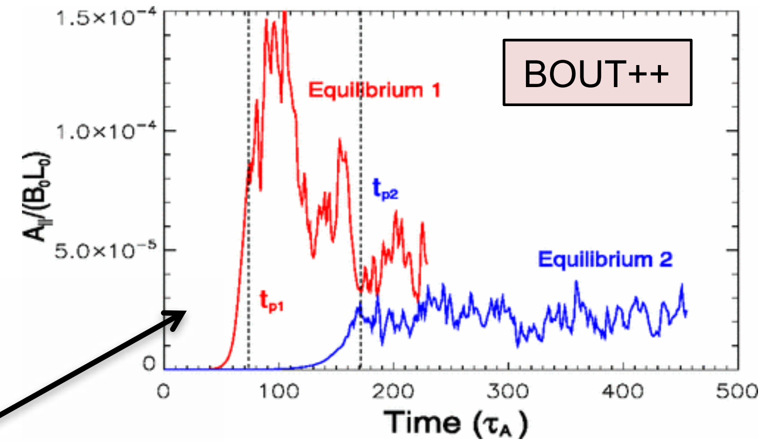
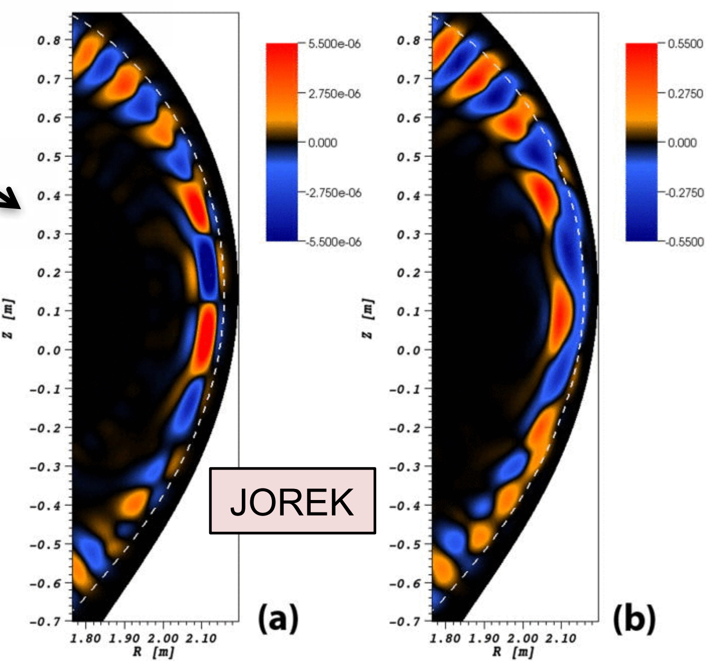


Beam emission spectroscopy captures the nonlinear, Alfven-scale dynamics of ELM events

- Edge localized modes (ELMs) are peeling-ballooning instabilities in the edge/pedestal region driven by pressure and current gradients
  - Unmitigated ELMs pose risk for ITER
- Nonlinear mechanisms impact ELM dynamics
  - Broadly: NL mode coupling, saturation mechanisms, filament dynamics
  - Hyper-resistivity is key for realistic ELM radial penetration (X. Xu et al, PRL, 2010)
  - Growth of sub-dominant linear modes in the NL phase (M. Holzl et al, PoP, 2012)
  - EHOs attributed to saturated PB modes (K. Burrell et al, PRL, 2009)
- Common diagnostic tools and analysis methods do not capture the nonlinear, Alfven-scale dynamics of ELMs
  - Heuristic classification schemes (Type I, III, etc.)
  - Sub-Alfvenic measurements with Thomson scattering and filterscopes
  - Linear stability threshold for peeling-ballooning modes





Fusion facilities with large data archives can exploit machine learning tools for large-scale analysis tasks

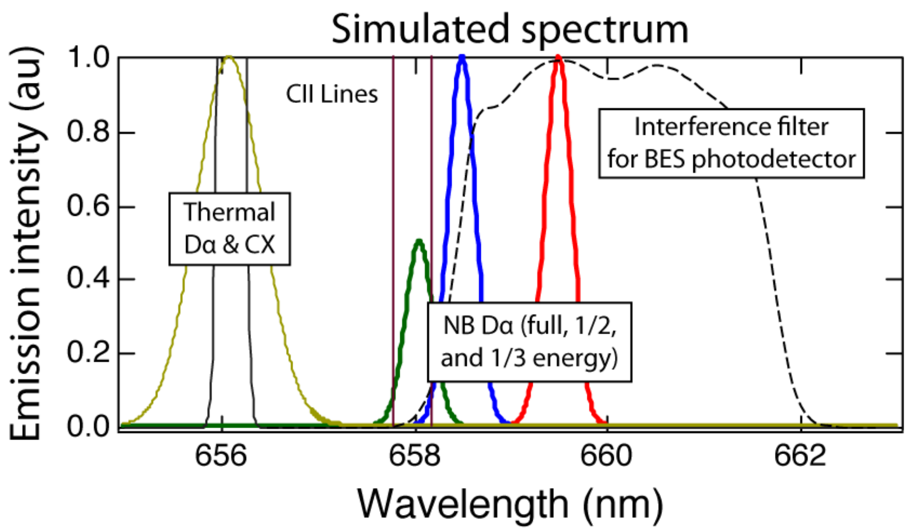
- Possible machine learning applications in fusion science
  - Identify common evolution patterns for ELM events
  - Untangle high-dimensional relationships at the LH transition
  - Autonomously find and classify disruptions in a data archive
  - Analyze data at scales not possible with manual inspection
  - NSTX/NSTX-U: About 40 TB of data obtained with R&D investment approaching $1B

- Many data-rich scientific fields successfully leverage machine learning techniques
  - Applications: Cancer genomics, exo-planet detection, seismic wave classification, seizure onset prediction, Higgs boson
  - High-level initiatives from funding agencies
  - Intersection of experimental science and high performance computing
  - Many “canned” algorithms in Matlab, SciPy, etc.

ELM evolution patterns on NSTX/NSTX-U

- Beam emission spectroscopy (BES) system on NSTX/NSTX-U
- Identification of ELM evolution patterns with unsupervised machine learning analysis on NSTX
  - Time-series similarity metrics
  - Hierarchical and k-means cluster analysis
  - Parameter regimes for identified evolution patterns
- 2D measurements of ELM events from NSTX-U

Beam emission spectroscopy (BES) measures Doppler-shifted D_α emission from a deuterium heating beam

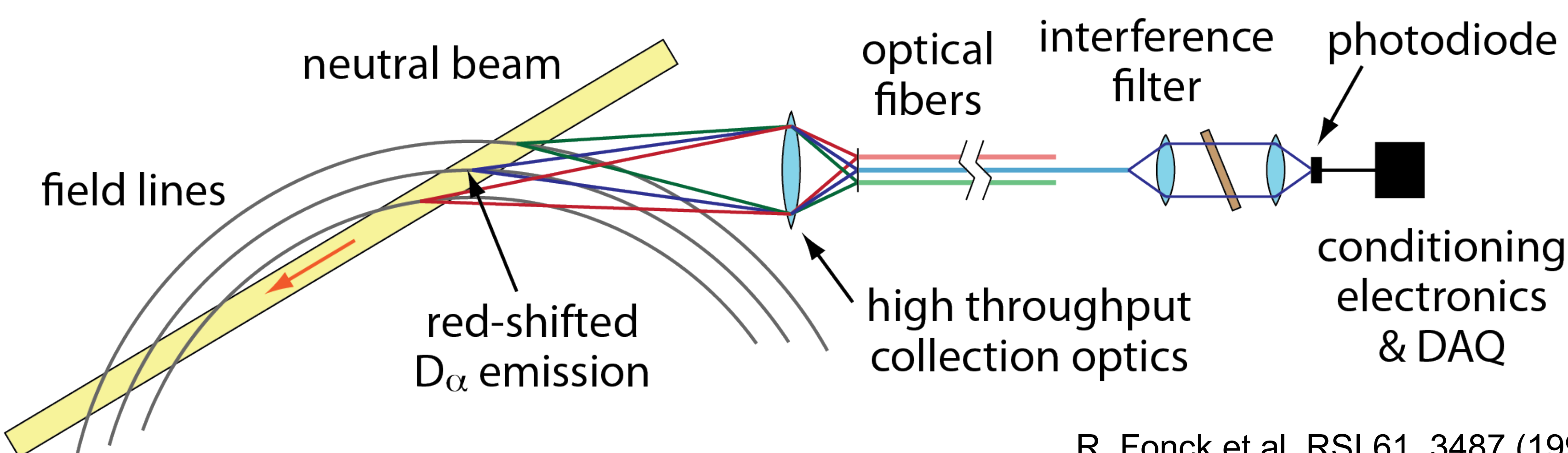


$$\frac{\delta I_{D\alpha}}{I_{D\alpha}} = \frac{\delta n}{n} \times C\left(E_{NB}, n, T_e, Z_{eff}\right)$$

