Data-Driven Detection, Identification, and Prediction of Accelerator Cavity Faults

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on behalf of
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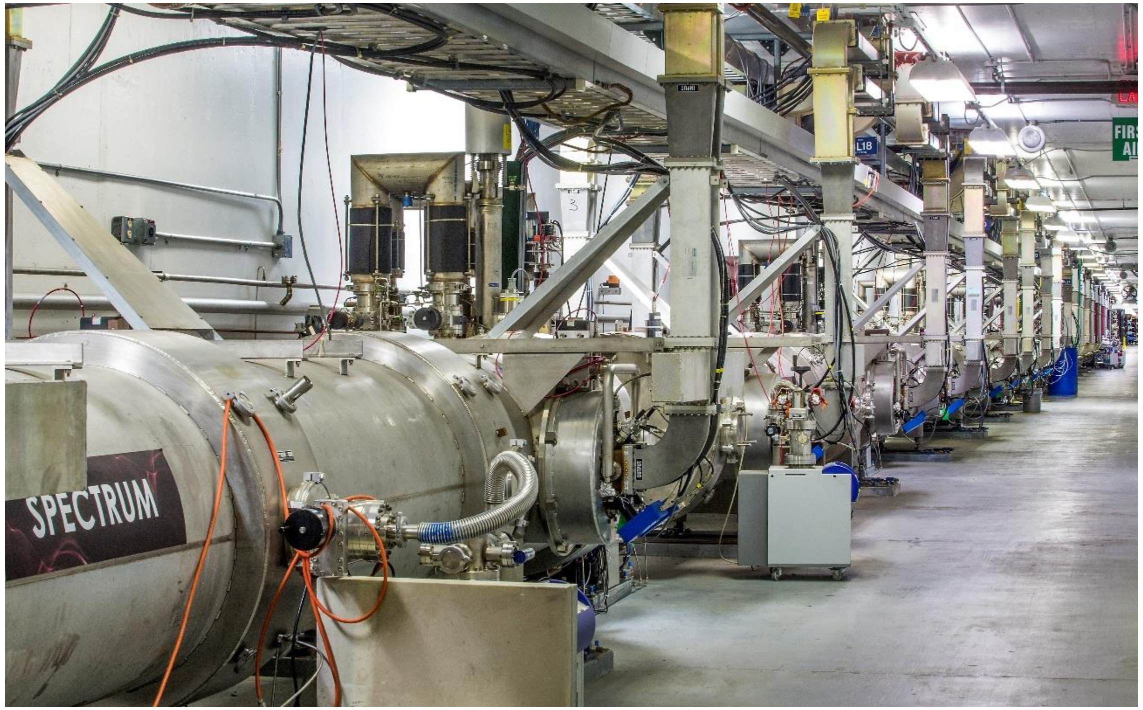
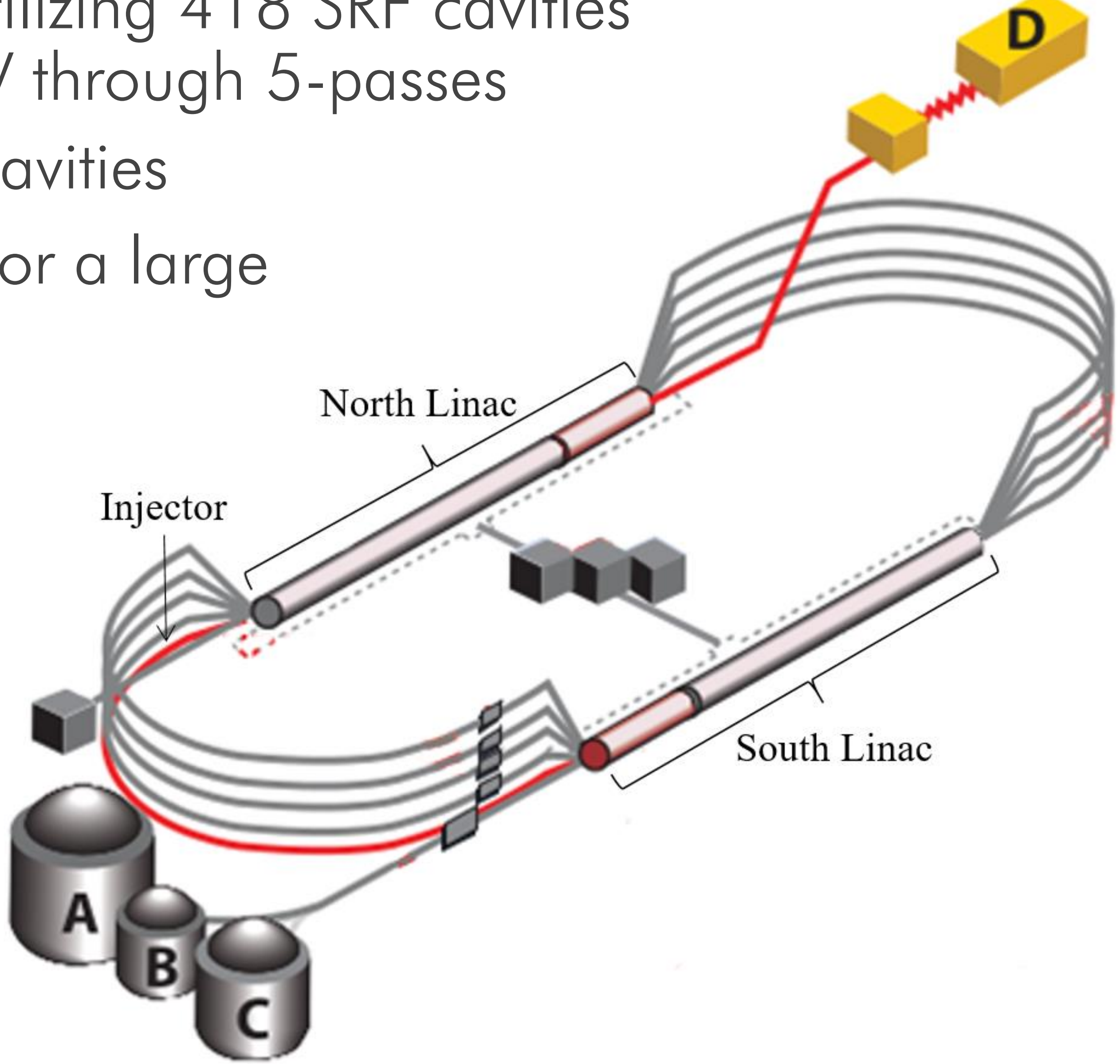
Outline

