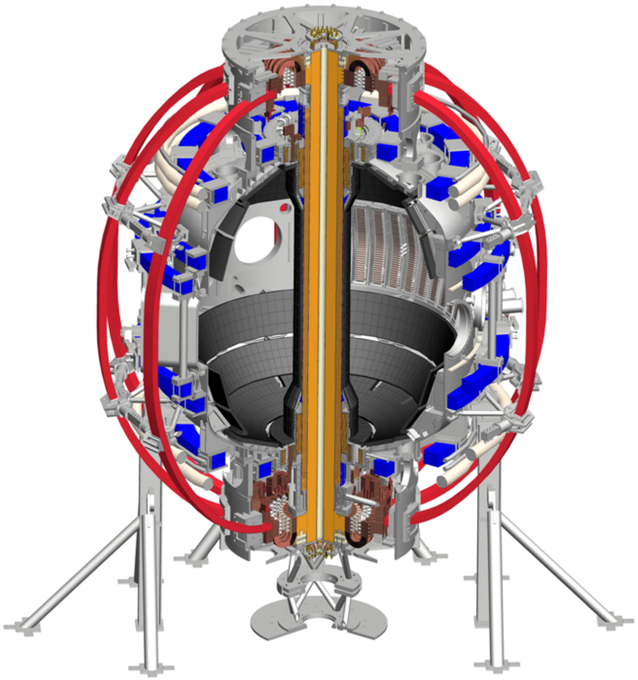
Investigation of ELM evolution patterns on NSTX-U with beam emission spectroscopy measurements



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Nonlinear ELM dynamics and measurement capabilities

- 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)
  - Reverse shear stabilization of low-n modes (P. Zhu et al, PoP, 2012)
  - EHOs attributed to saturated PB modes (K. Burrell et al, PRL, 2009)
- Common ELM analysis tools/methods do not capture the nonlinear, Alfven-scale evolution dynamics
  - Heuristic classification schemes (Type I, III, etc.)
  - Sub-Alfvenic measurements with Thomson scattering and filterscopes
  - Peeling-ballooning/KBM linear stability threshold
- 2D BES measurements on NSTX-U and DIII-D can capture the Alfven-scale evolution of ELM events

ELM evolution patterns on NSTX/NSTX-U

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

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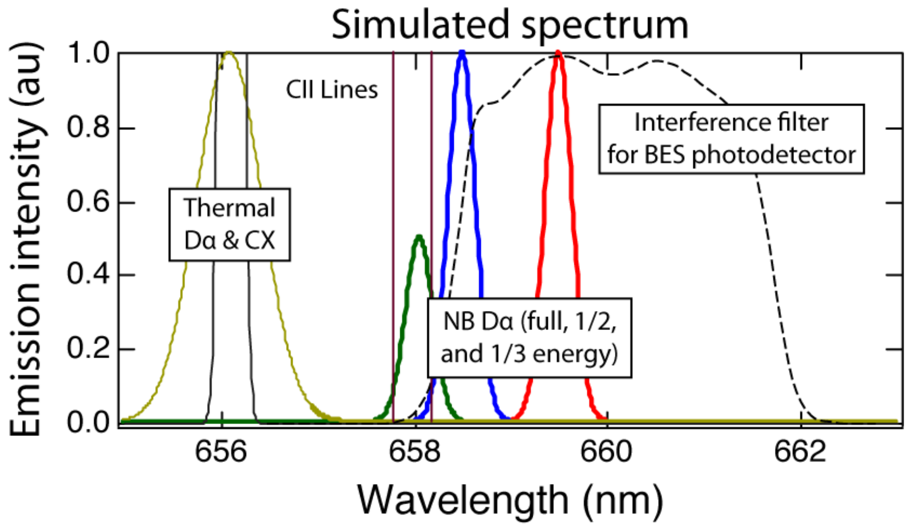
Beam emission spectroscopy (BES) measures Doppler-shifted D_α emission from a deuterium heating beam

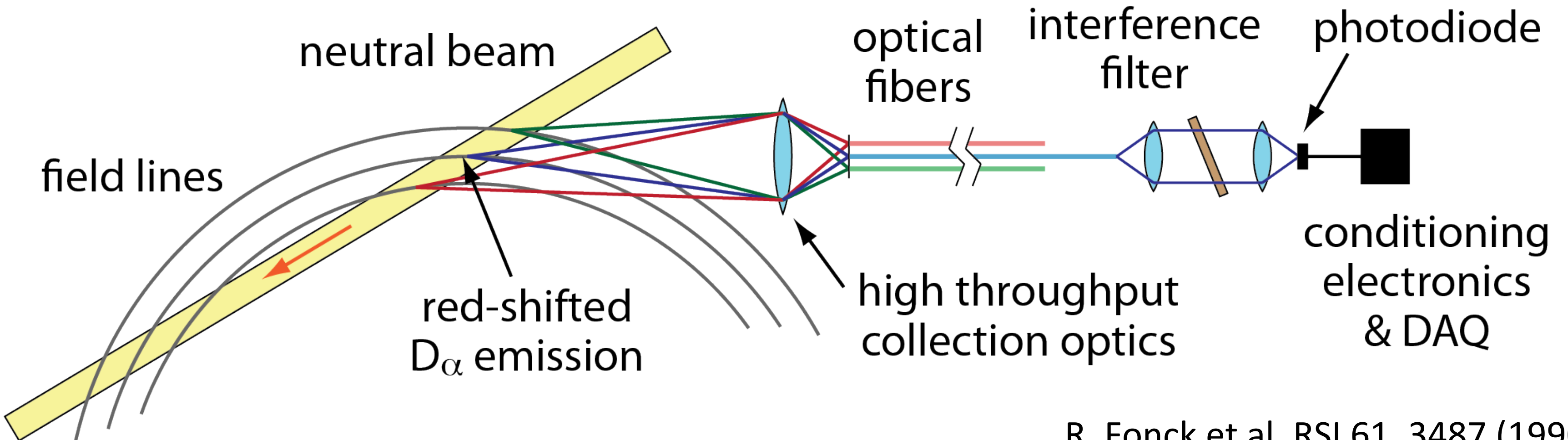


$$\frac{\delta I_{D\alpha}}{I_{D\alpha}} = \frac{\delta n}{n} \times C\left(E_{NB}, n, T_e, Z_{eff}\right)$$

neutral beam D_α emission

density fluctuation

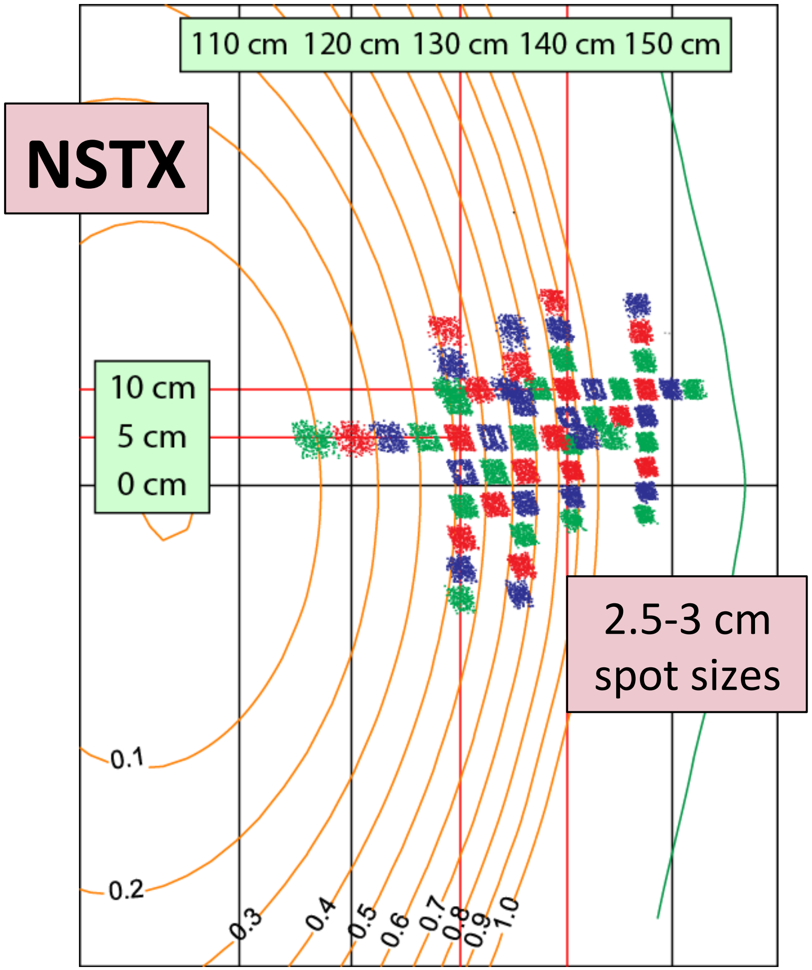
C ≈ 1/2

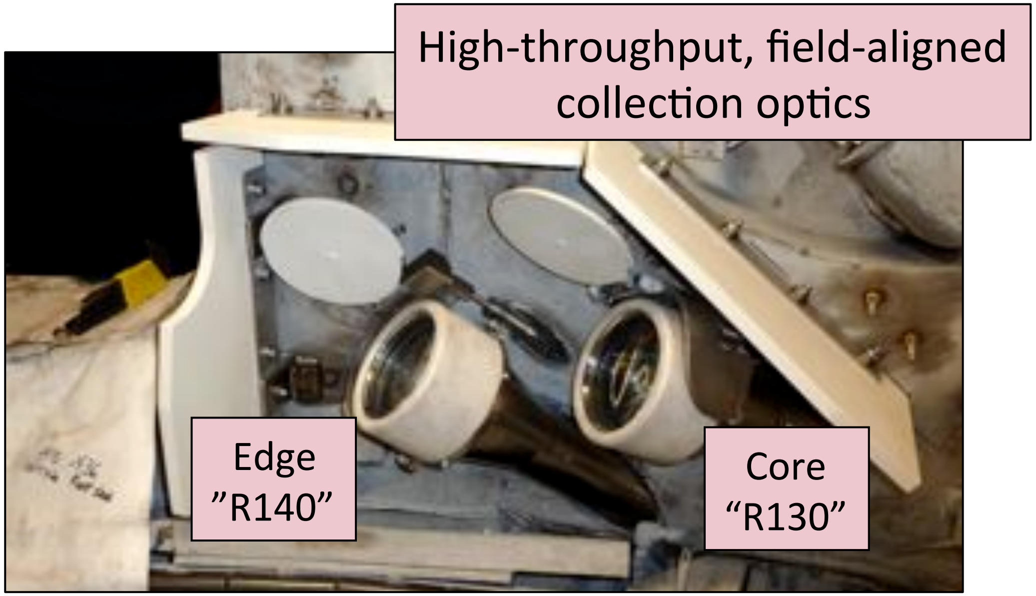


R. Fonck et al, RSI 61, 3487 (1990)

R. Fonck et al, PRL 70, 3736 (1993)

Radial and poloidal coverage on NSTX





Measurements are sensitive to density fluctuations on the ion gyroscale with $k_\perp \rho_i \leq 1.5$