neutral beam D_α emission

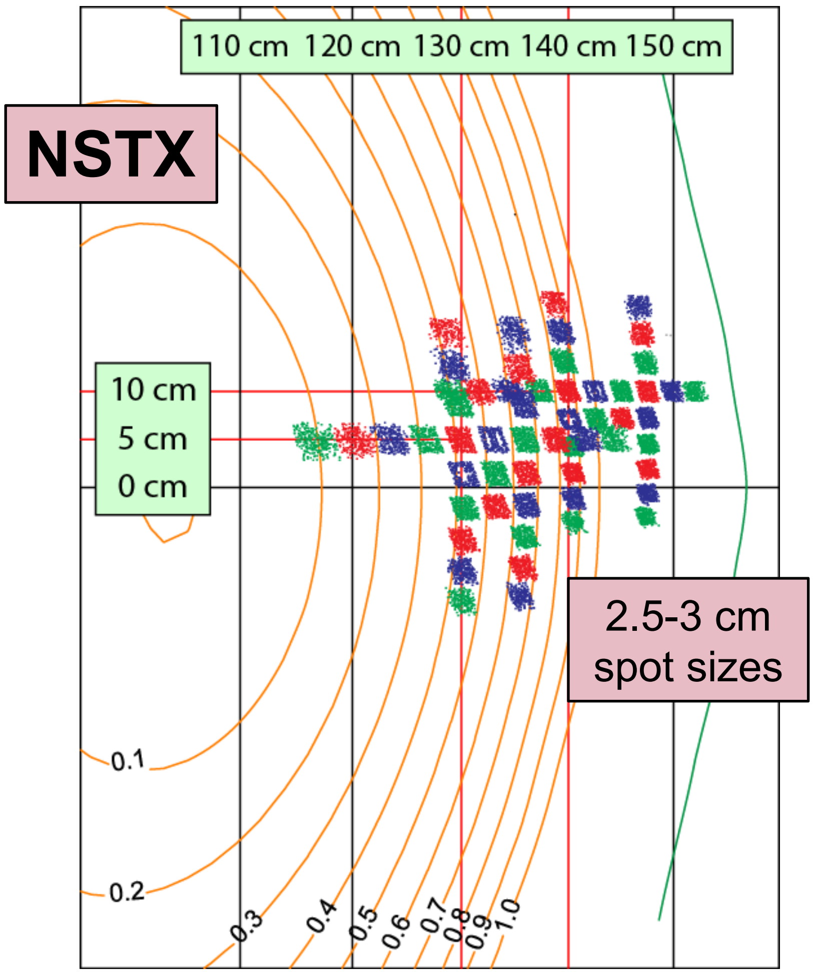
density fluctuation

C ≈ 1/2

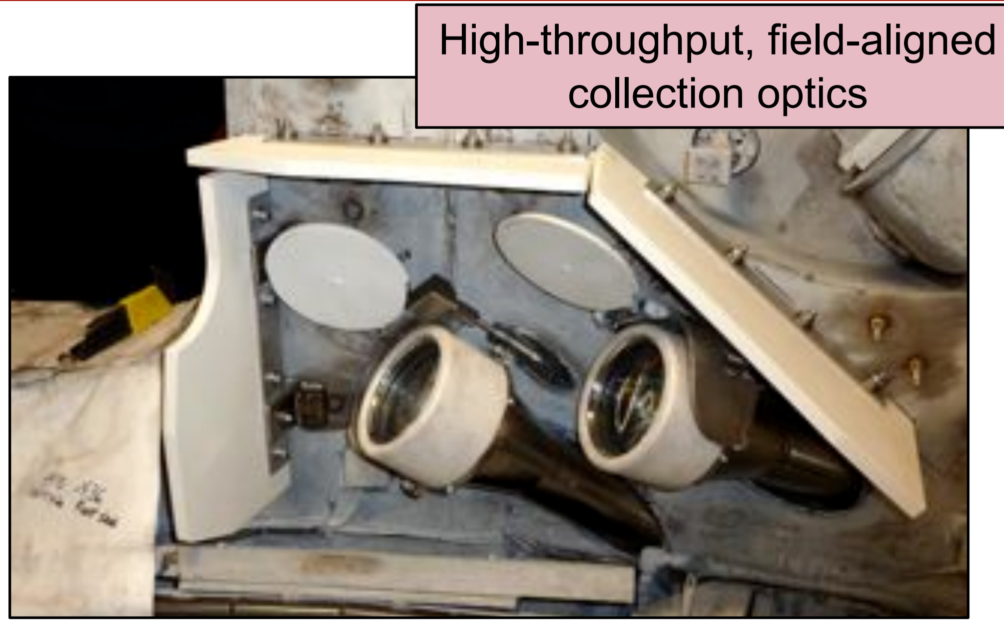


R. Fonck et al, RSI 61, 3487 (1990)
R. Fonck et al, PRL 70, 3736 (1993)

Radial and poloidal coverage on NSTX



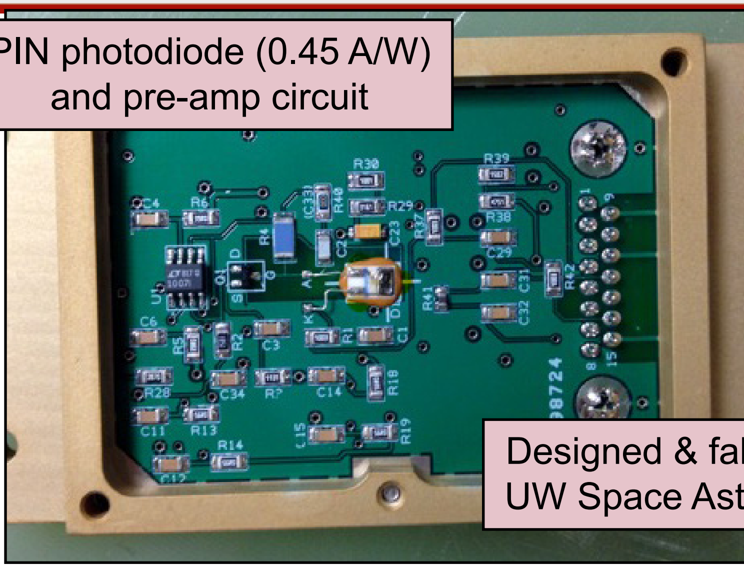
D. Smith et al, RSI 81, 10D717 (2010)
N. Schoenbeck et al, RSI 81, 10D718 (2010)
D. Smith et al, RSI 83, 10D502 (2012)



- Measurements are sensitive to density fluctuations on the ion gyroscale with $k_\perp \rho_i \leq 1.5$
- Applications: ELMs, LH transition, EHOs, turbulence, velocimetry, Alfven eigenmodes, etc.

Low noise, high quantum efficiency detectors achieve photon-noise-limited measurements up to about 500 kHz

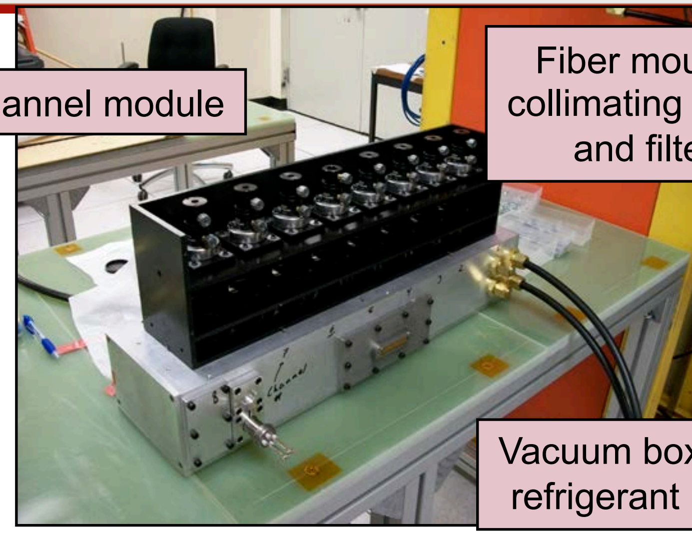
PIN photodiode (0.45 A/W) and pre-amp circuit