- ***Overview and Motivation***
- ***Case Study I: Detection***
  - ✓Cavity Instability Detection
- ***Case Study II: Identification***
  - ✓Cavity Fault Identification
- ***Case Study III: Prediction***
  - ✓Cavity Fault Prediction
- ***Data Quality Management***
- ***Summary***

Continuous Electron Beam Accelerator Facility

- CEBAF is a CW recirculating linac utilizing 418 SRF cavities to accelerate electrons up to 12 GeV through 5-passes
- the heart of the machine is the SRF cavities
- cavity instabilities and trips account for a large percentage of machine down time





Case Study I: Detection

- **Goal:**

  Automate the process of identifying unstable SRF cavities.

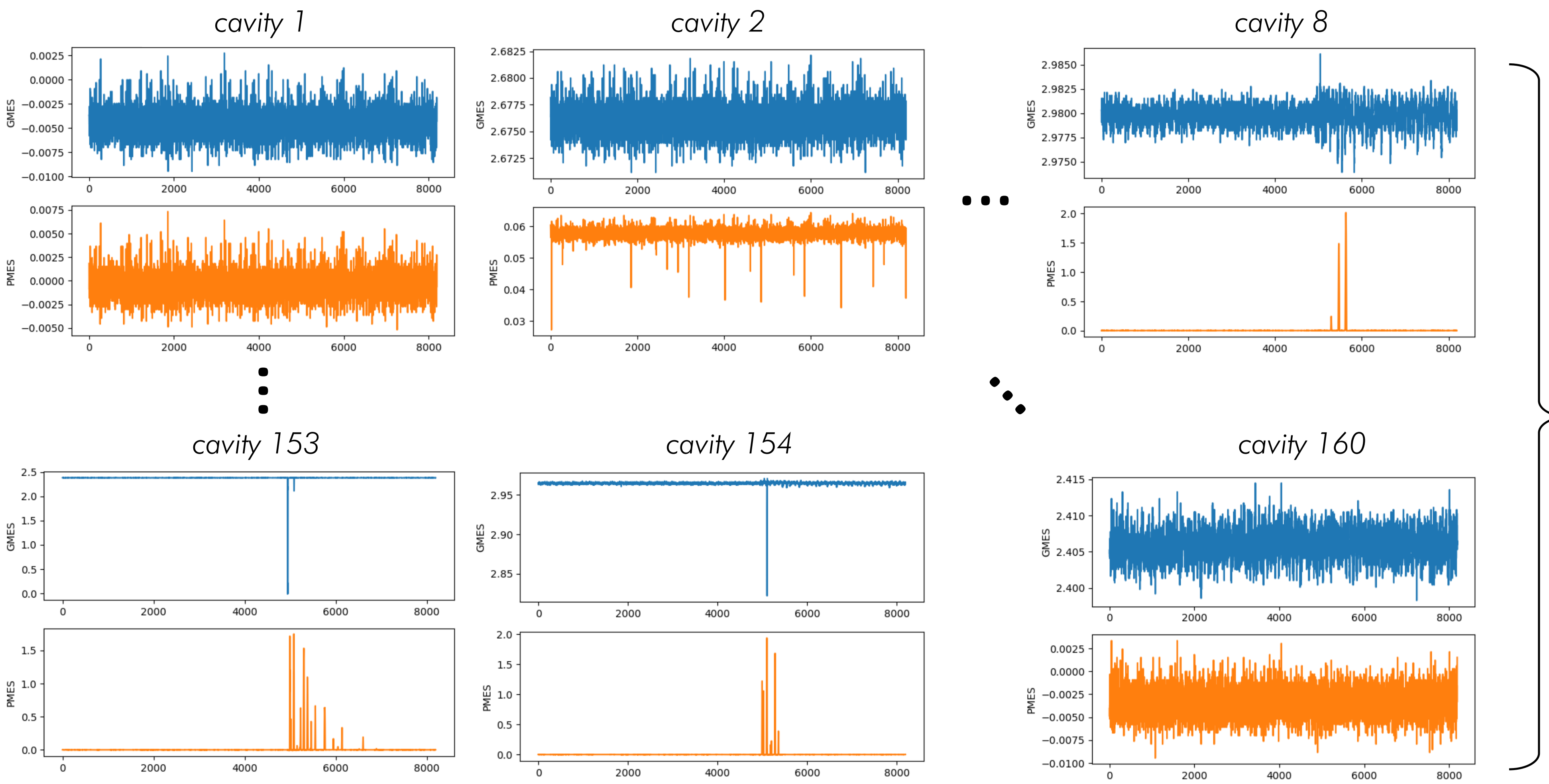
- **Description:**

  SRF cavities can become unstable and lead to a machine trip, *without presenting a fault themselves*. Identifying these unstable cavities with present diagnostics is difficult and time-consuming.