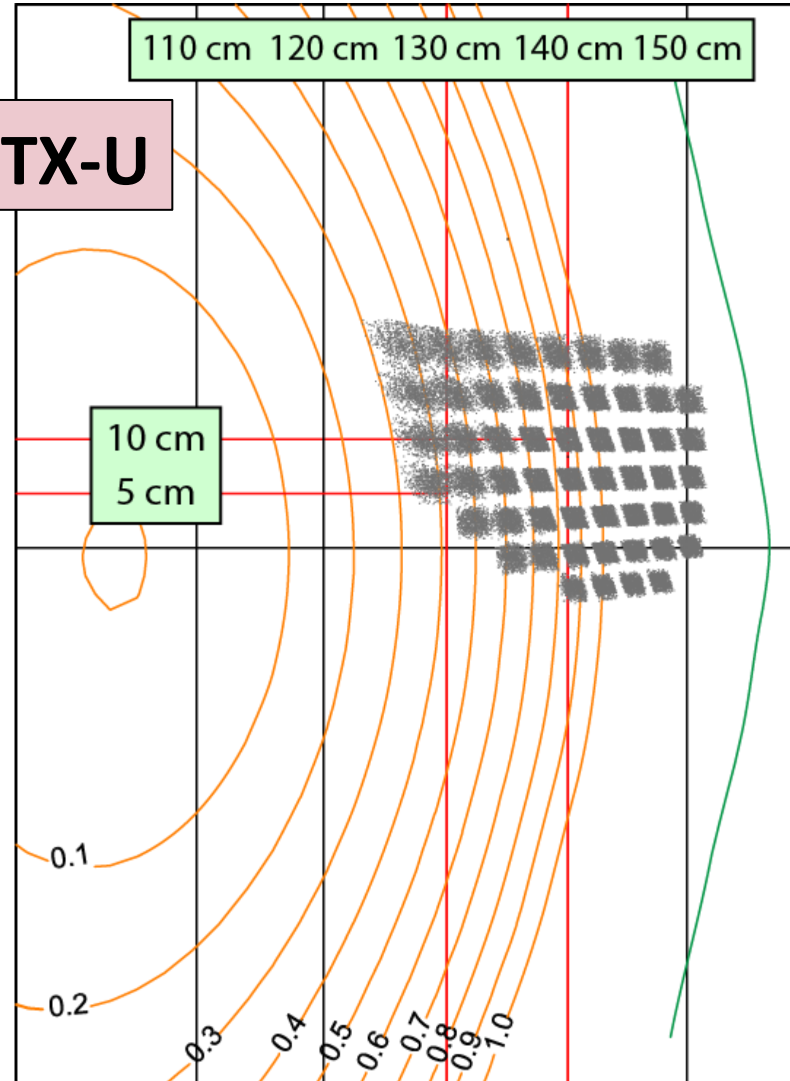
D. Smith et al, RSI 81, 10D717 (2010)
N. Schoenbeck et al, RSI 81, 10D718 (2010)
D. Smith et al, RSI 83, 10D502 (2012)

Upgraded 2D coverage on NSTX-U

2D fiber assembly
w/ 54 bundles of 3x3 fibers

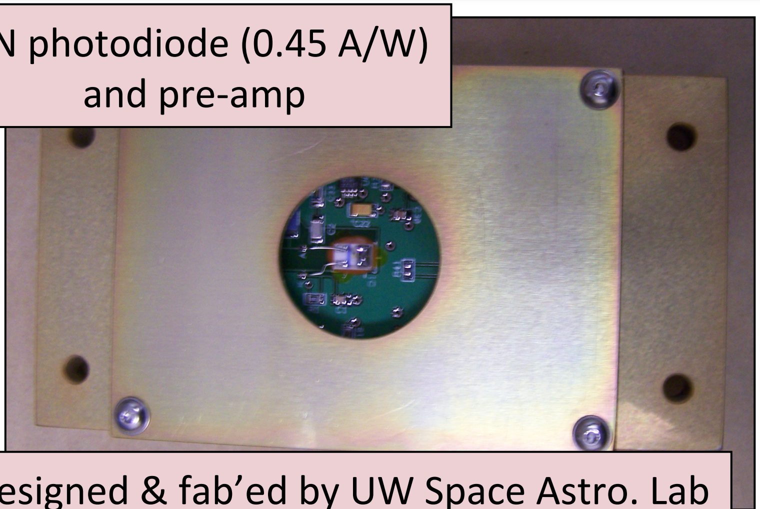
Designed & fab'ed
by UW Phys. Sci. Lab

NSTX-U



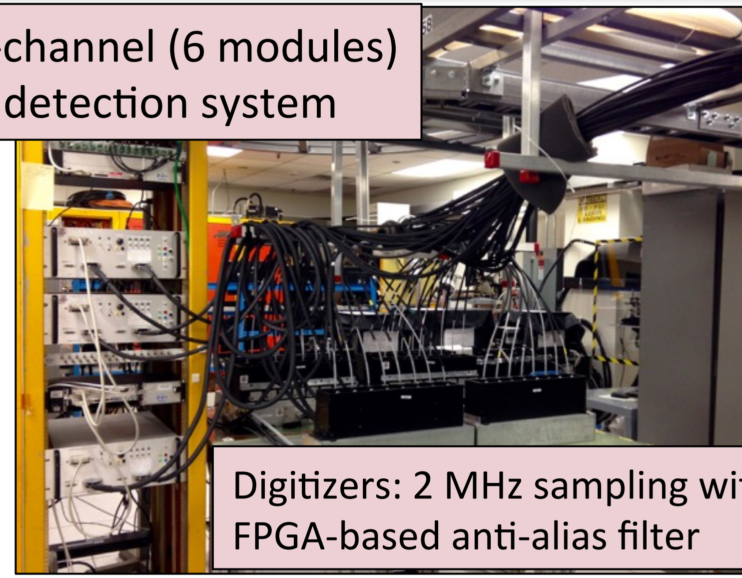
Low-noise, high quantum efficiency detection system

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



Designed & fab'ed by UW Space Astro. Lab

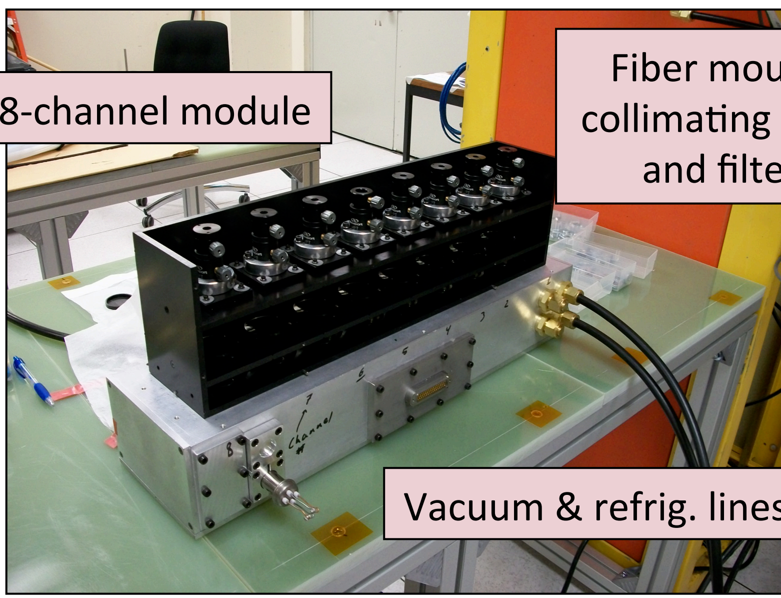
48-channel (6 modules) detection system



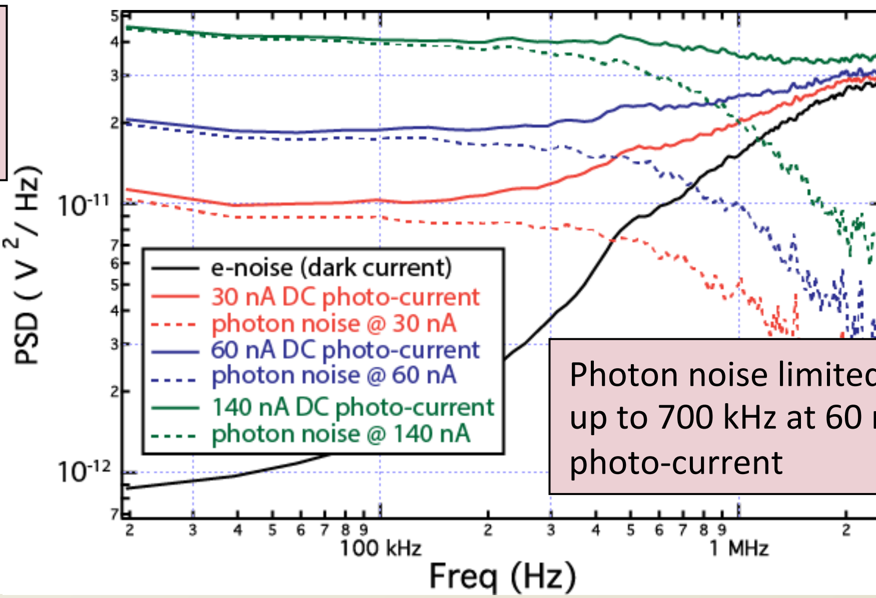
Digitizers: 2 MHz sampling with FPGA-based anti-alias filter

8-channel module

Fiber mount, collimating lens, and filter



Vacuum & refrig. lines



Photon noise limited up to 700 kHz at 60 nA photo-current

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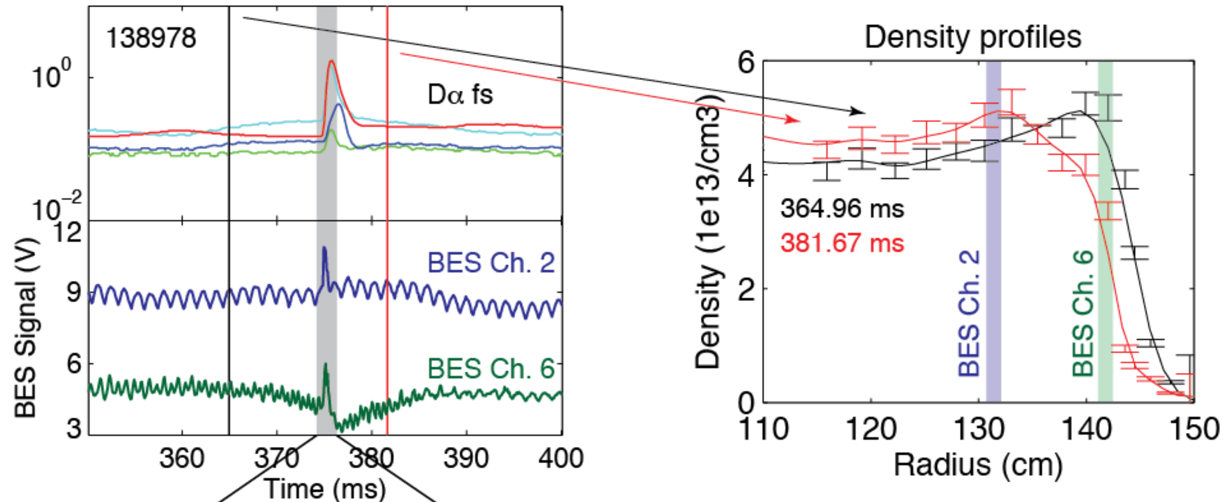
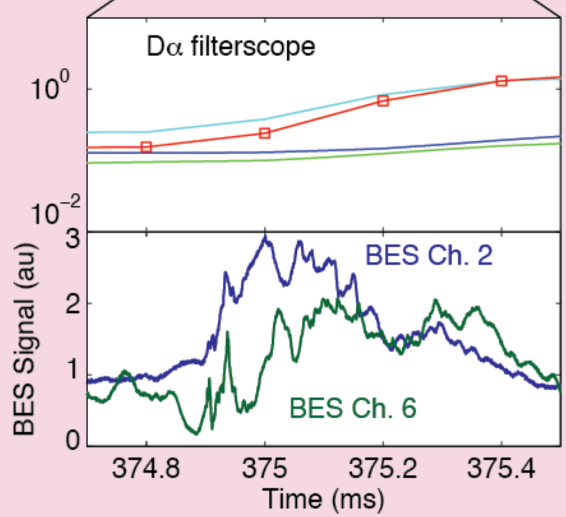
BES measurements with sub-μs time resolution capture the Alfven-scale evolution and radial profile of ELM events