Designed & fab'ed by UW Space Astro. Lab

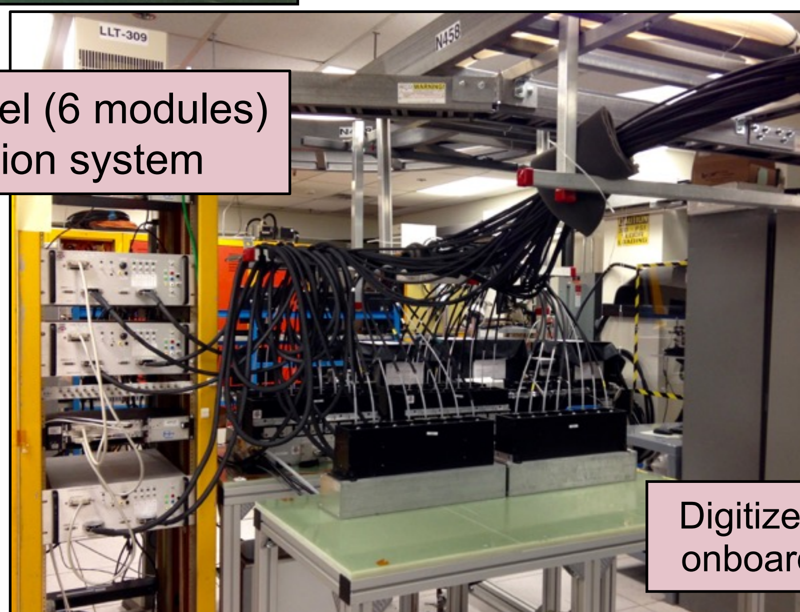
8-channel module

Fiber mount, collimating lens, and filter



Vacuum box with refrigerant lines

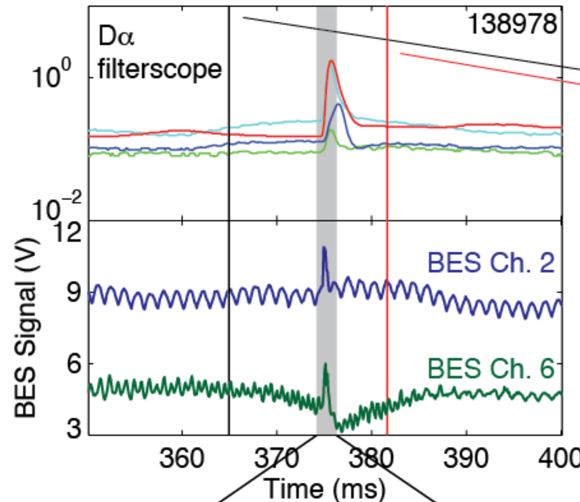
48-channel (6 modules) detection system

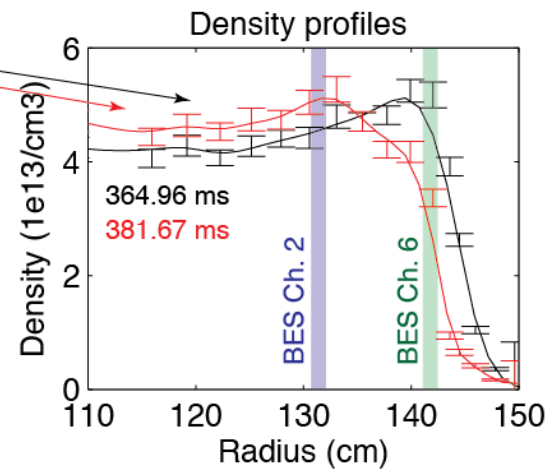


Digitizers: 2 MHz sampling with onboard FPGA-based FIR filter

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

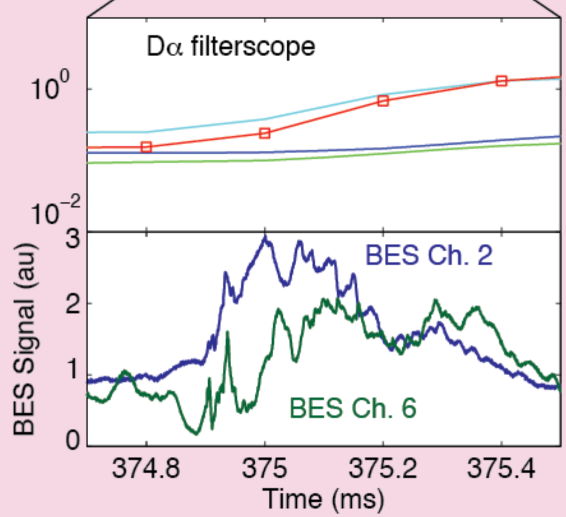
Common measurements for ELM characterization do not capture the Alfven-scale evolution of ELM events

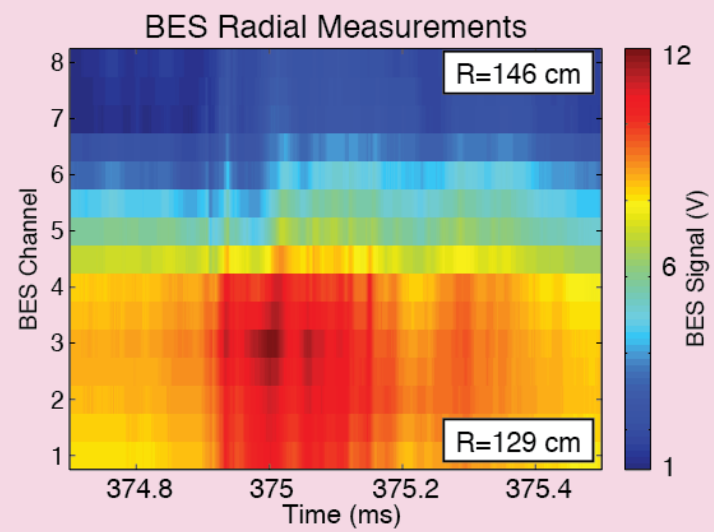




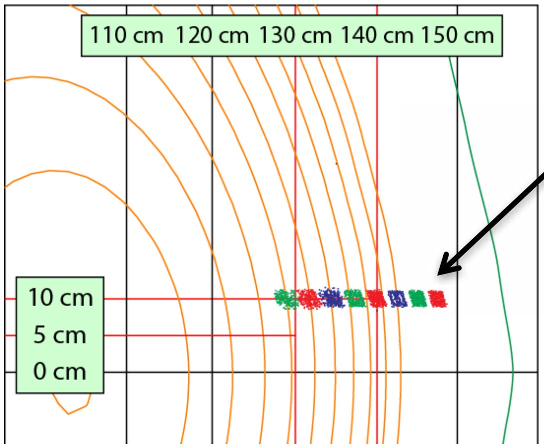
BES captures the Alfven-scale evolution and radial variation of ELM events

$\Delta t/\tau_A \sim 0.1$



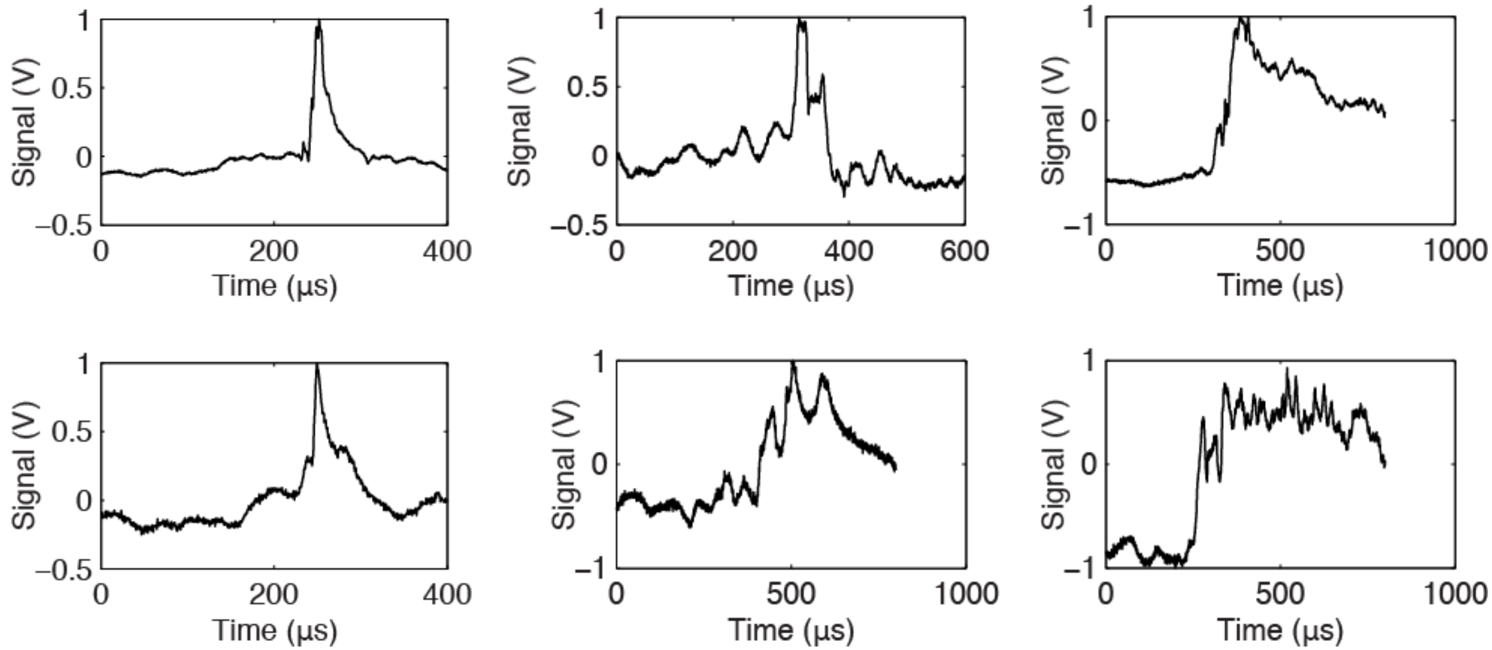


Goal – Identify common evolution patterns (if any) in a database of Type I ELM time-series data