- **Solution:**

  1) develop and install a new fast DAQ system for the legacy SRF cavities
  2) apply unsupervised learning to identify unstable cavities (i.e. which cavity isn't behaving like the others?)
     - labeling is expensive
     - human labeling can be subjective
     - avoid issues with data drift (look for a cavity that is unlike it's neighbors *now*, at a particular timestamp, and not compared to historical data)

Filter and Collect Raw Signals from an Event



data from an event on Feb. 1, 2023 03:36:14 AM

- filter collects data when a fault involves a BLM, ion chamber, or BLA trip but <u>*not*</u> a cavity trip
- 1 event = 20 cryomodules x 8 cavities/cryomodule x 2 signals/cavity = 320 signals

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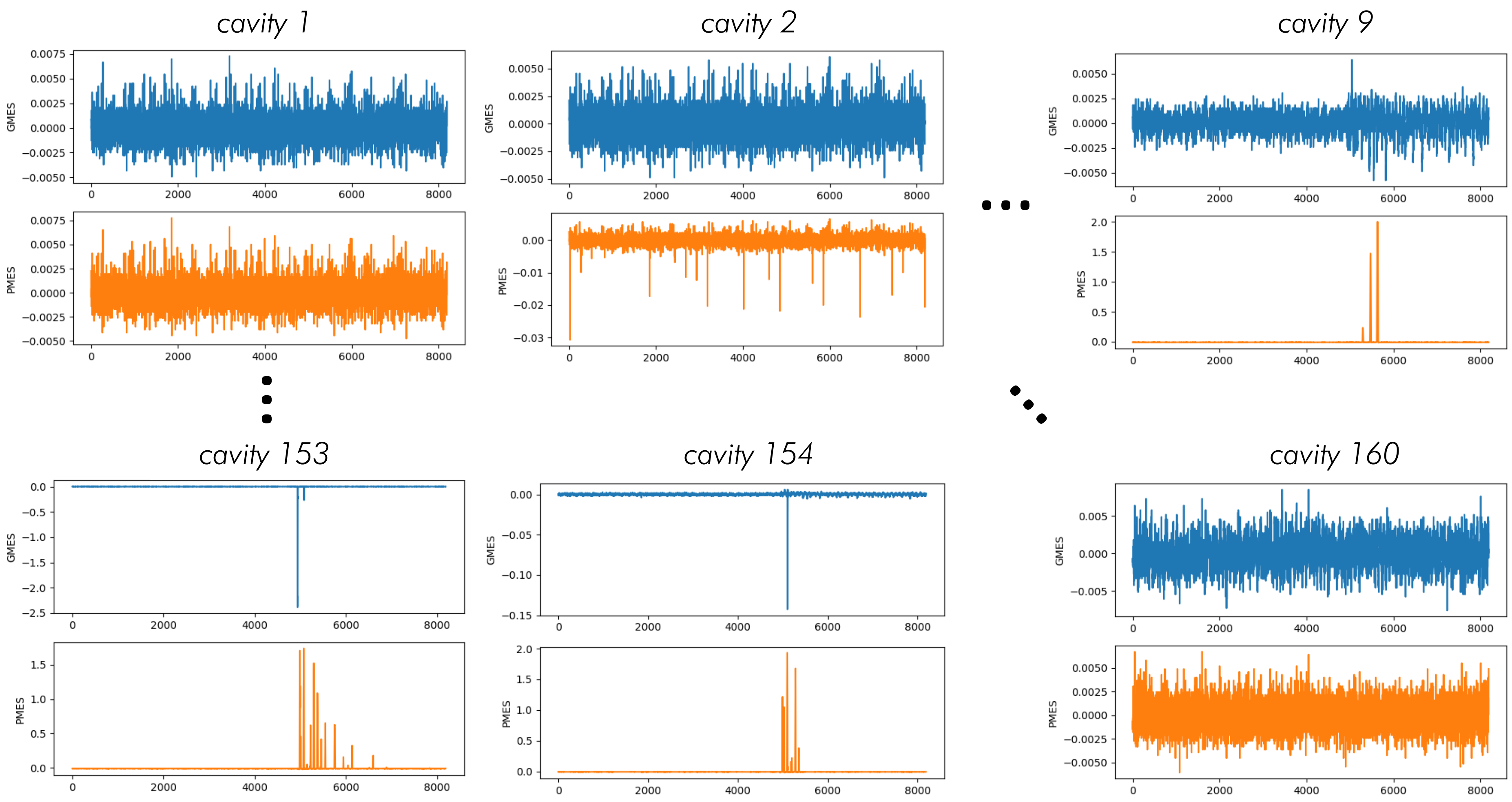
Pre-Process and Extract Features



160 × 2*n*-features

$$\begin{bmatrix} f_{1,1} & \cdots & f_{1,2n} \\ \vdots & \ddots & \vdots \\ f_{160,1} & \cdots & f_{160,2n} \end{bmatrix}$$

- standardize data
- extract *n*-features per signal using `tsfresh` and concatenate