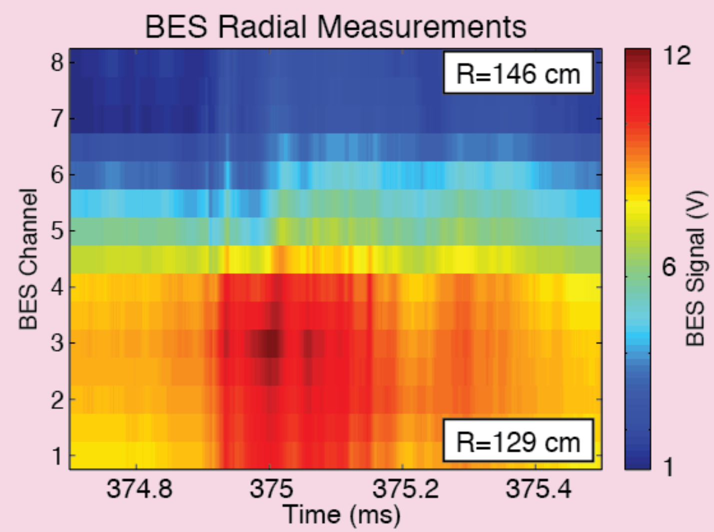
Common measurements for ELM characterization do not capture the Alfven-scale evolution of ELM events



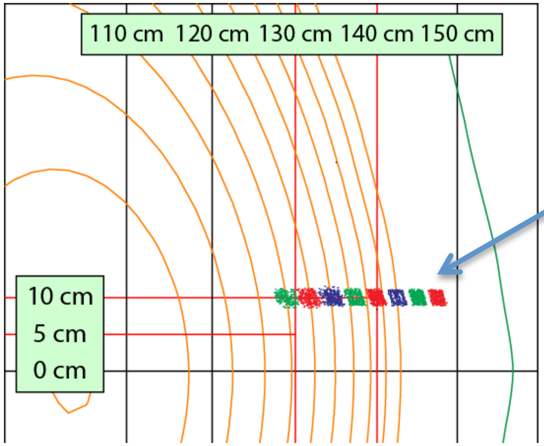
BES captures the Alfven-scale evolution of ELM events

$\Delta t/\tau_A \sim 0.1$



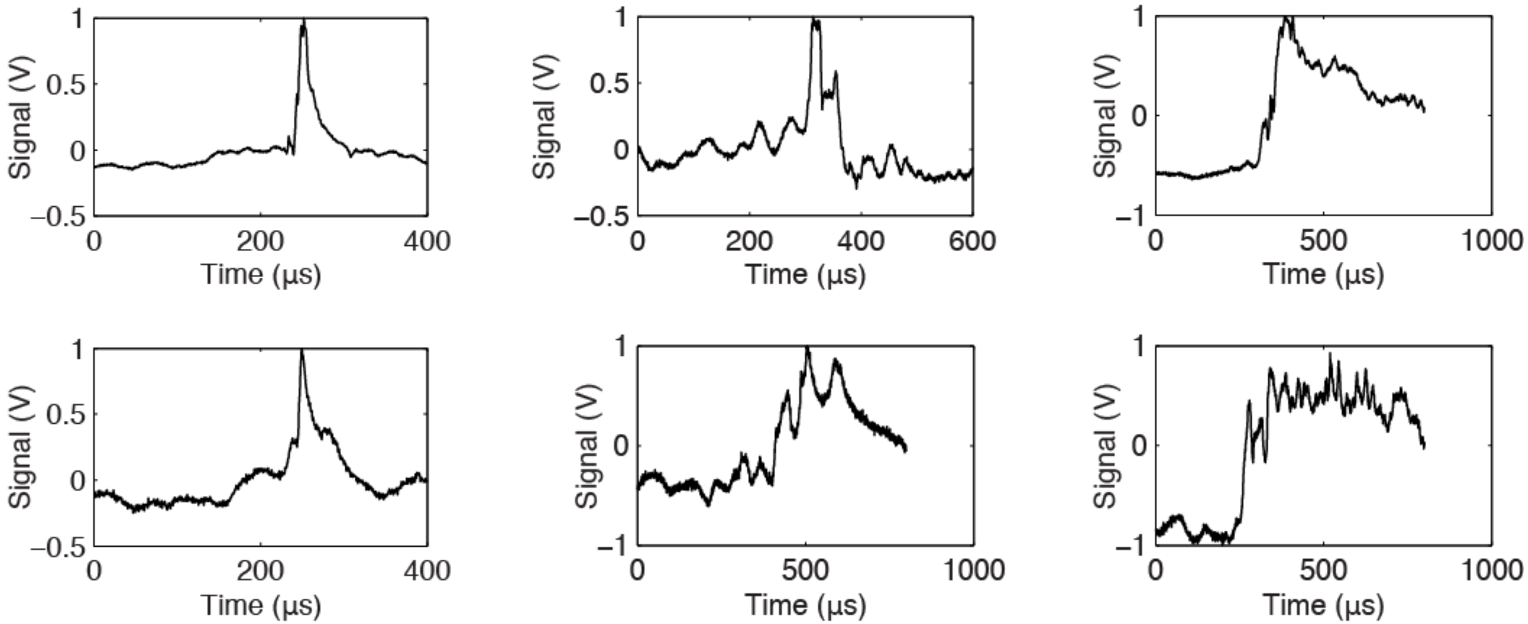


Goal – Identify common evolution patterns (if any) in ELM time-series data



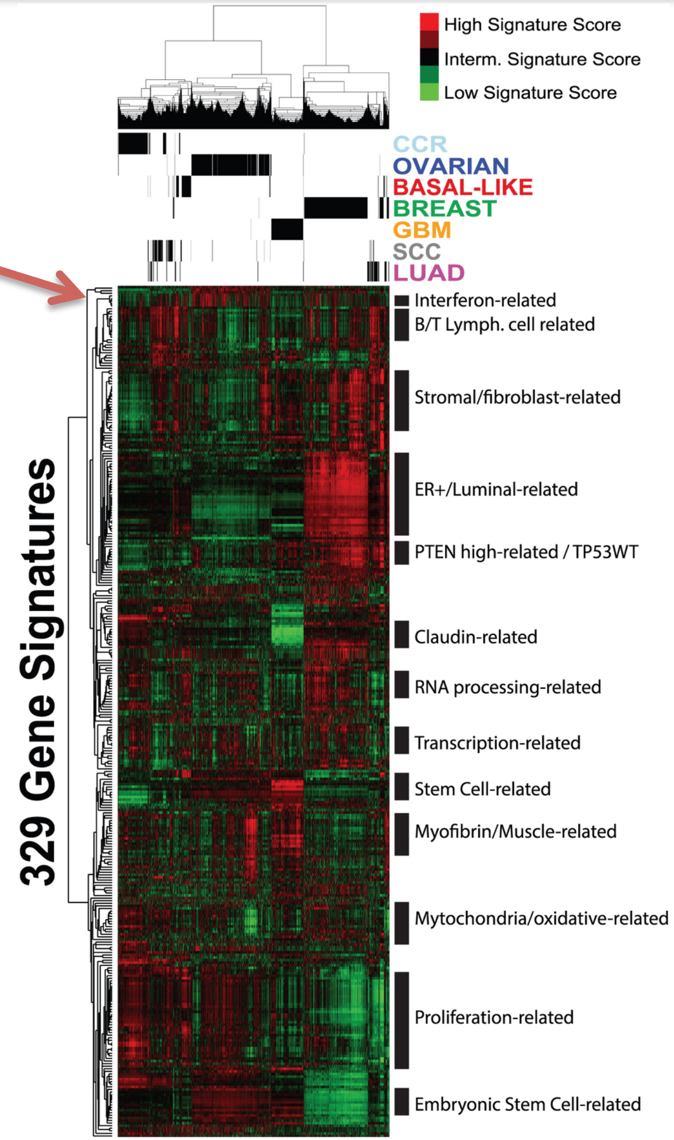
- Database of 51 ELM events measured with BES
  - 8 radial BES channels spanning pedestal region
  - 34 NSTX discharges from 8 run days spanning 4 months
  - 1%-16% stored energy loss and observable pedestal collapse
  - Most likely type I ELMs

Examples from the ELM database



Method – Apply unsupervised machine learning techniques and time-series similarity metrics to identify common evolution patterns

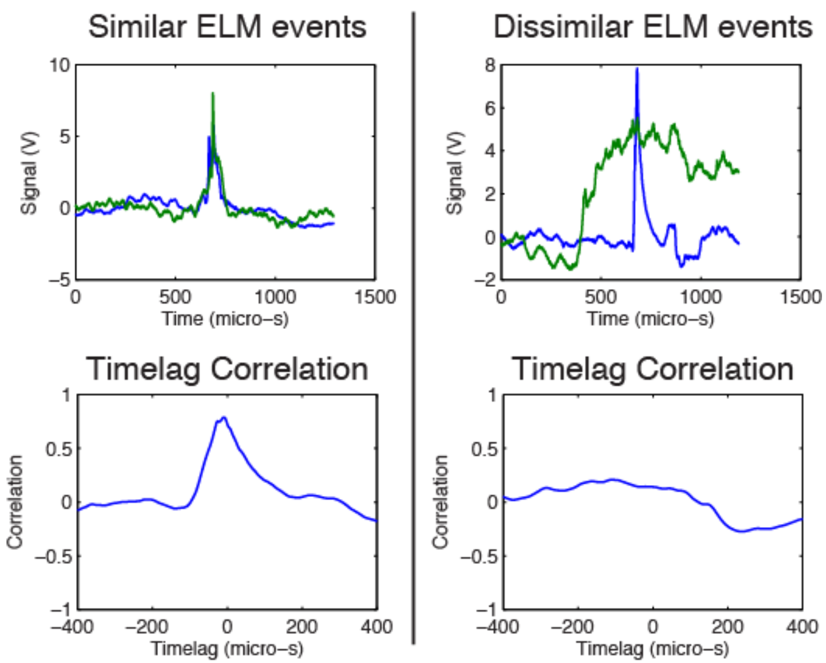
- Hierarchical clustering
  - Popularized in genomics
  - Produces a multi-level hierarchy of similar objects
  - Requires an **intrinsic similarity metric** to quantify similarity among time-series
- Time-series similarity metrics
  - Time-lag cross-correlation
  - Euclidean distance
  - Dynamic time warping (DTW)
  - Wavelet decomposition
- K-means clustering
  - Groups similar objects into k mutually exclusive clusters
  - Requires an **extrinsic similar metric** to quantify similarity among time-series
  - Optimum cluster number found by trial-and-error



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

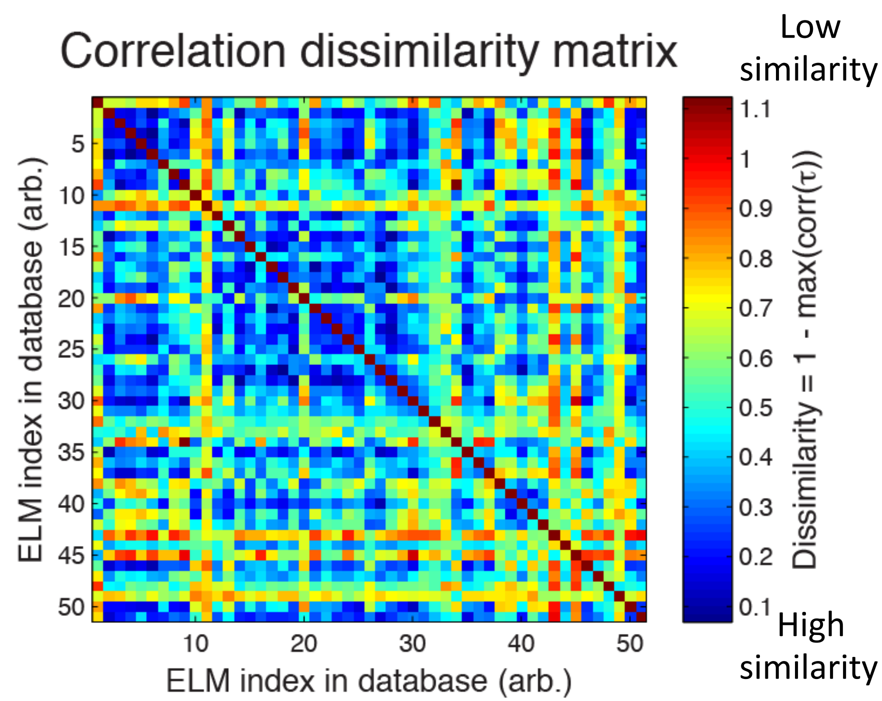
Hierarchical clustering (I) – Assemble pair-wise similarity metrics into a dissimilarity matrix