- 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

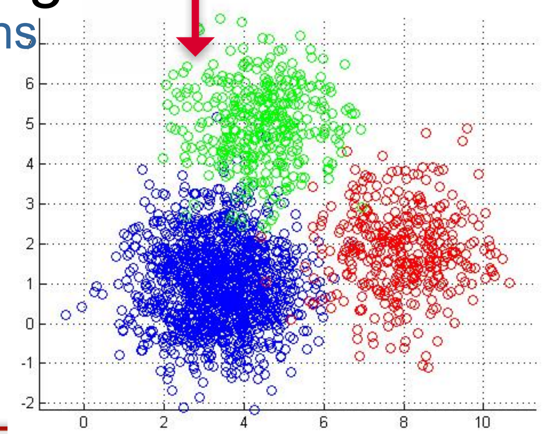


Method – Apply unsupervised machine learning techniques to identify common ELM evolution patterns

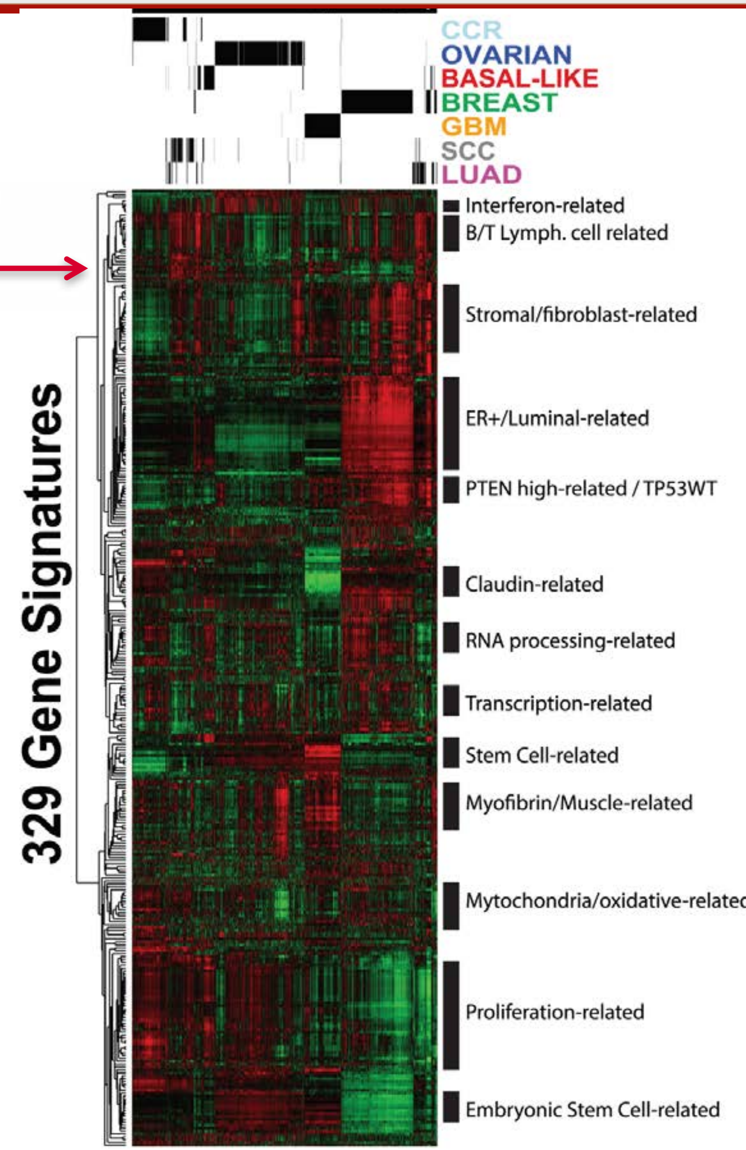
- Hierarchical clustering
  - Produces a multi-level hierarchy of objects
  - Popularized in genomics
  - Requires an **similarity metric** to quantify similarity among time-series
- Time-series similarity metrics
  - Time-lag cross-correlation
  - Euclidean distance
  - Dynamic time warping (DTW)
  - Wavelet decomposition

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

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



Mathworks.com

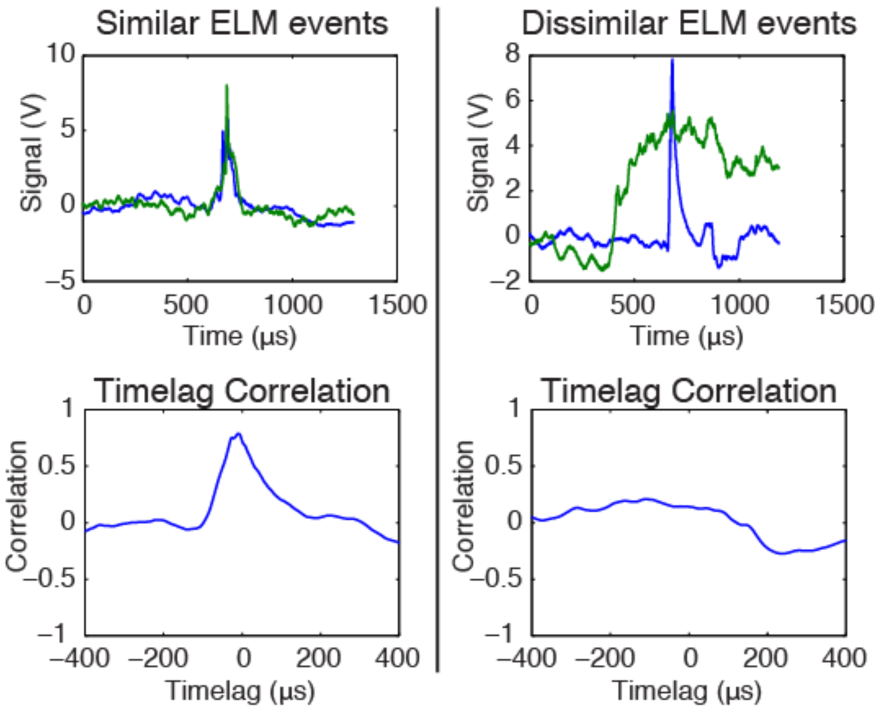


Prat et al, Scientific Reports 3, 3544 (2013)

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

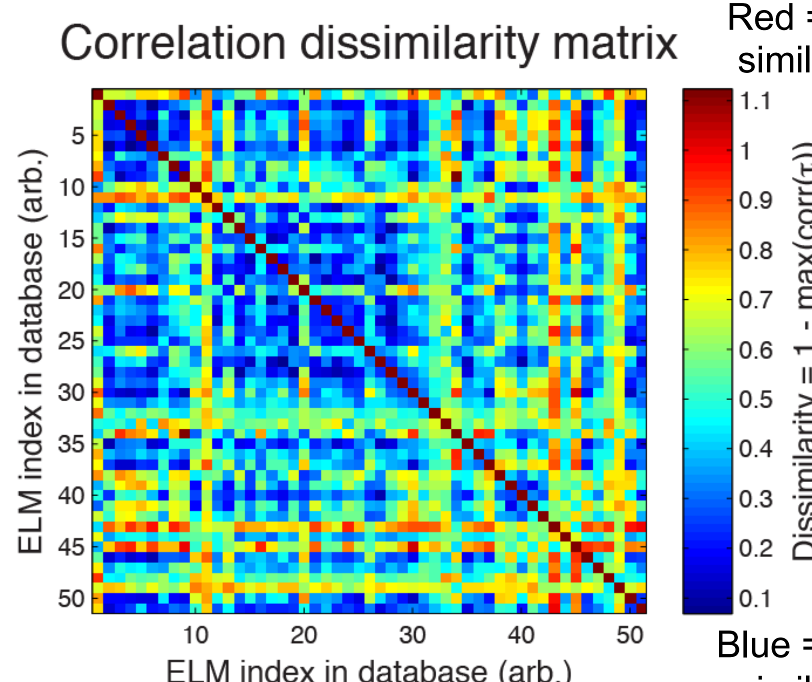
Time-lag cross-correlation can quantify the similarity of ELM time-series data