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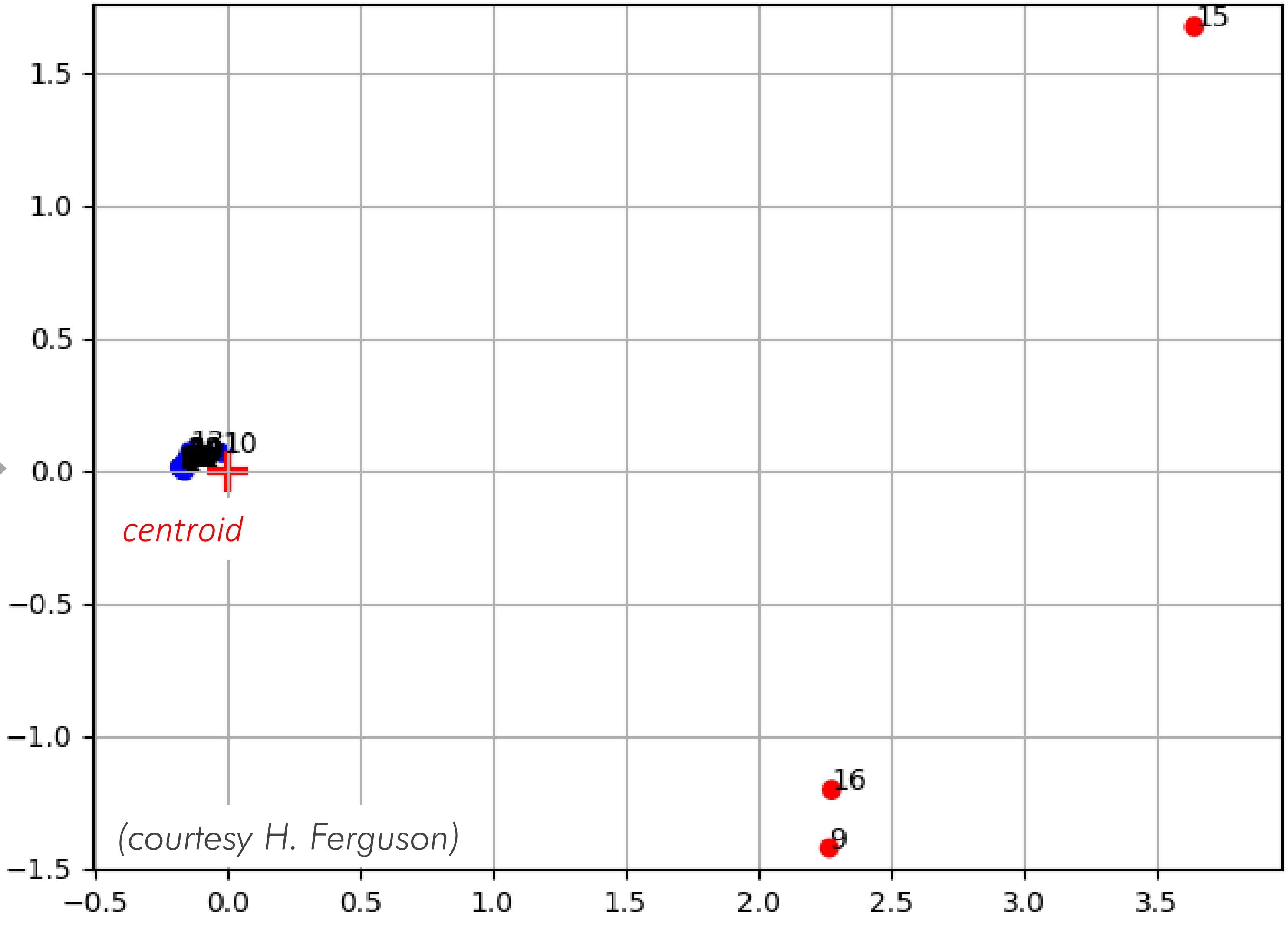
Principal Component Analysis (PCA)

- use PCA to reduce dimensionality from $2n$ to 2 for visualization
- compute centroid of cluster
- compute distance of every data point from centroid and plot

PCA

$160 \times 2n$-features $\Rightarrow$ 160×2 $\Rightarrow$

$$\begin{bmatrix} f_{1,1} & \cdots & f_{1,2n} \\ \vdots & \ddots & \vdots \\ f_{160,1} & \cdots & f_{160,2n} \end{bmatrix} \begin{bmatrix} PCA_{1,1} & PCA_{1,2} \\ \vdots & \vdots \\ PCA_{160,1} & PCA_{160,2} \end{bmatrix}$$



(courtesy H. Ferguson)