1) Time-lag cross-correlation can quantify the similarity of ELM events

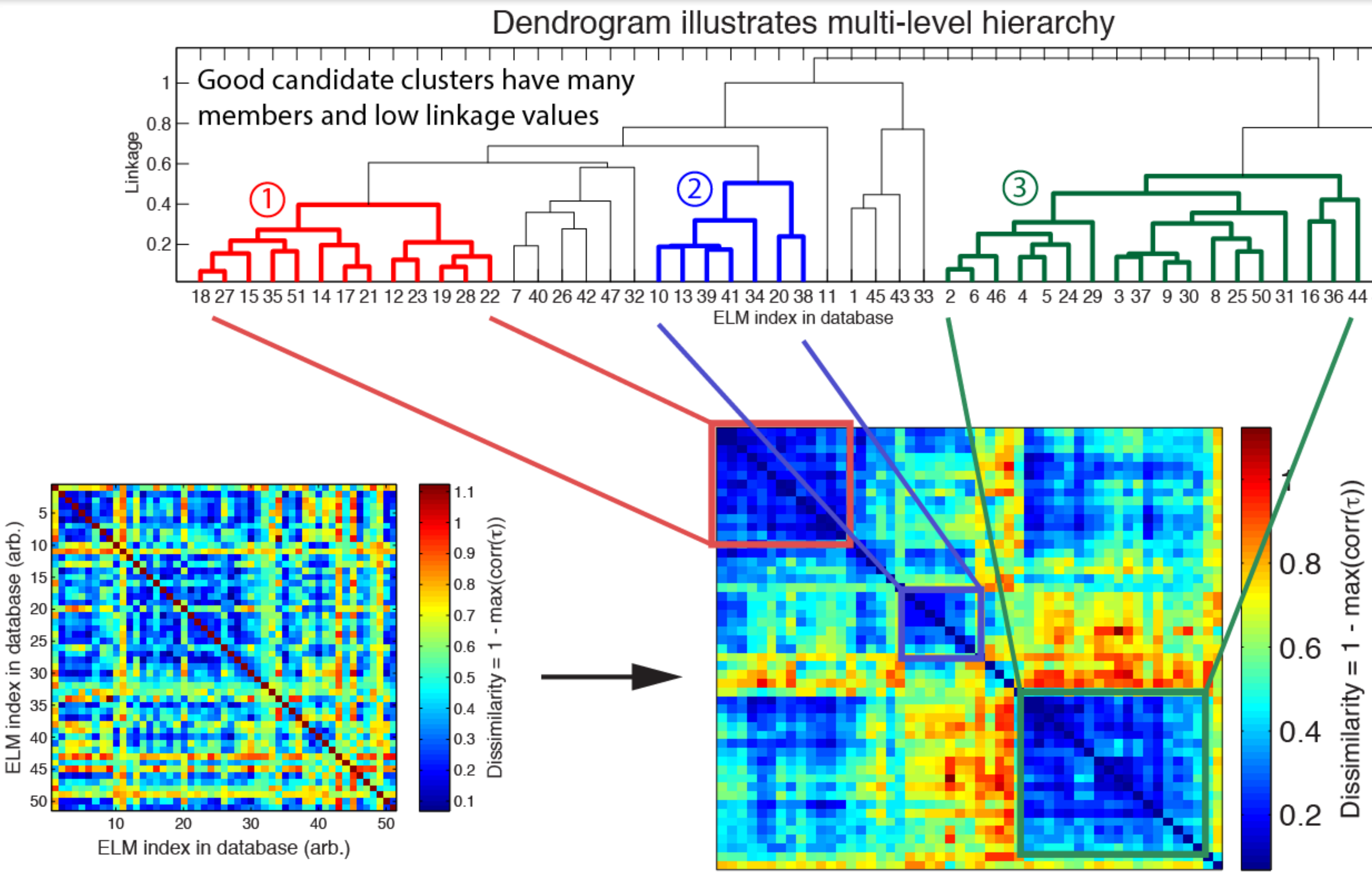


Larger max correlation ➞ more similar

2) Assemble pair-wise metrics into a dissimilarity matrix



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

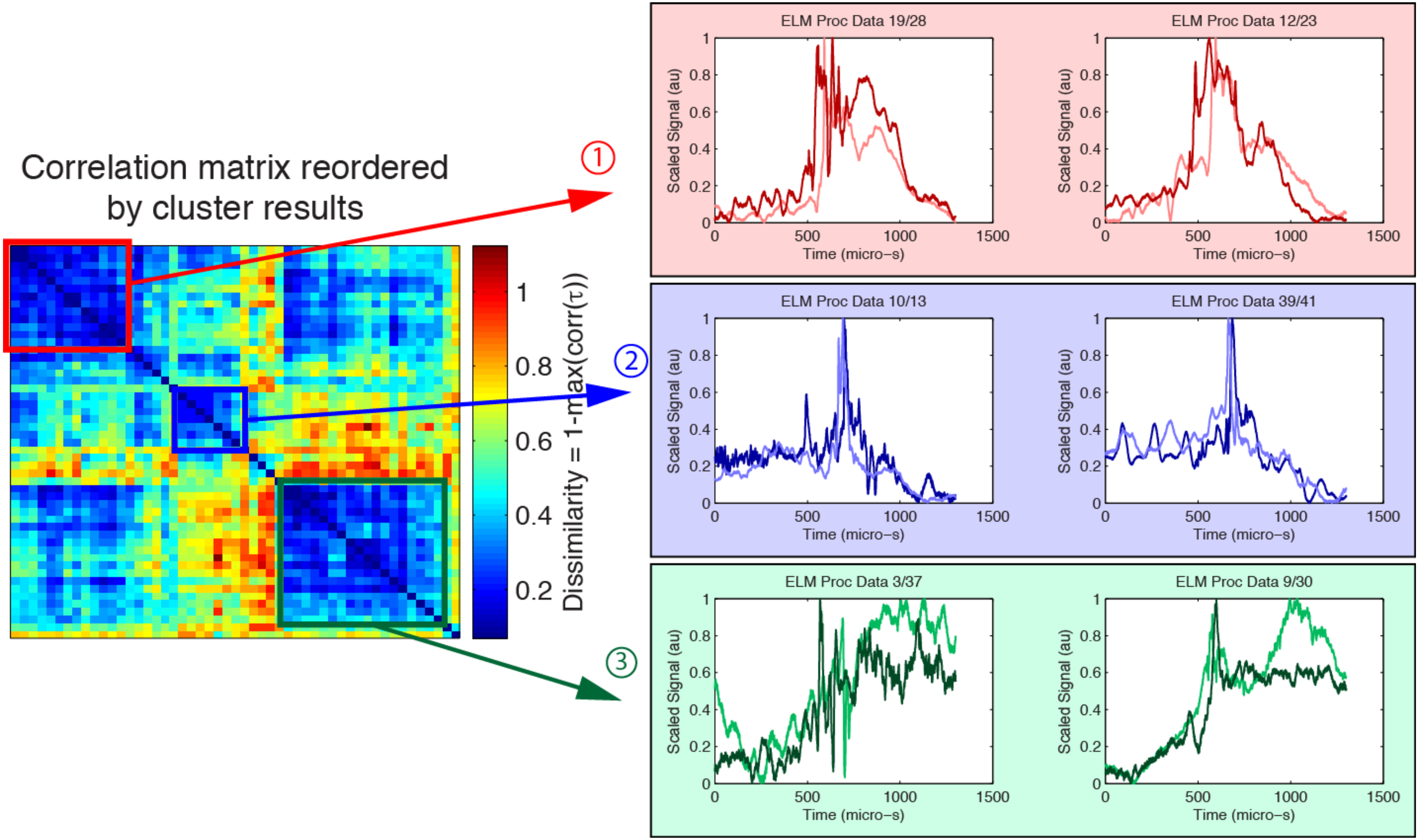


Original dissimilarity matrix

Reordered dissimilarity matrix

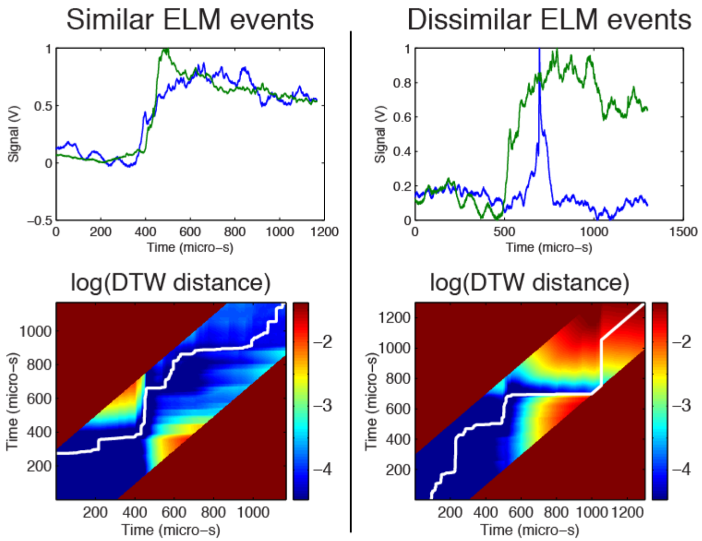
D. Smith et al, PPCF 58, 045003 (2016)

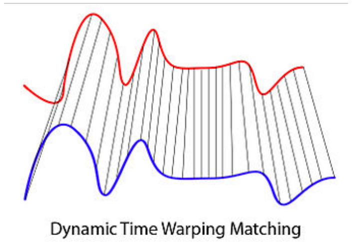
The identified ELM groups show similar evolution characteristics