Assemble pair-wise metrics into a dissimilarity matrix



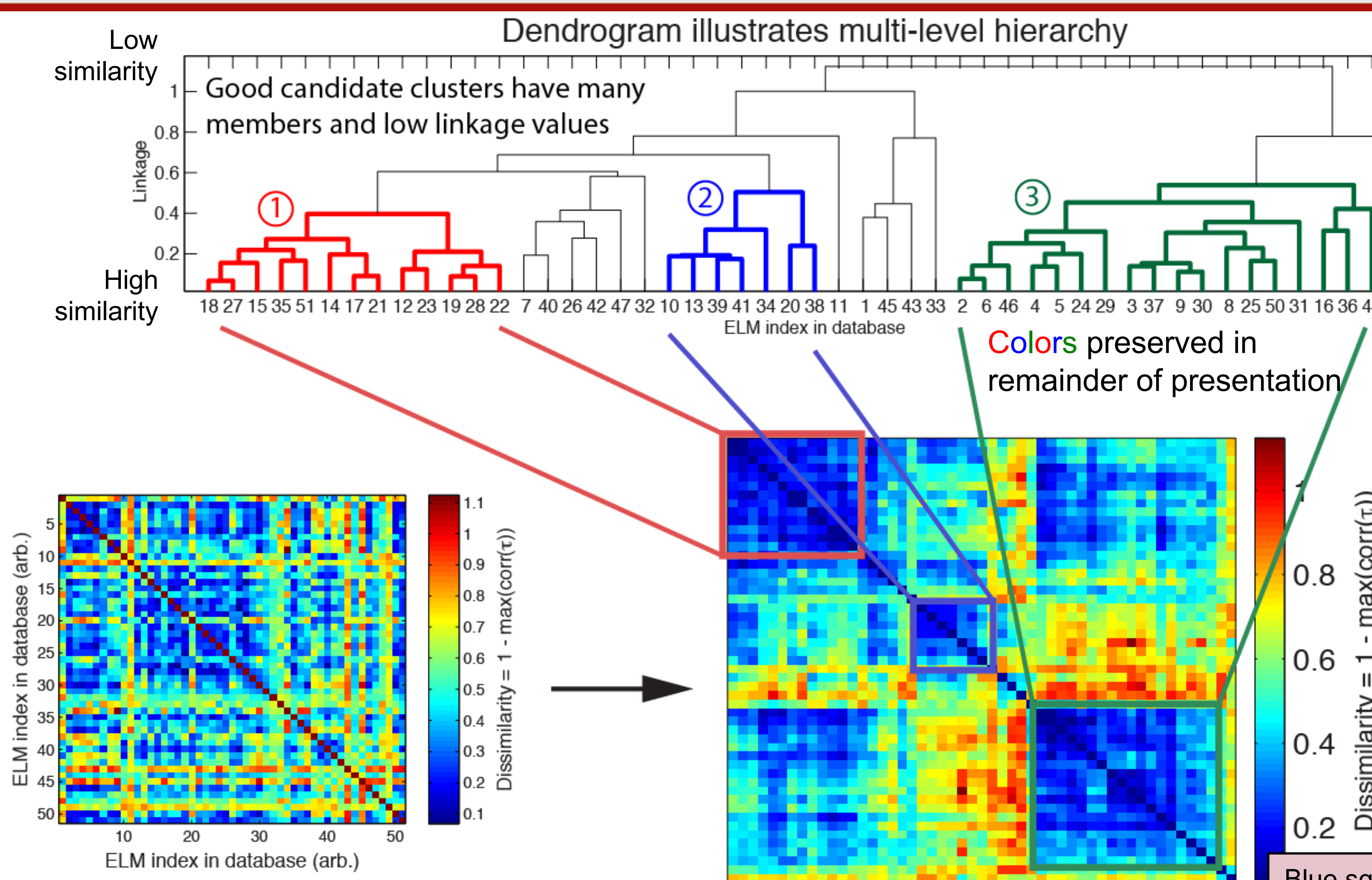
Larger max correlation → more similar

Red = low similarity



Blue = high similarity

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



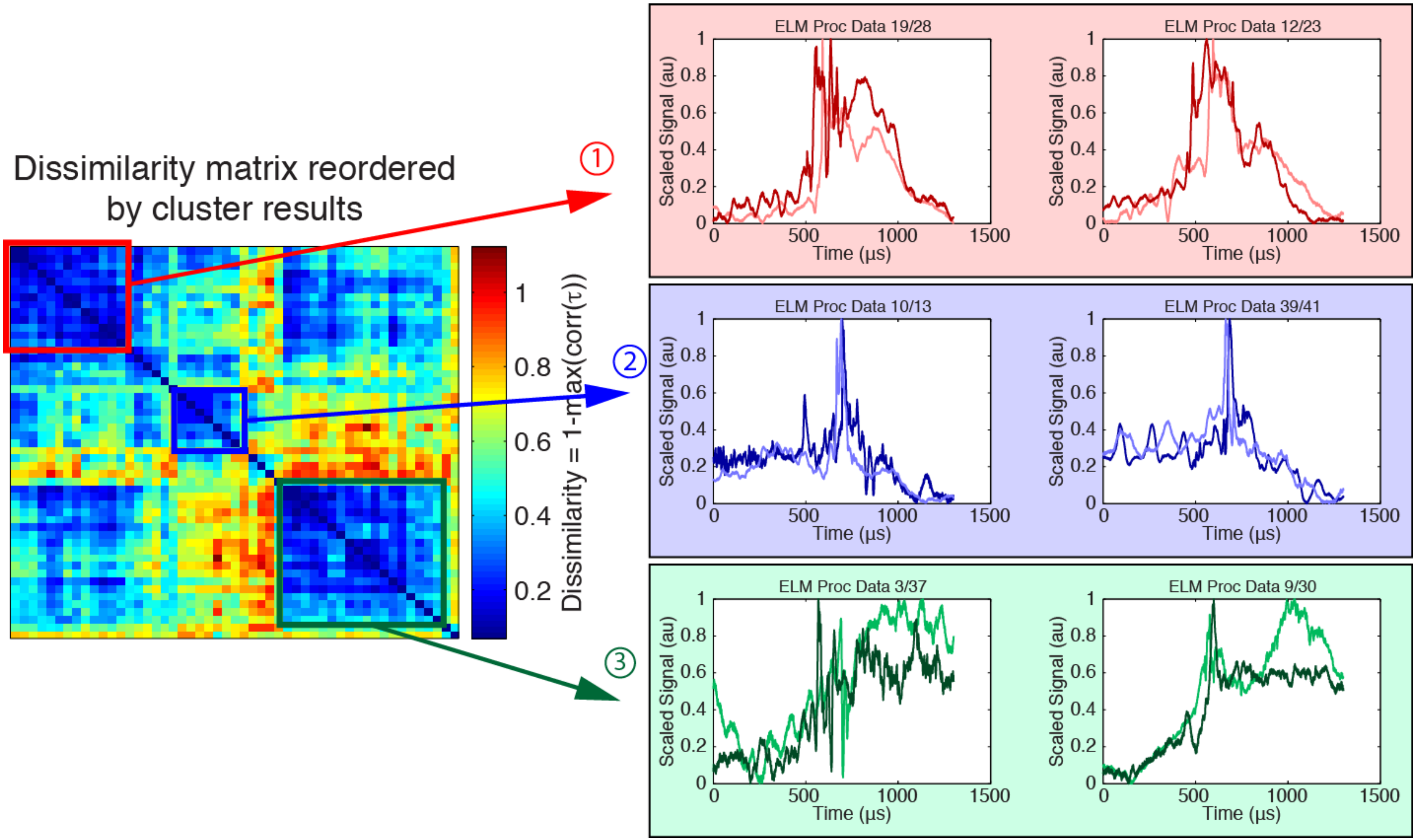
Original dissimilarity matrix

Reordered dissimilarity matrix

Blue squares on diagonal are good candidate clusters

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

The identified ELM groups show similar evolution characteristics



K-means clustering – Group objects into mutually exclusive groups

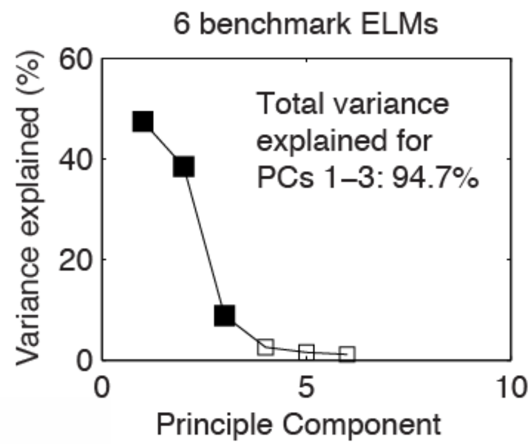
- Requires extrinsic similarity metrics
  - Designate benchmark ELMs to serve as extrinsic metrics
- Utilize PCA to visualize high-dim. results in low-dim. sub-space