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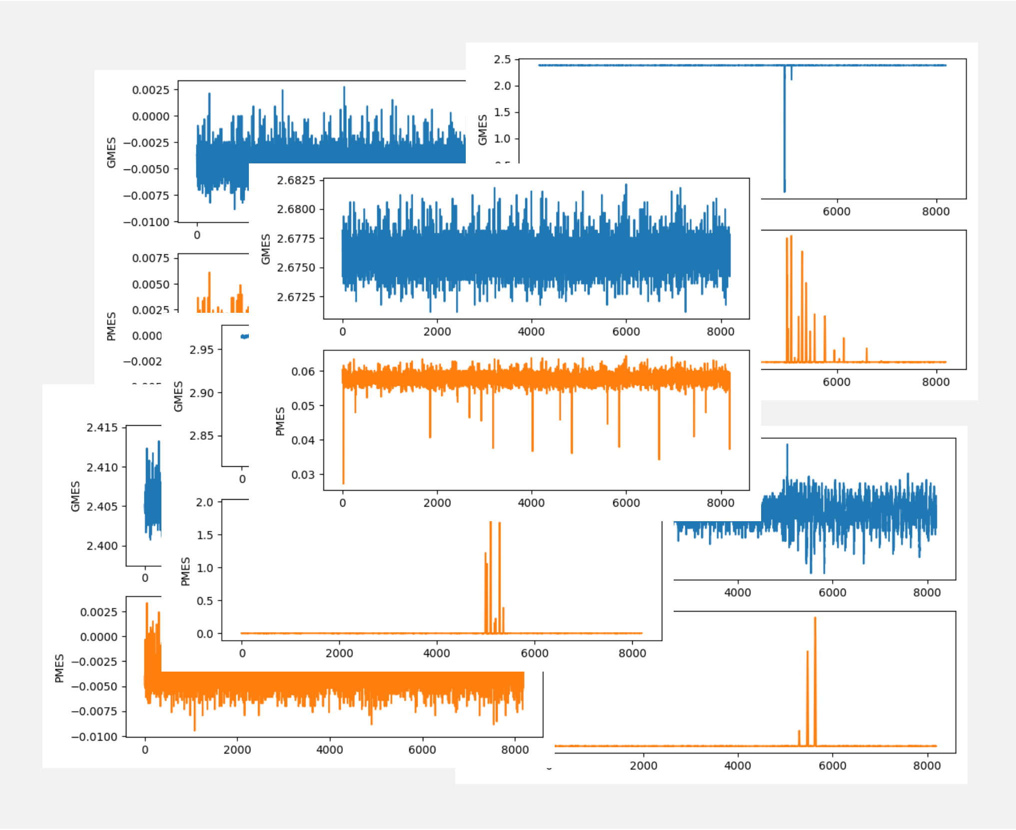
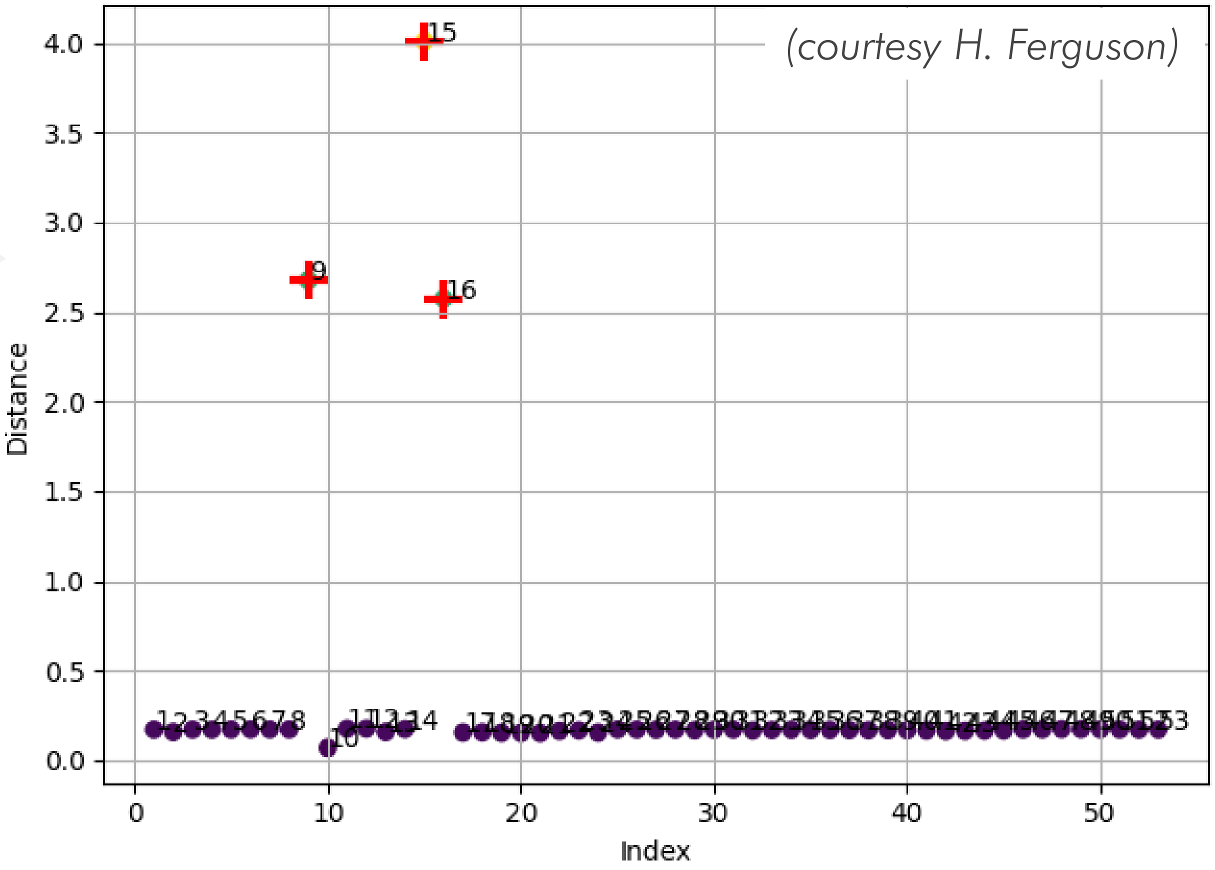
Distance from Centroid