Now try other similarity metrics

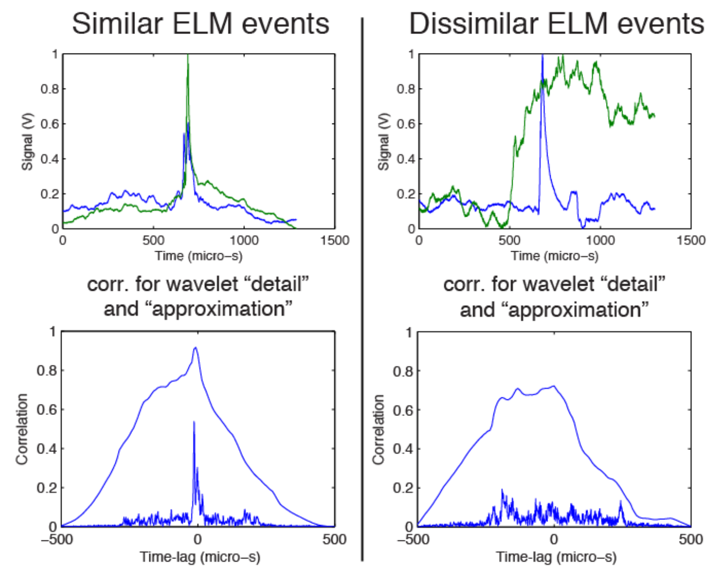
Dynamic time warping

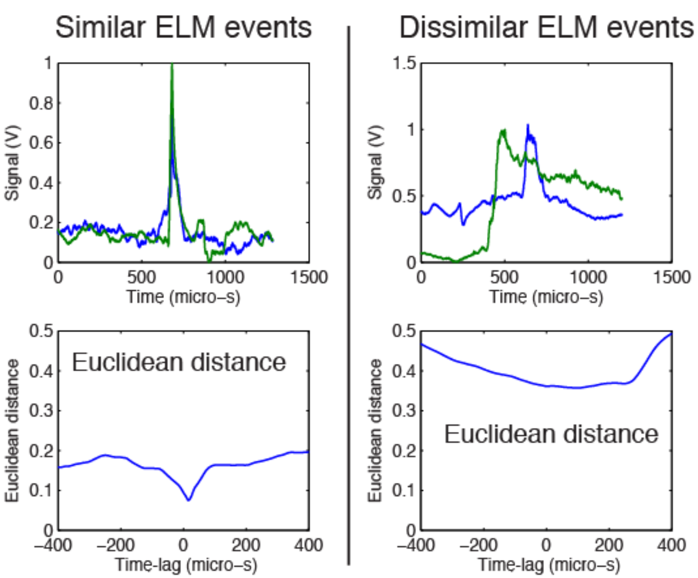




Wikipedia

Cross-corr. of wavelet-transformed signals

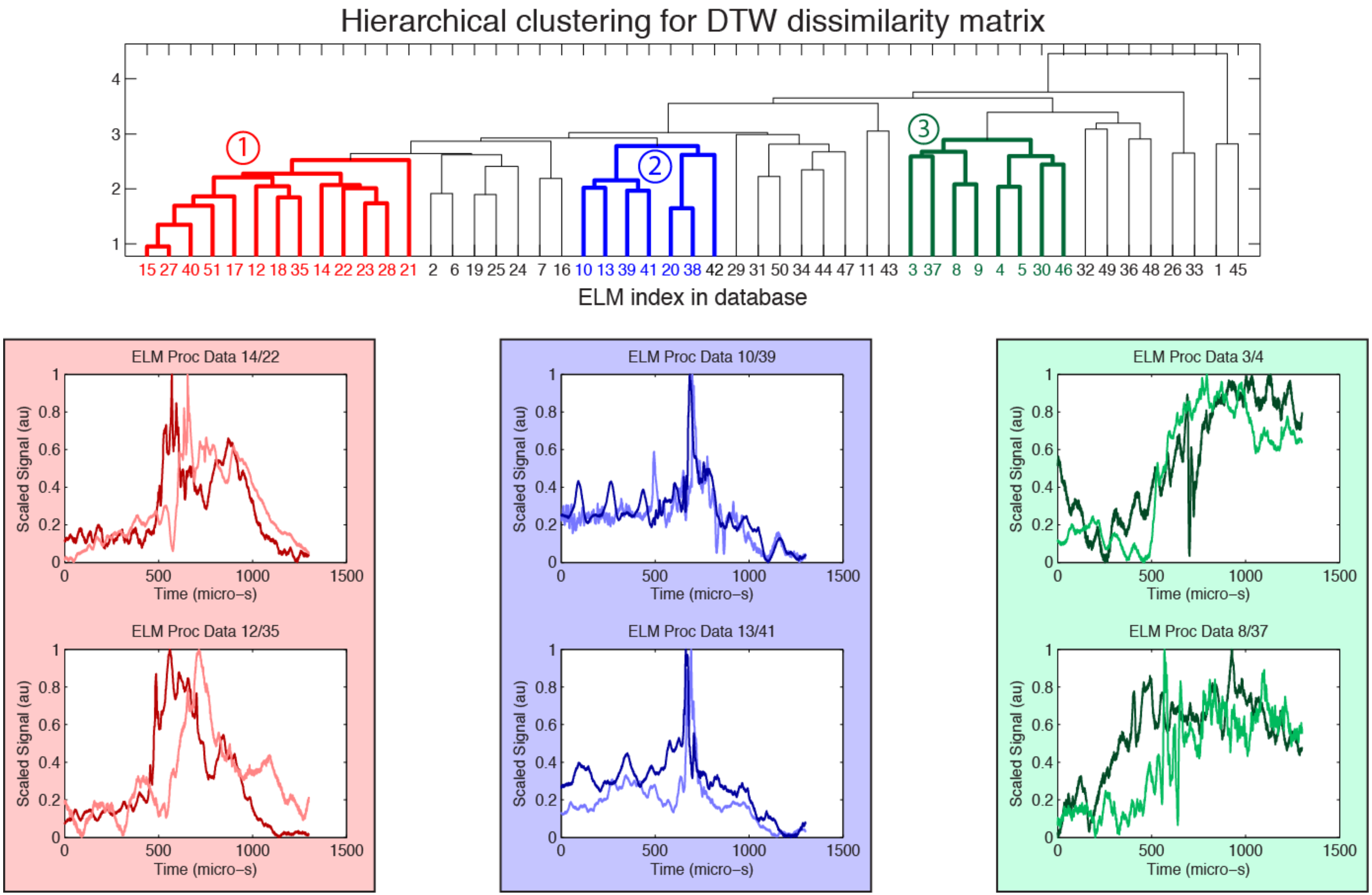




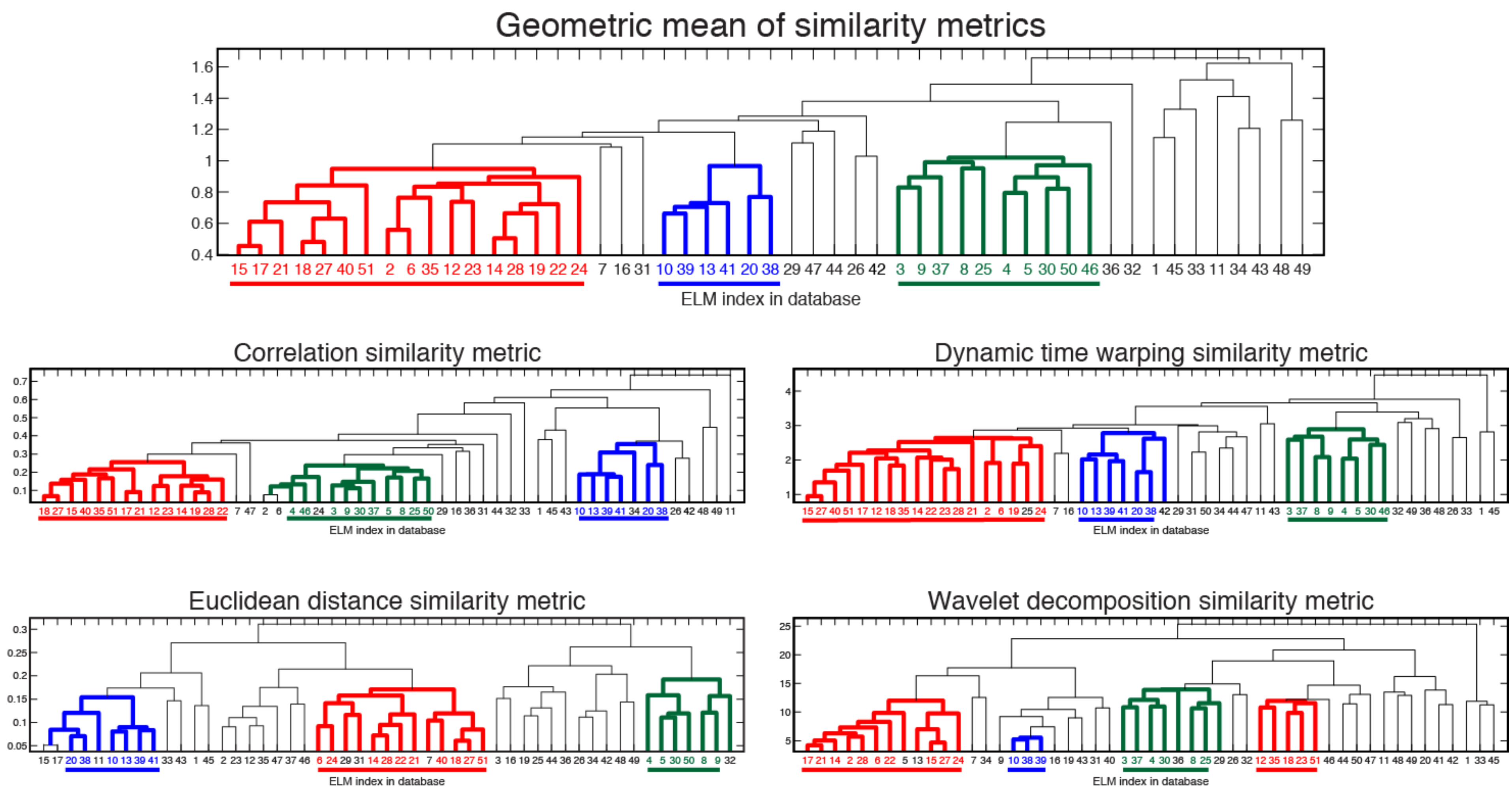
Euclidean distance

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

For instance, dynamic time warping (DTW) yields cluster results similar to time-lag correlation



Similar ELM groups from different metrics suggests that the ELM groups are robust results



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

K-means clustering (I) – Group objects into mutually exclusive groups

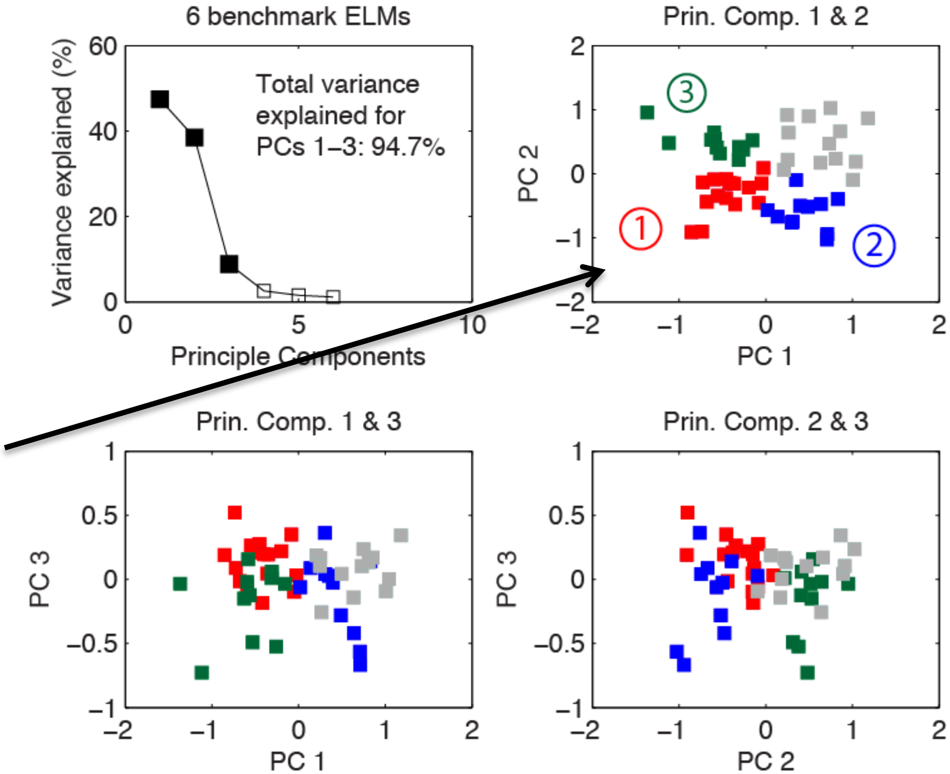
- Requires extrinsic similarity metrics
  - Designate benchmark ELMs to serve as extrinsic metrics
- Visualize results in low-dimensional space from PCA