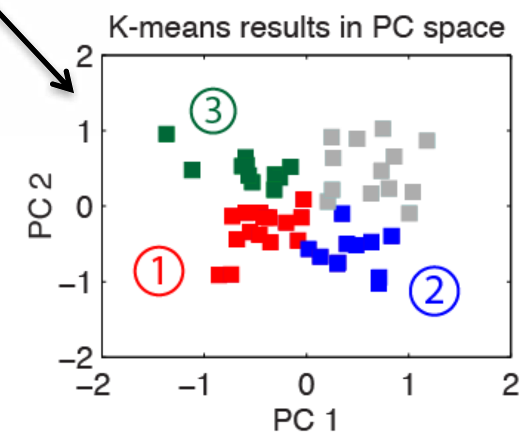
6 benchmark ELMs

# of clusters	Mean ratio*
2	0.49
3	0.51
4	**0.52**
5	0.48
6	0.46
7	0.45

*Out-of-cluster/in-cluster distance ratio

Optimal



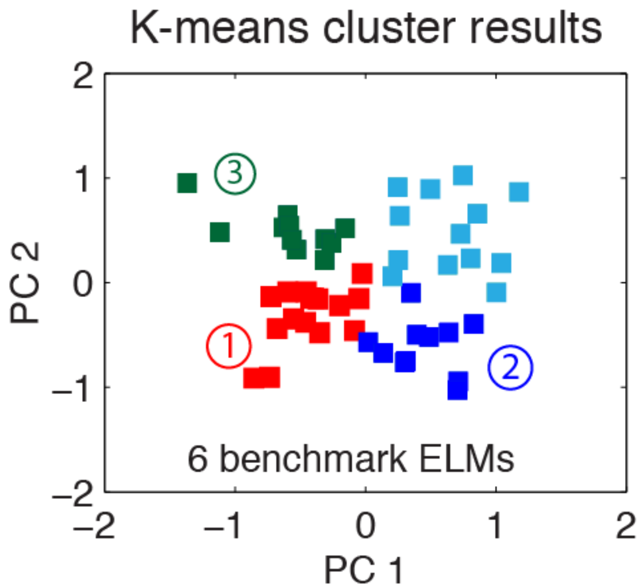


4th group?

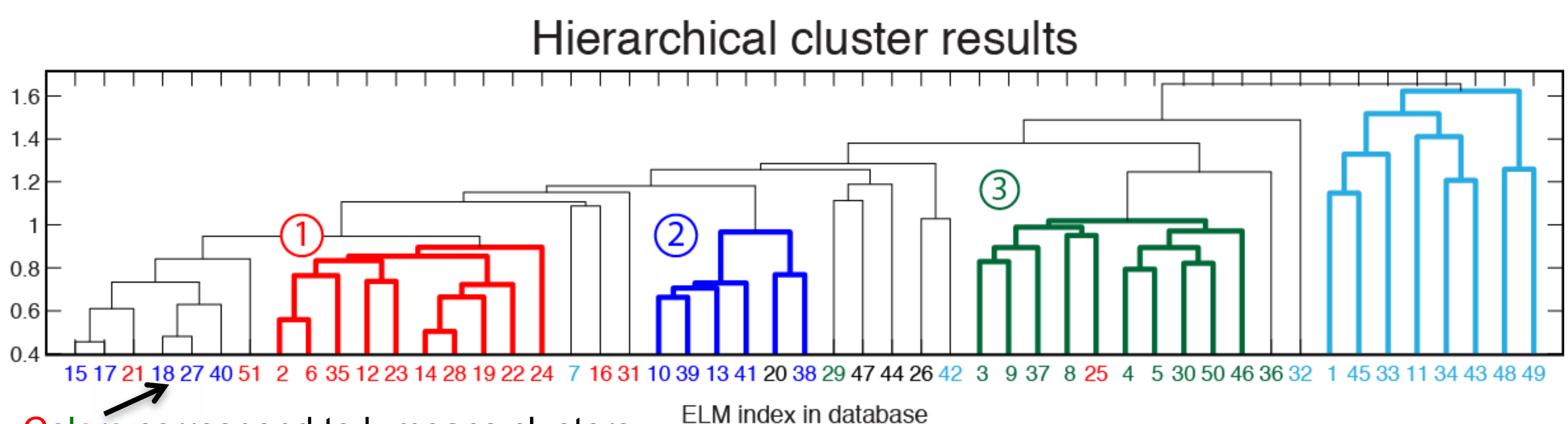
D. Smith et al, PPCF 58, 045003 (2016)

Clusters are highly consistent for calculations with different benchmark ELMs

k-means clustering and hierarchical clustering yield consistent results



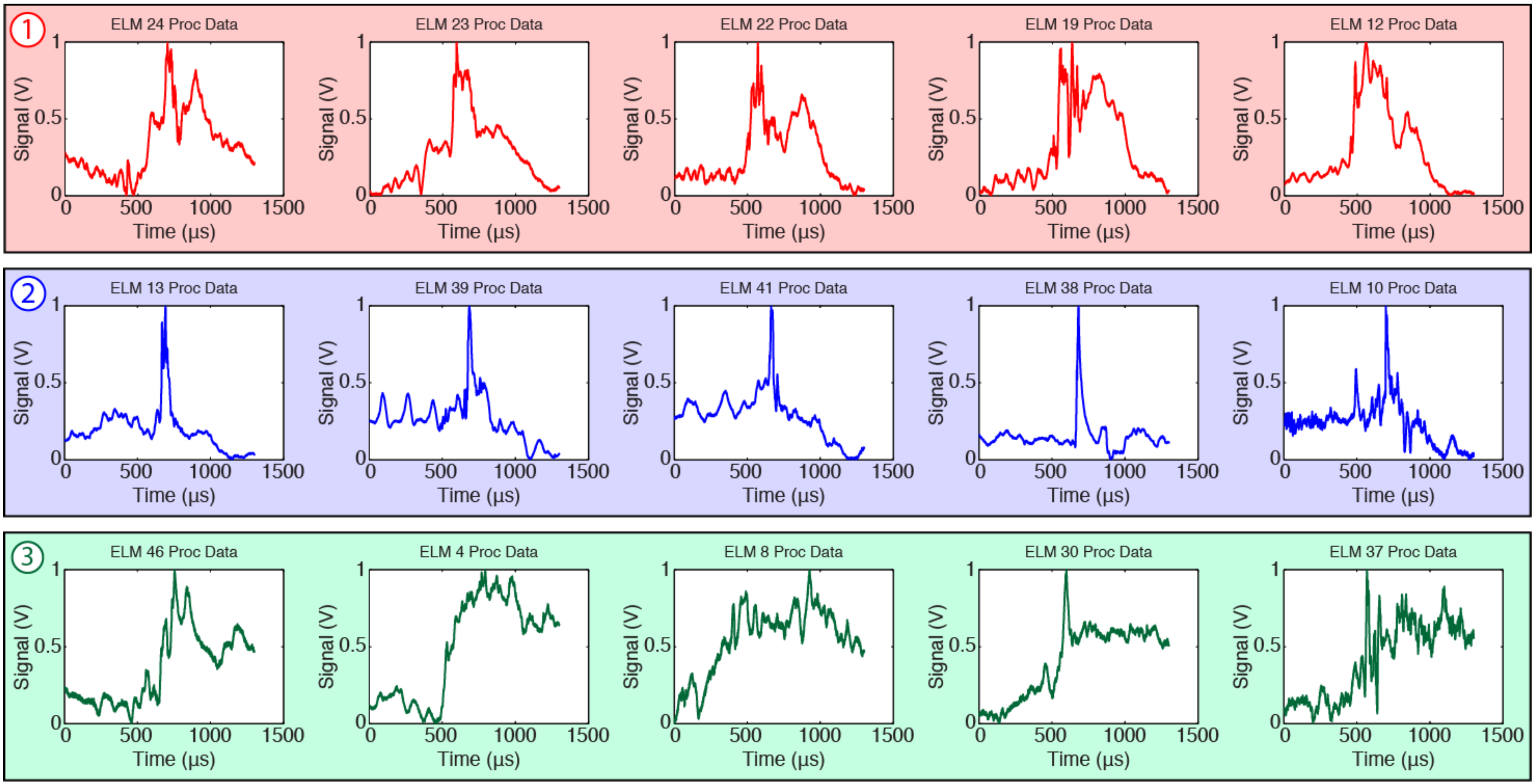
- Red, Blue, and Green groups in k-means results are **largely consistent** with previous hierarchical cluster results
- The Cyan group in k-means corresponds to poorly linked ELMs in the hierarchical cluster