1 event = 160 cavities × 2 signals/cavity × 8,192 points/signal





- anomalous cavities are easily identified as outliers

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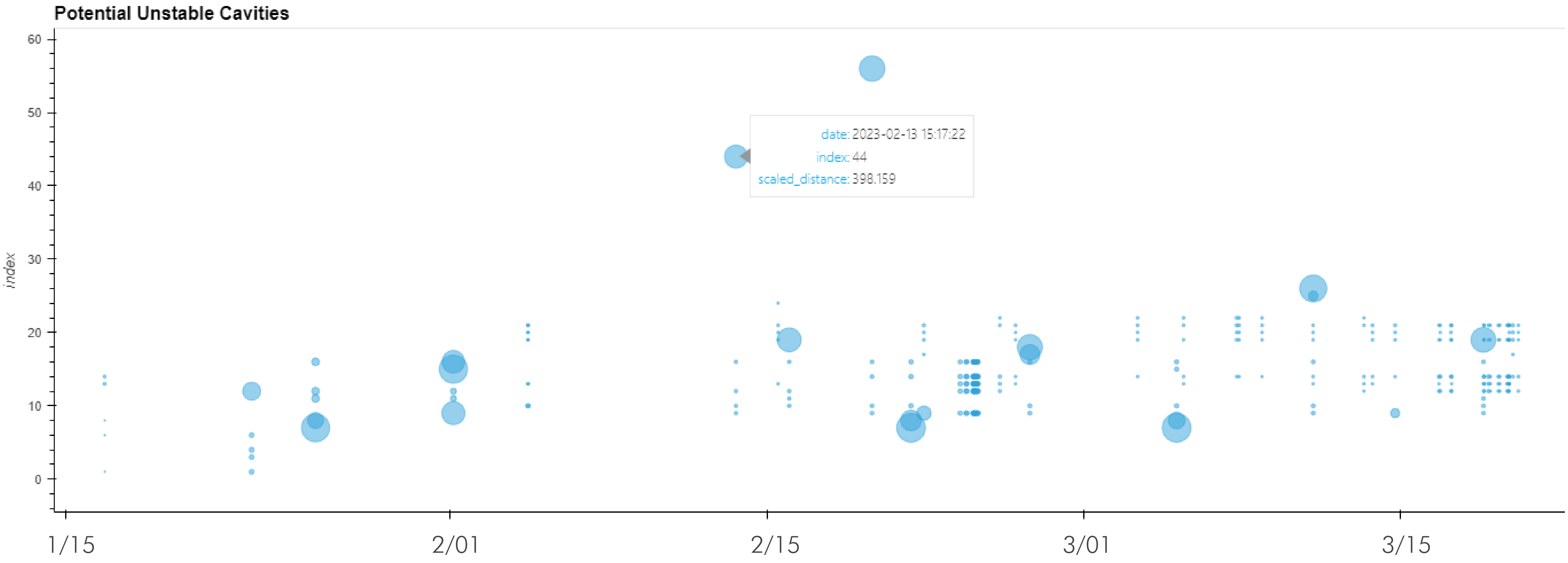
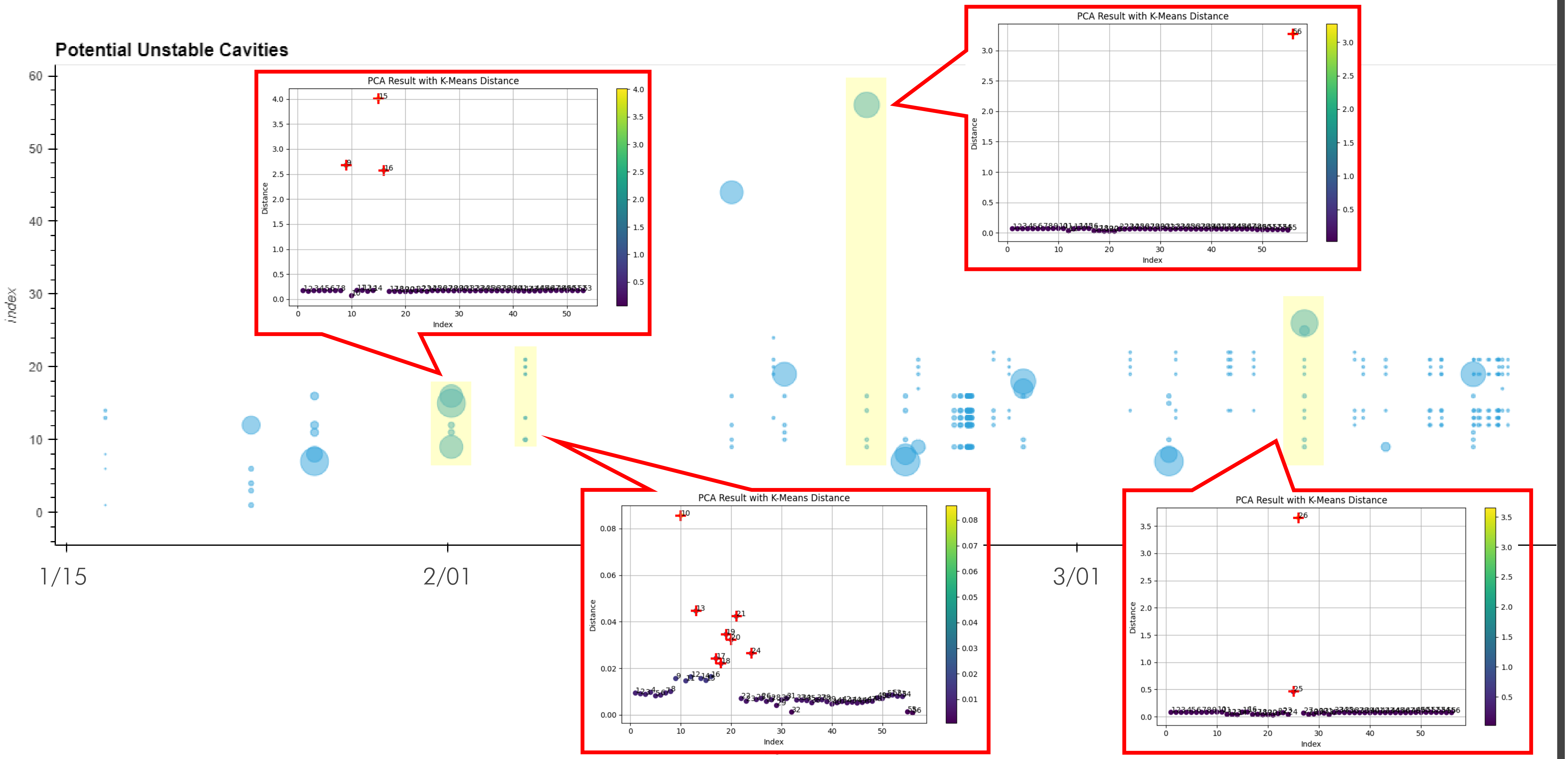
Timeline View: Multiple Events