K-means clustering
with 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

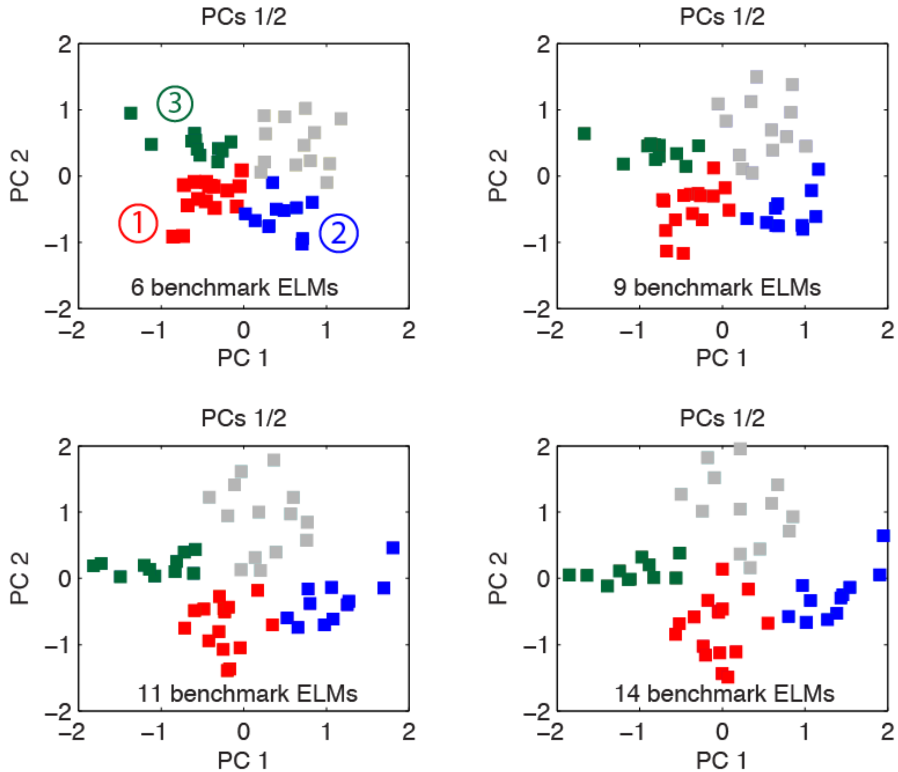
*Out-of-cluster/in-cluster distance ratio

Optimal



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

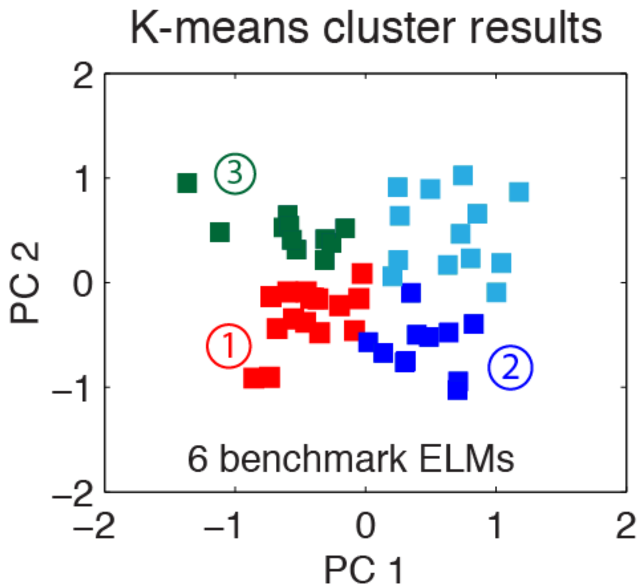
K-means clustering (II) – Different sets of benchmark ELMs yield similar results



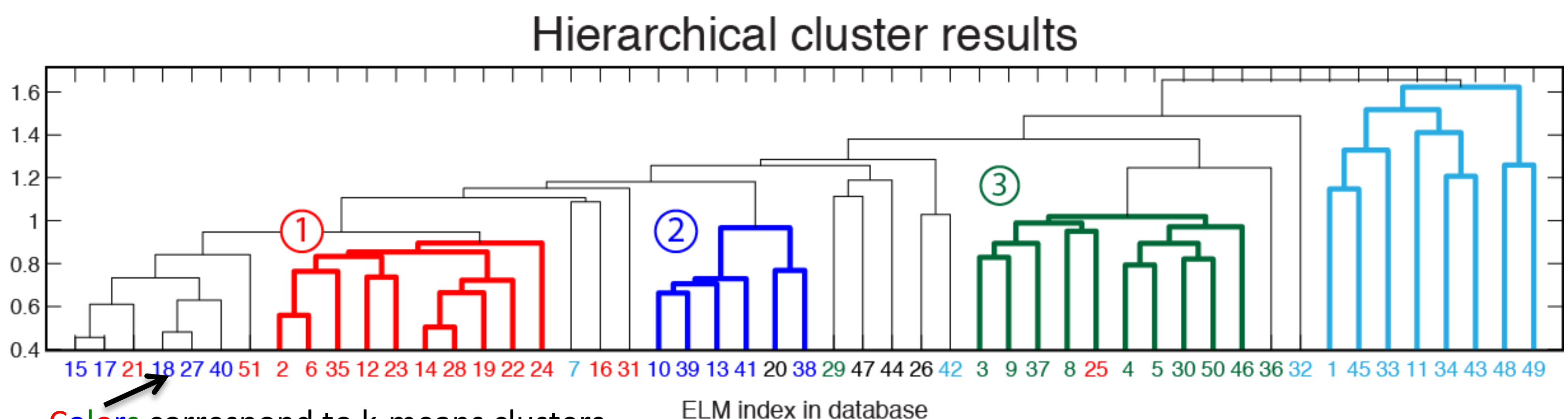
# of benchmark ELMs	Optimal cluster #	Mean ratio
6	4	0.52
9	4	0.52
11	4	0.53
14	4	0.52

- Clusters are highly consistent for calculations with different benchmark ELMs
- Red cluster ELMs: 2, 35, 23, 19, 22, 12, 28, 14, 51, 24
- Blue cluster ELMs: 13, 15, 10, 39, 41, 40, 38, 17, 27, 18
- Green cluster ELMs: 30, 4, 50, 3, 5, 36, 29, 9, 8, 46

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

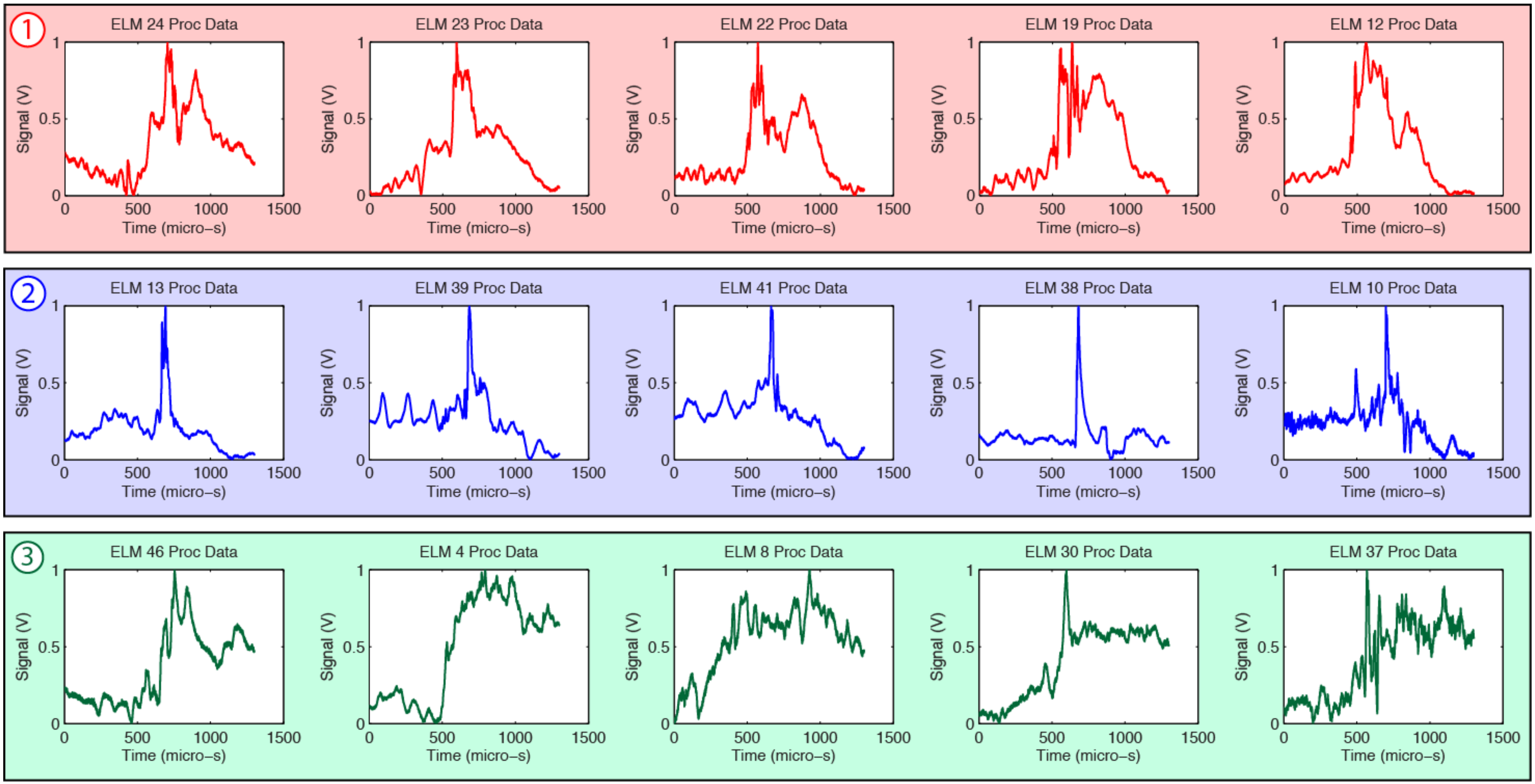


Colors correspond to k-means clusters

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

ELMs with similar evolution characteristics

This analysis demonstrates that machine learning techniques can identify patterns and similarities in time-series data



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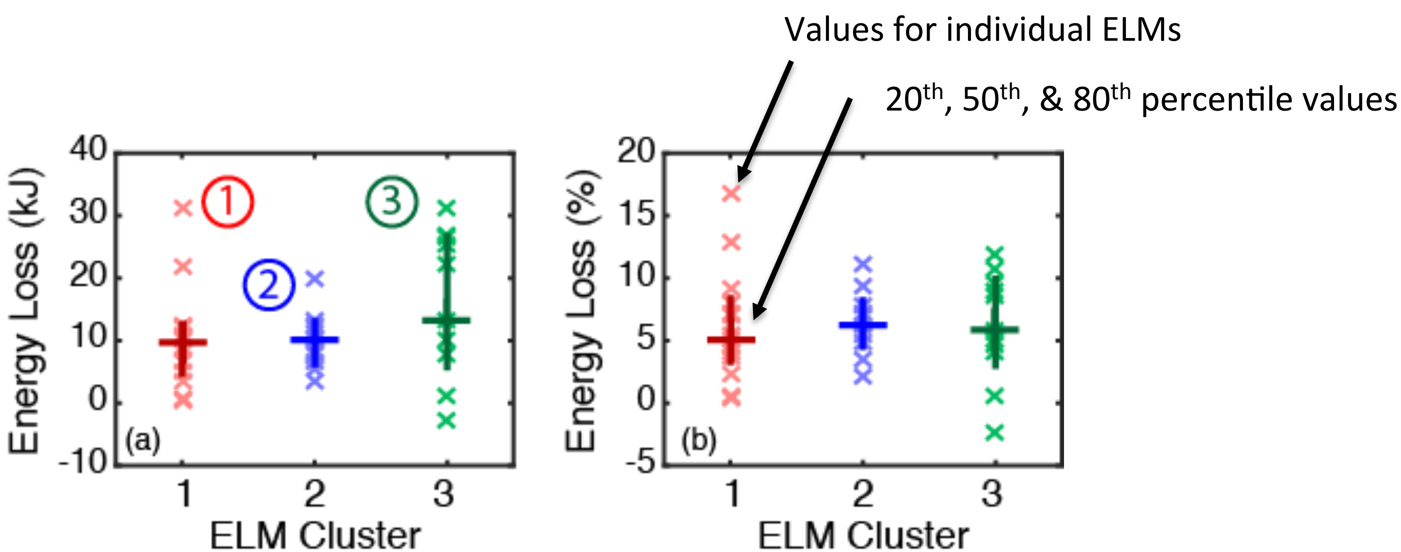
Identified ELM groups exhibit similar stored energy losses