Colors correspond to k-means clusters

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

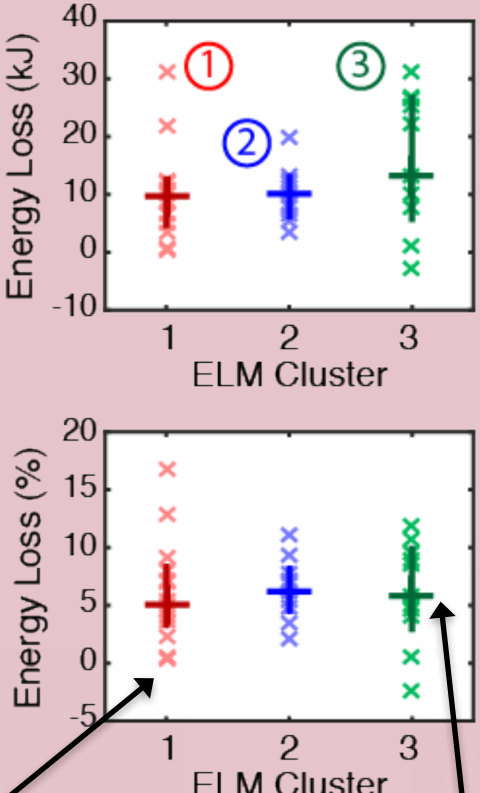
ELM evolution patterns identified with machine learning techniques



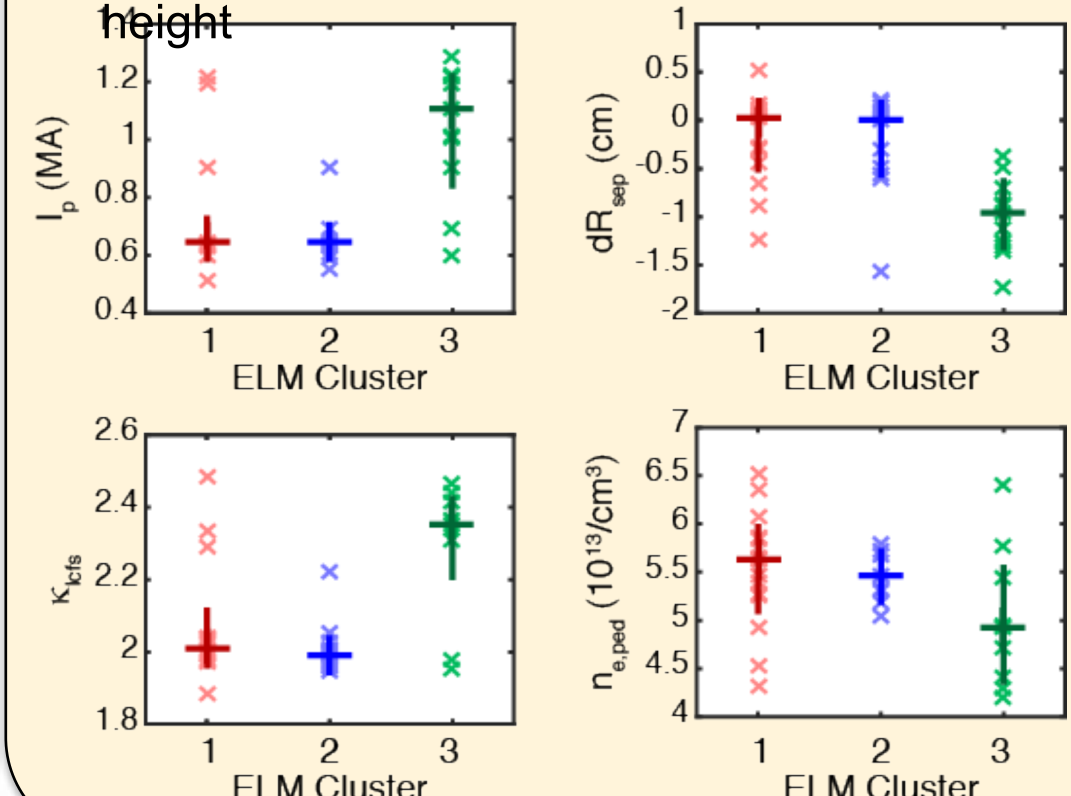
Next step: autonomously discover and tag ELMs in the NSTX/NSTX-U data archive

The identified ELM groups correspond to parameter regimes for I_p, κ, dR_{sep}, and $n_{e,ped}$, but not stored energy loss

The identified ELM groups exhibit similar stored energy loss …



… but different regimes for ELM-relevant parameters like plasma current, magnetic balance, elongation, and pedestal density height