- plot the top 5 distances as a function of time from 61 events in early 2023
  - ✓ y-axis is cavity index
- marker size is proportional to distance from centroid
  - ✓ the bigger the marker, the more anomalous the cavity behavior



Timeline View: Multiple Events



Case Study II: Identification

- **Goal:**

  Classify cavity faults to:

  1) provide feedback to control room operators (short term)
  2) provide data-driven guidance for maintenance activities (long term)

- **Description:**

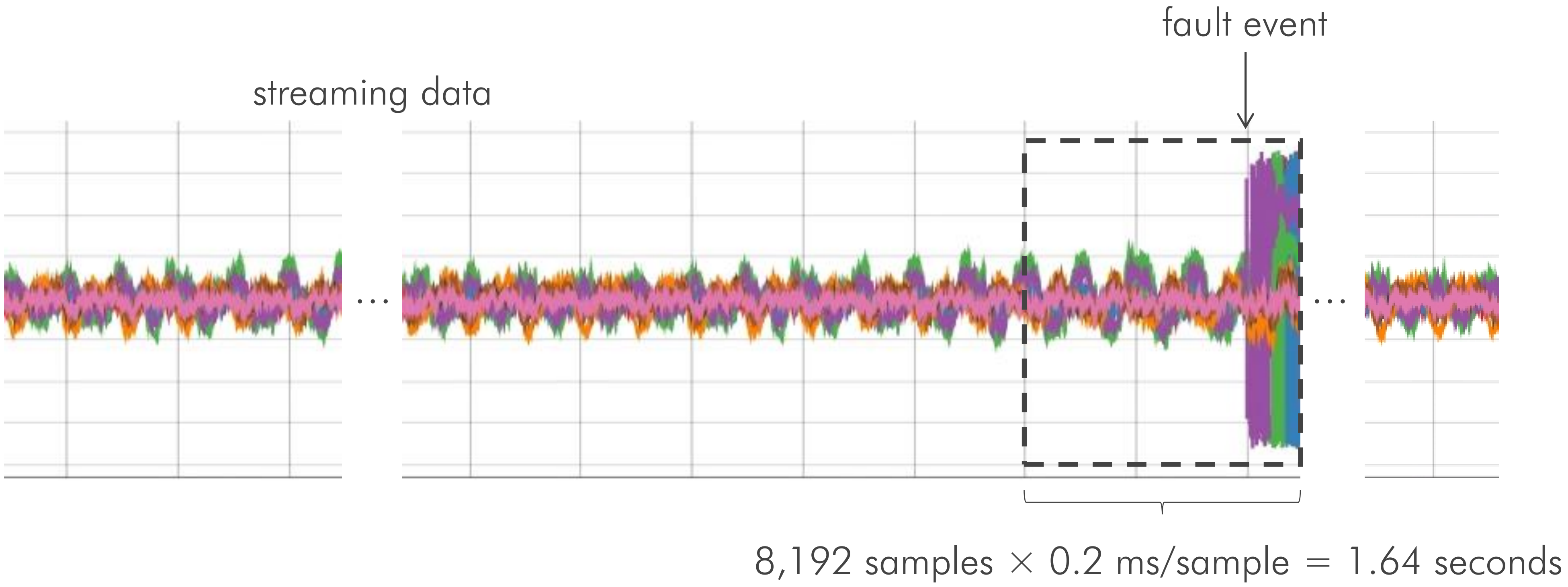
  A DAQ captures fast-sampled RF signals from (C100) cavity fault events and writes the data to file for offline analysis.

- **Solution:**

  Leverage several thousands of labeled fault events to train a DL model in a supervised way to classify time series signals.