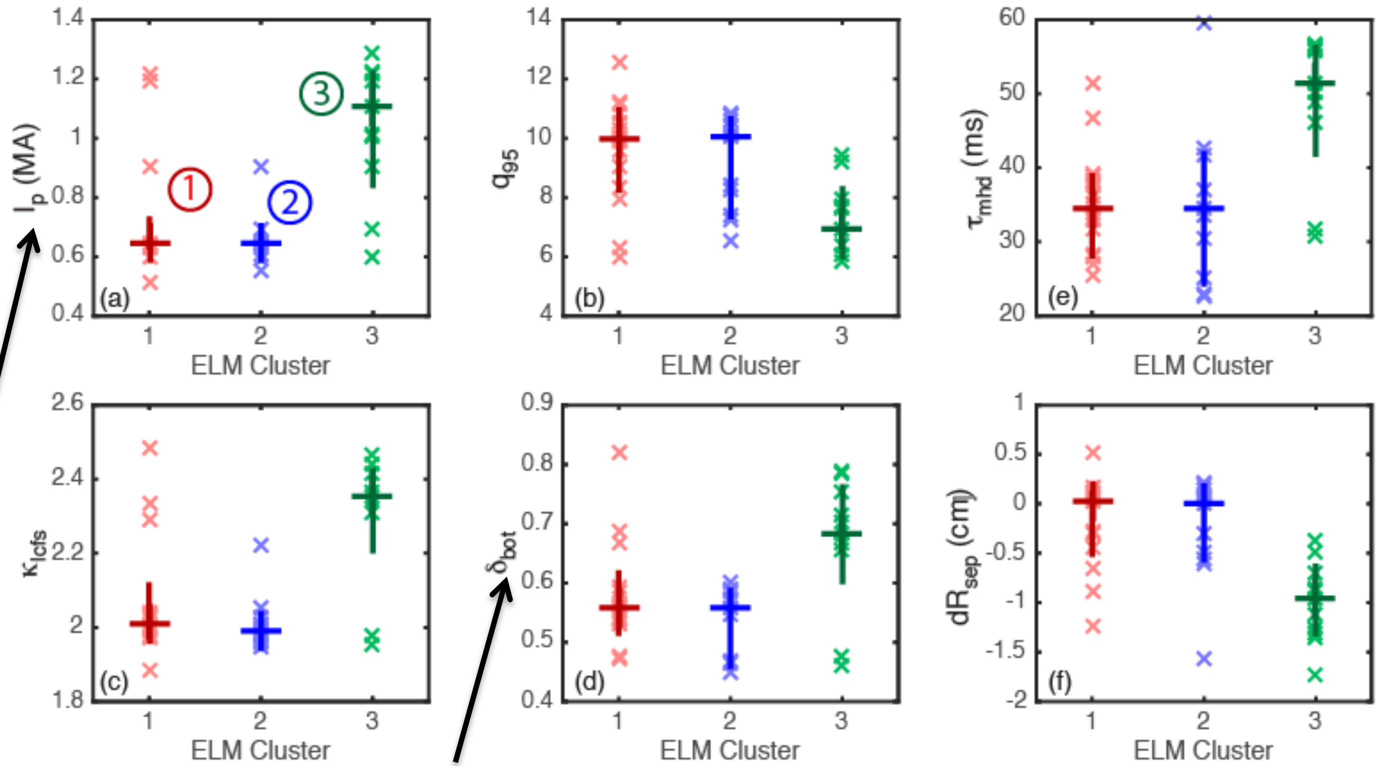


- Stored energy loss can’t differentiate the identified ELM groups

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

Identified ELM groups correlate with distinct parameter regimes (I)

- Red and Blue ELM groups exhibit similar parameter regimes
- Observed evolution patterns and associated parameter regimes suggest genuine variations in underlying nonlinear dynamics

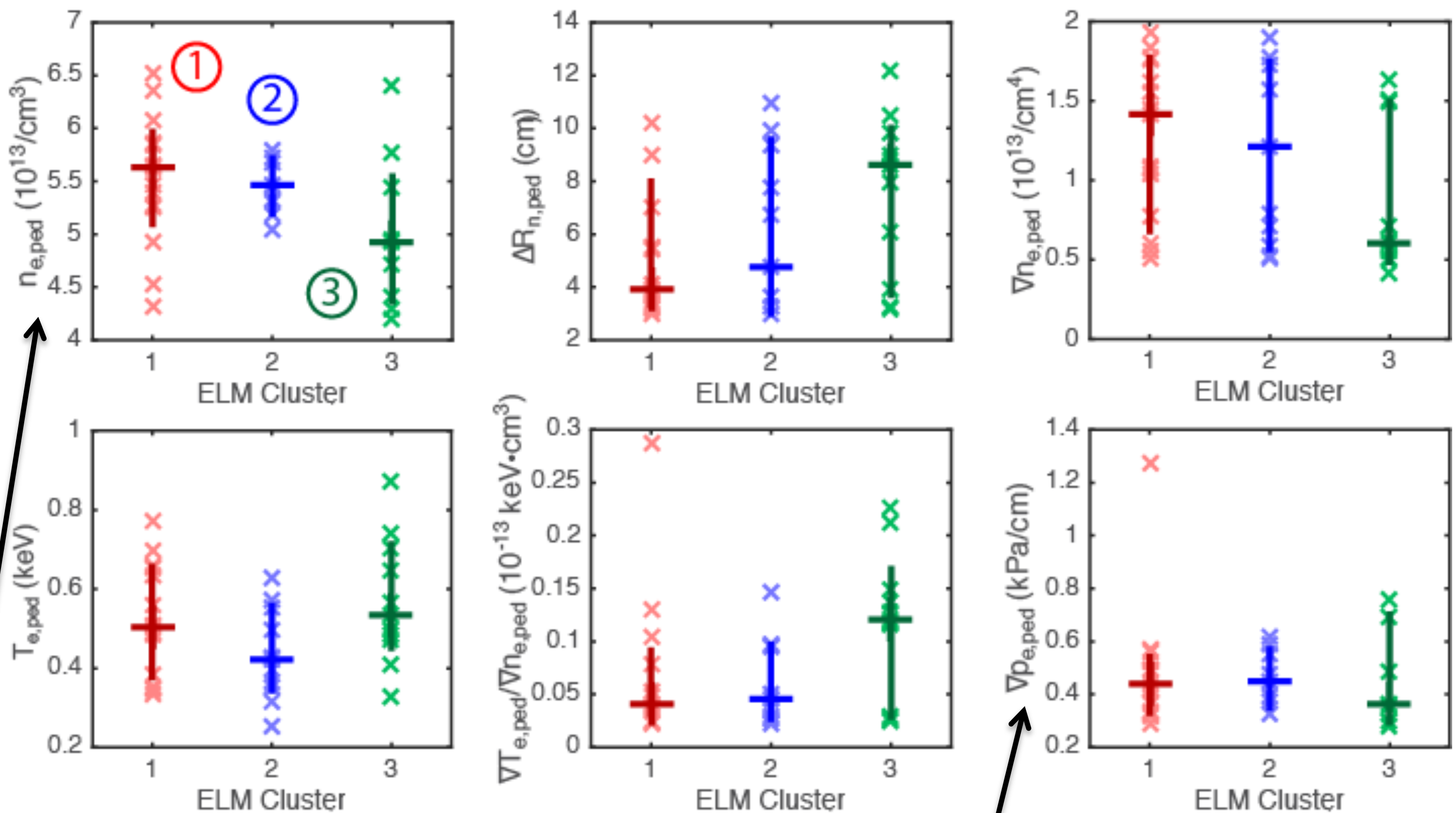


Higher triangularity is stabilizing for PB modes (Snyder, PPCF, 2004)

At higher Ip, most unstable mode shifts to lower n (Liu, PoP, 2014)

Higher Ip is stabilizing for PB (Snyder, PPCF, 2004)

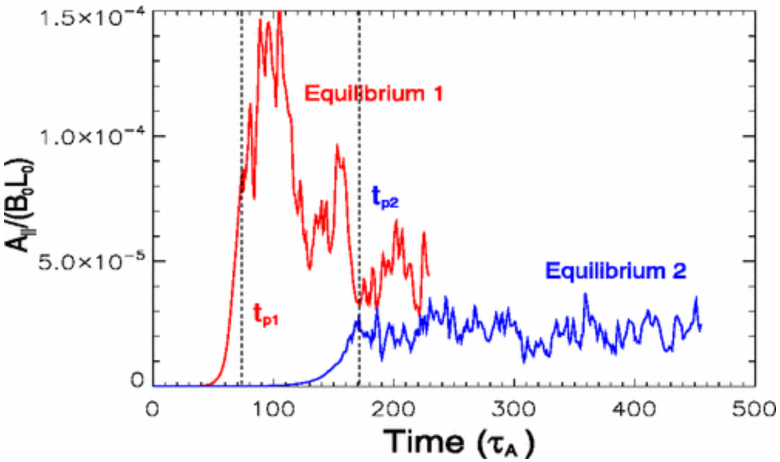
Identified ELM groups correlate with distinct parameter regimes (II)



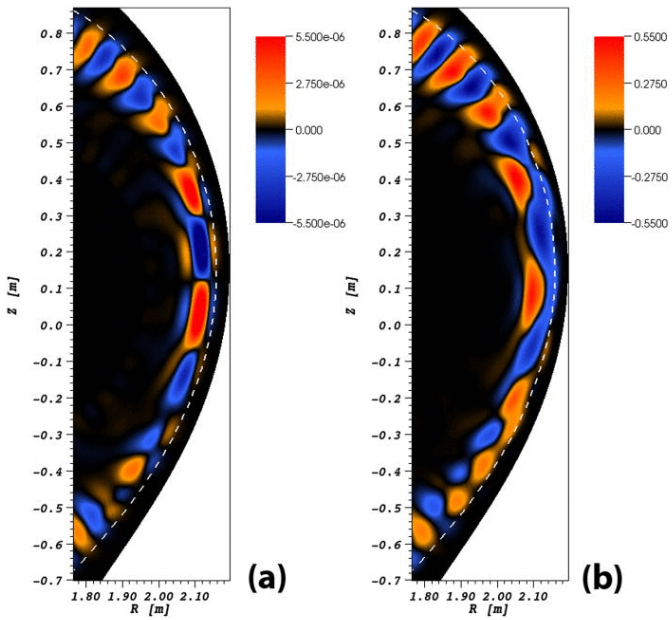
Pedestal density parameters appear to differentiate the ELM groups