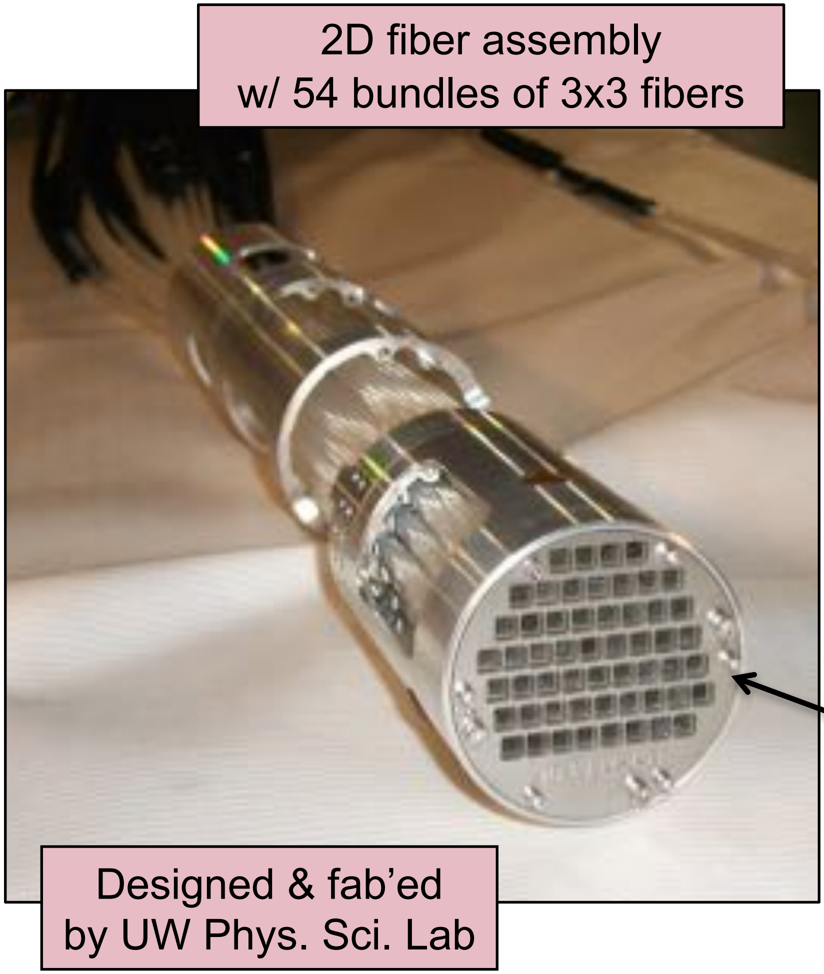


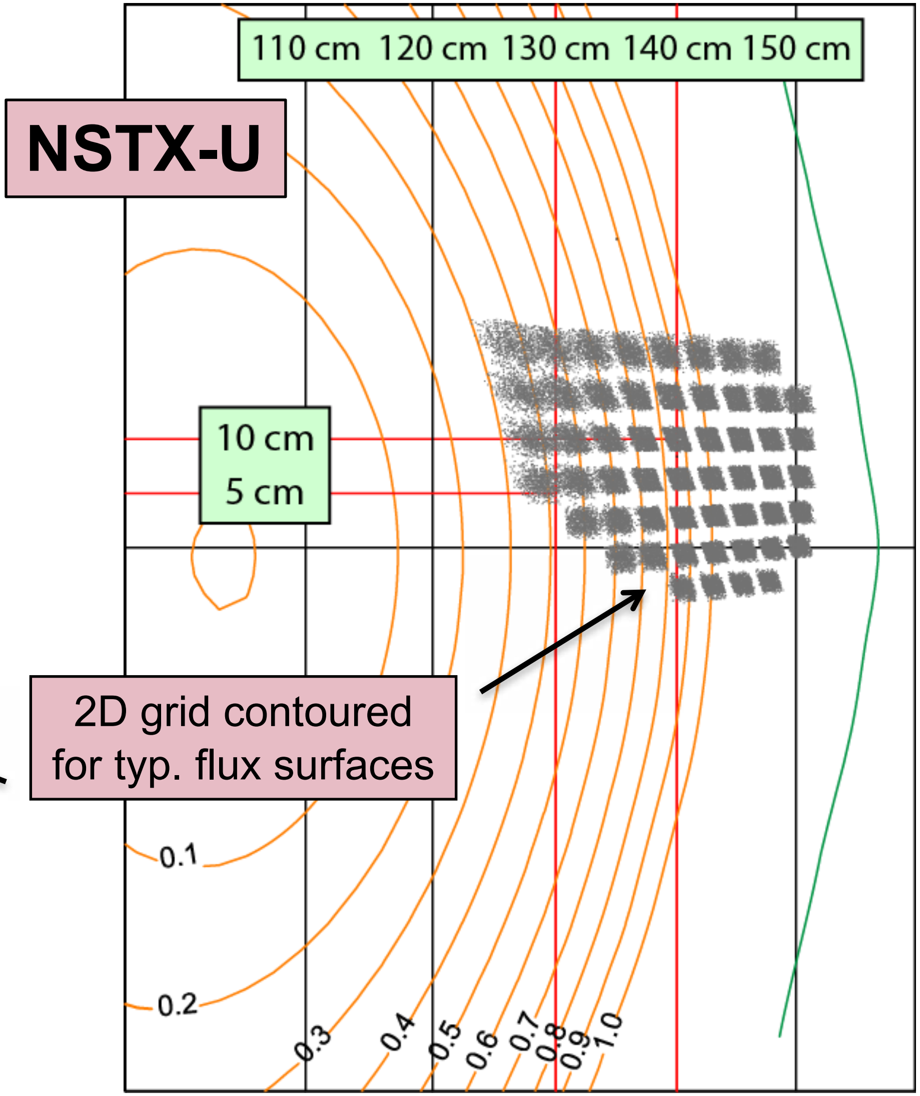
Individual ELMs

20th, 50th, & 80th percentile values

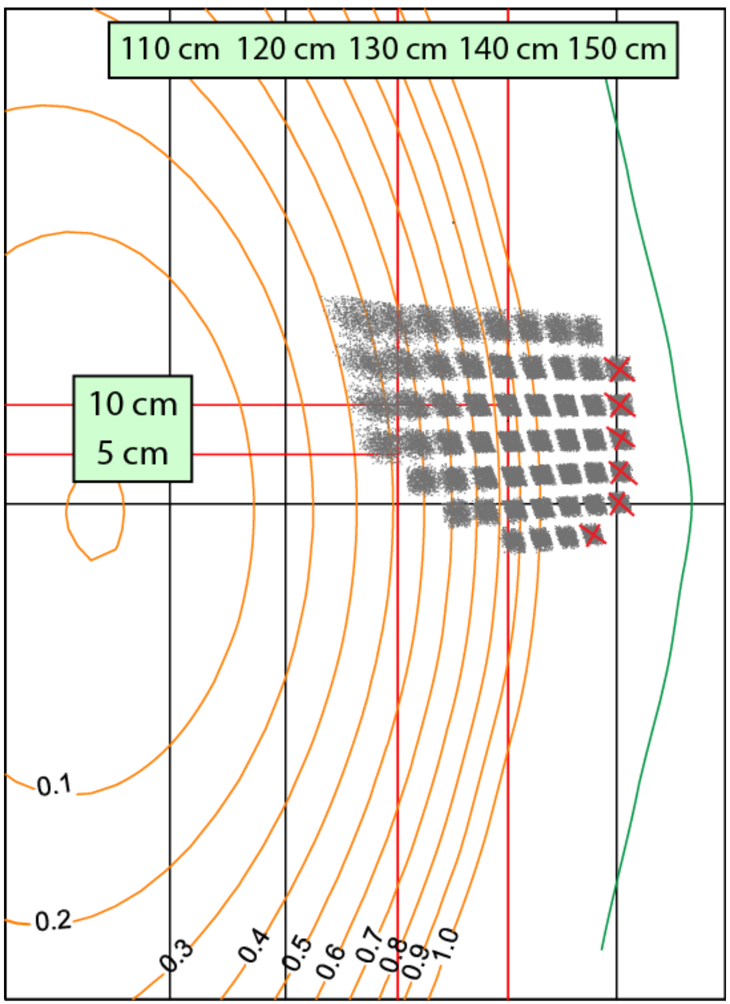
Work-in-progress: NL BOUT++ simulations to investigate the identified ELM groups and parameter regimes

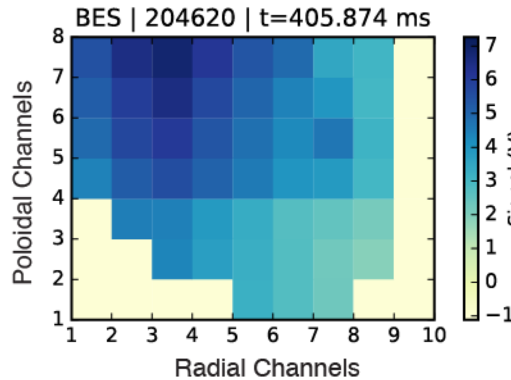
Upgraded 2D coverage on NSTX-U

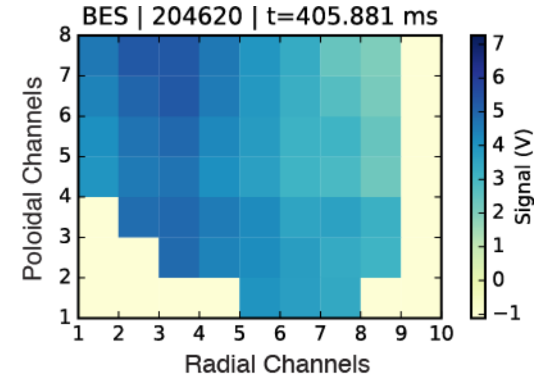


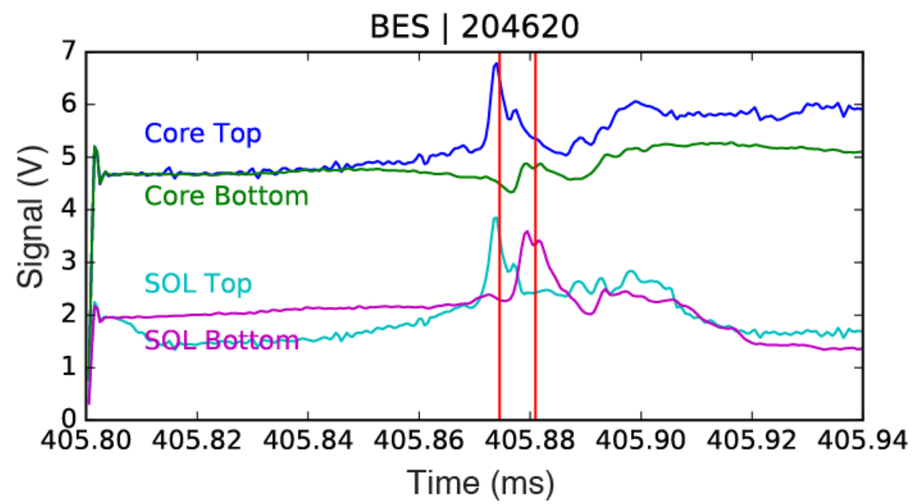


2D BES measurement of ELM event on NSTX-U









2D BES measurement captures downward motion of ELM structure

Summary

- BES measurements with Alfvenic time resolution capture the nonlinear evolution of ELM events on NSTX
- Unsupervised machine learning algorithms identified groups of ELMs with similar evolution characteristics
  - The identified ELM groups correspond to specific parameter regimes relevant to ELM physics: I_p, κ, dR_{sep}, $n_{e,ped}$
  - Working towards NL simulations to clarify the mechanisms at play in the identified ELM groups and parameter regimes
  - D. Smith et al, PPCF 58, 045003 (2016)
- 2D BES measurements are now available on NSTX-U
- Excellent opportunities to exploit machine learning tools for analysis tasks not feasible with manual inspection