The pressure gradient does not appear to differentiate the ELM groups

Nonlinear ELM simulations provide time evolution and 3D perturbations

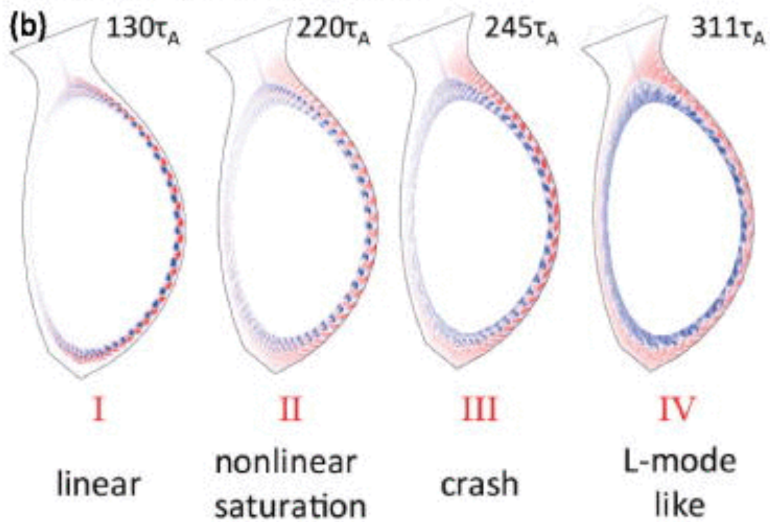


X. Xu et al, PRL, 2010



M. Holzl et al, PoP, 2012

Simulated pressure perturbations



Z. Liu et al, PoP, 2014

Work-in-progress:
Nonlinear BOUT++ simulations for the identified ELM evolution patterns and parameter regimes

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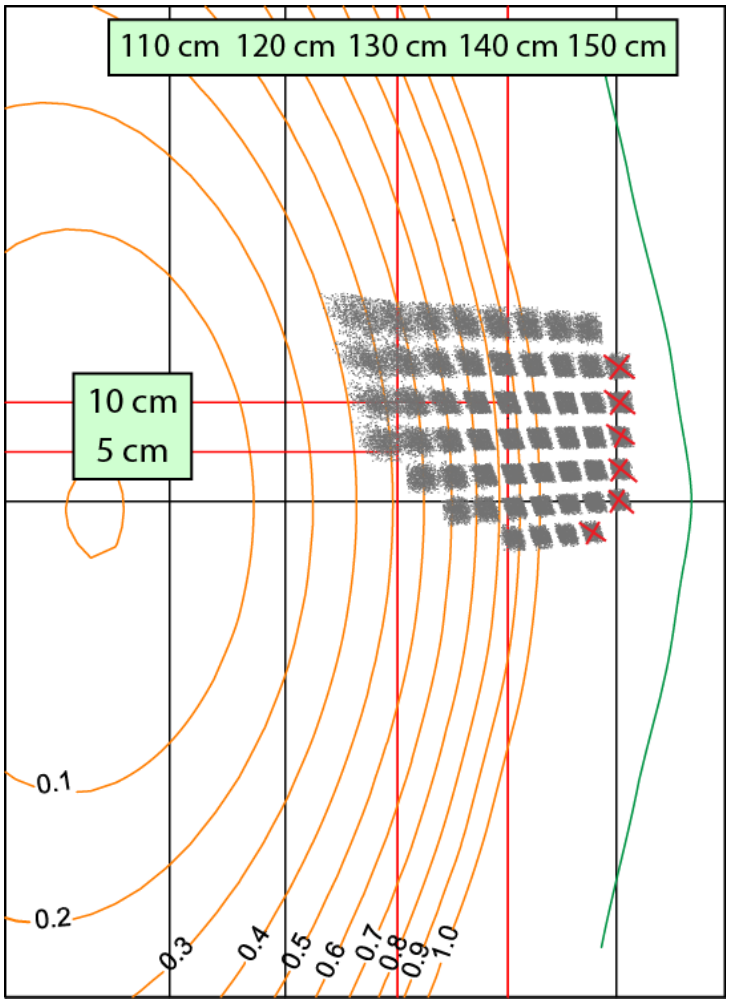
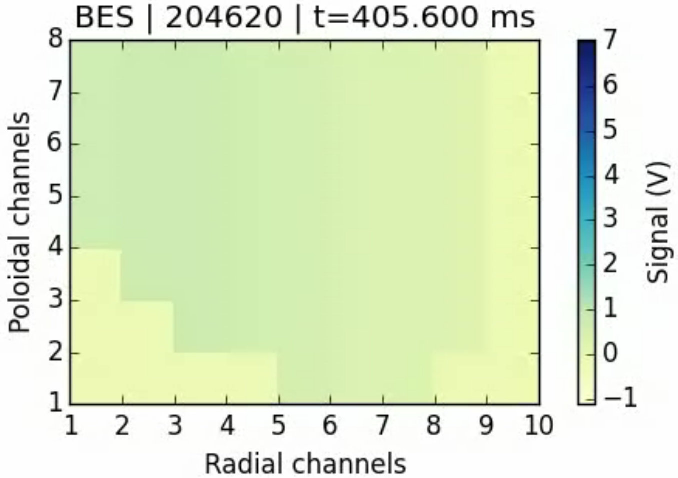
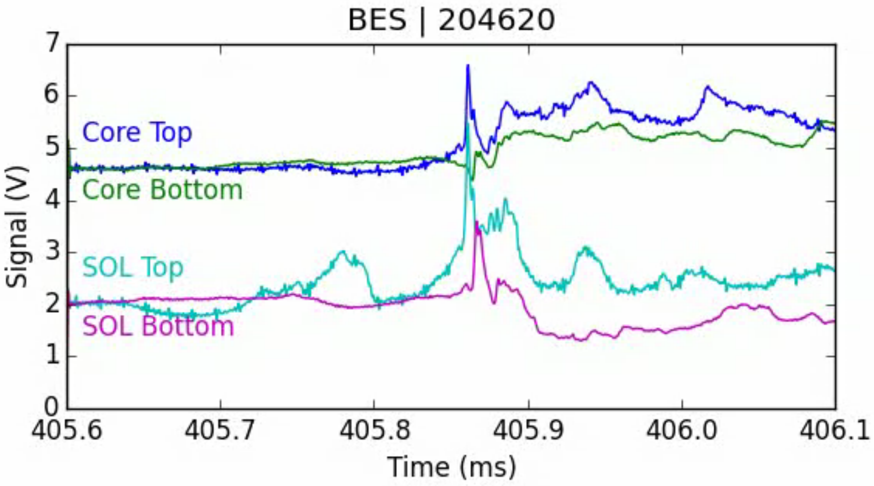
2D BES measurement of ELM event on NSTX-U







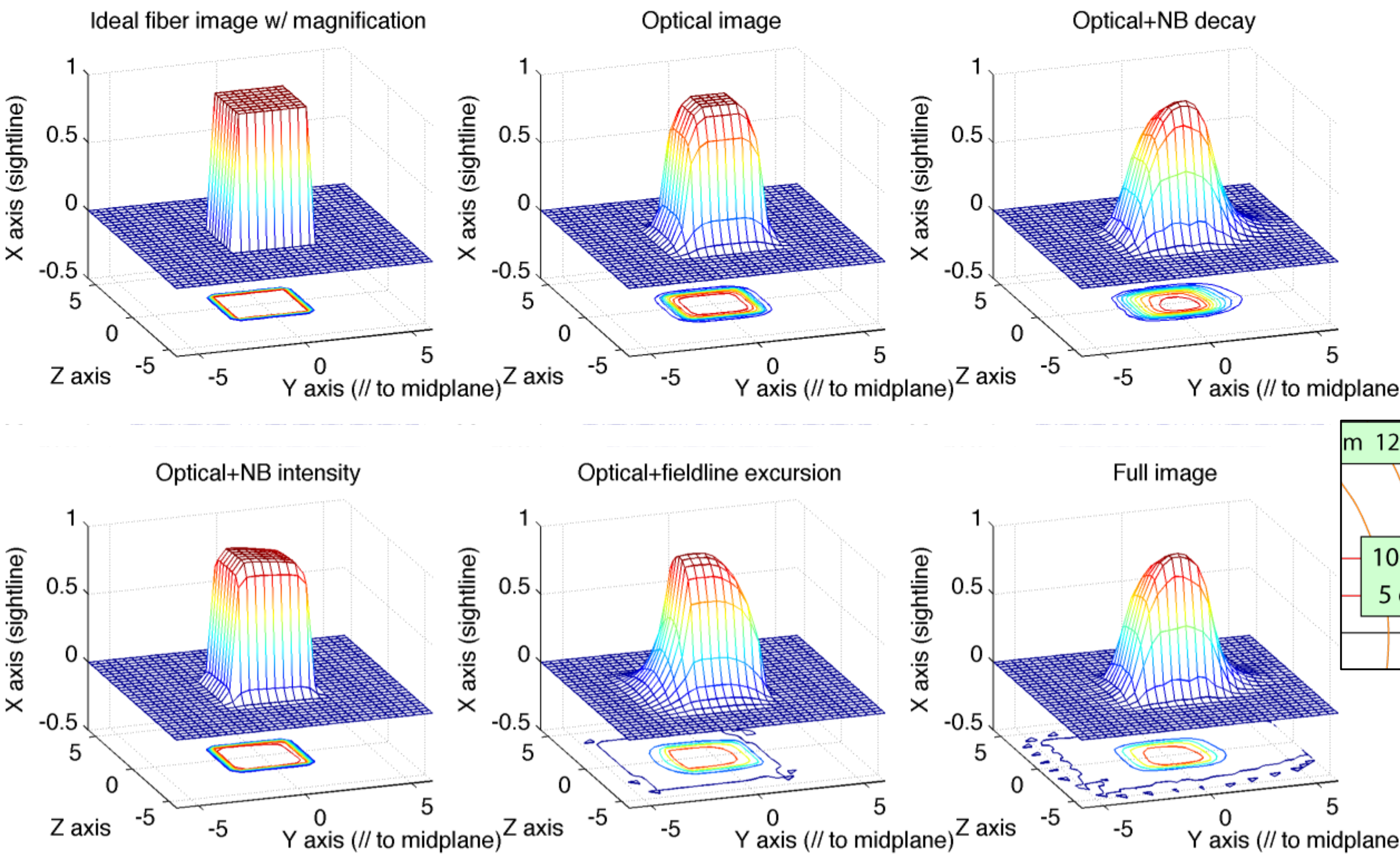
Summary

- 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 correlate with parameter regimes relevant to ELM physics
    - Ip, q-95, δ, dR_{sep}, $n_{e,ped}$, $\Delta R_{n,ped}$
    - Working towards NL simulations to clarify the mechanisms at play in the identified ELM groups
- 2D BES measurements are now available on NSTX-U
- Machine learning techniques can leverage large data archives for pattern recognition, relationship discovery, and automated classification

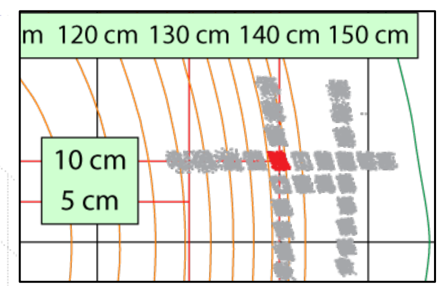
Backup

Point spread function calculations indicate NB excited state lifetimes and fieldline trajectory blur the $1/e^2$ spot size by 10%

	Fiber bundle	Optical Image	Opt + D* Lifetime	Opt + NB int.	Opt + B Misalign.	All Effects
Rad. $1/e^2$ width (cm)	3.2	4.0	4.4	3.2	4.4	4.4
Rad. displ. (cm)	0	0	0.5	0	-0.5	0.3



X (au) image int.
Y (cm) ~ radial
Z (cm) ~ binormal



Simulated fiber image

Machine learning techniques can boost the scientific impact of large data archives

- Many data-rich scientific fields successfully leverage machine learning techniques
  - Unsupervised pattern recognition, relationship discovery in complex datasets, automated data classification
  - Cancer genomics, exo-planet detection, seismic wave classification, seizure onset prediction
  - ML techniques excel when the quantity of data exceeds the capacity for human inspection
- NSTX/NSTX-U data archive
  - About 40 TB of data obtained with R&D investment approaching $1B
  - ML tools can leverage large data archive with automated, whole-archive analysis