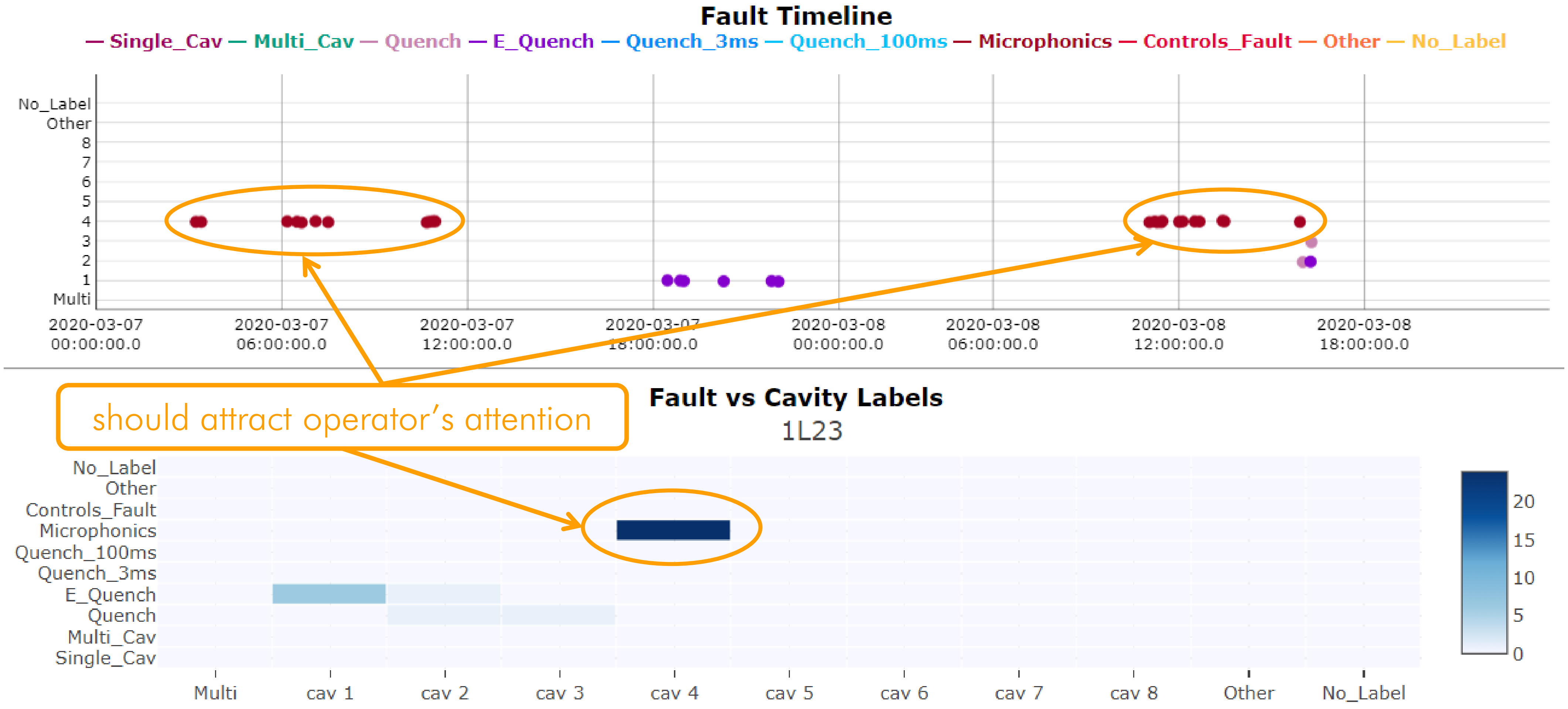
Data Acquisition System

- a waveform harvester was developed to capture RF time-series signals after a fault and write them to file for later analysis
  - ✓ each of the 17 harvested waveform signals is 8,192 points long
  - ✓ trigger set such that 94% of the recorded data precedes the fault and 6% after
  - ✓ pre-fault data provides valuable information about the root cause of the trip



Visualization and Communication

- for ML models to be effective, information must be communicated clearly and concisely
- visualize spatial and temporal nature of model predictions



(C. Tennant, PRAB **23**, 114601 (2020))

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Case Study III: Prediction

- **Goal:**

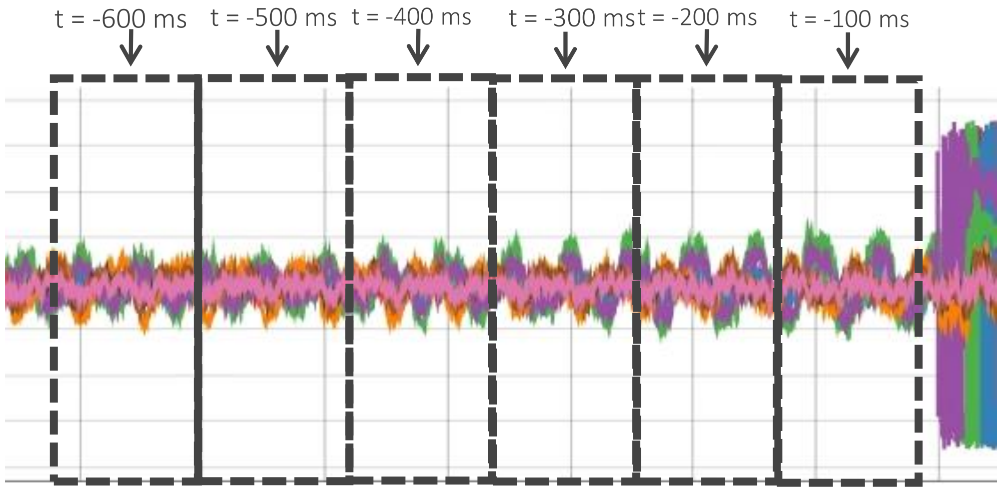
  Proactively *predict* if a cavity fault will occur.

- **Description:**

  Currently deployed ML models analyze data after a fault has occurred. Investigate the use of machine learning to predict if a fault will occur from pre-fault data.

- **Solution:**

  Train a 1D CNN – LSTM model architecture to discriminate between "stable" and "impending fault" signals.



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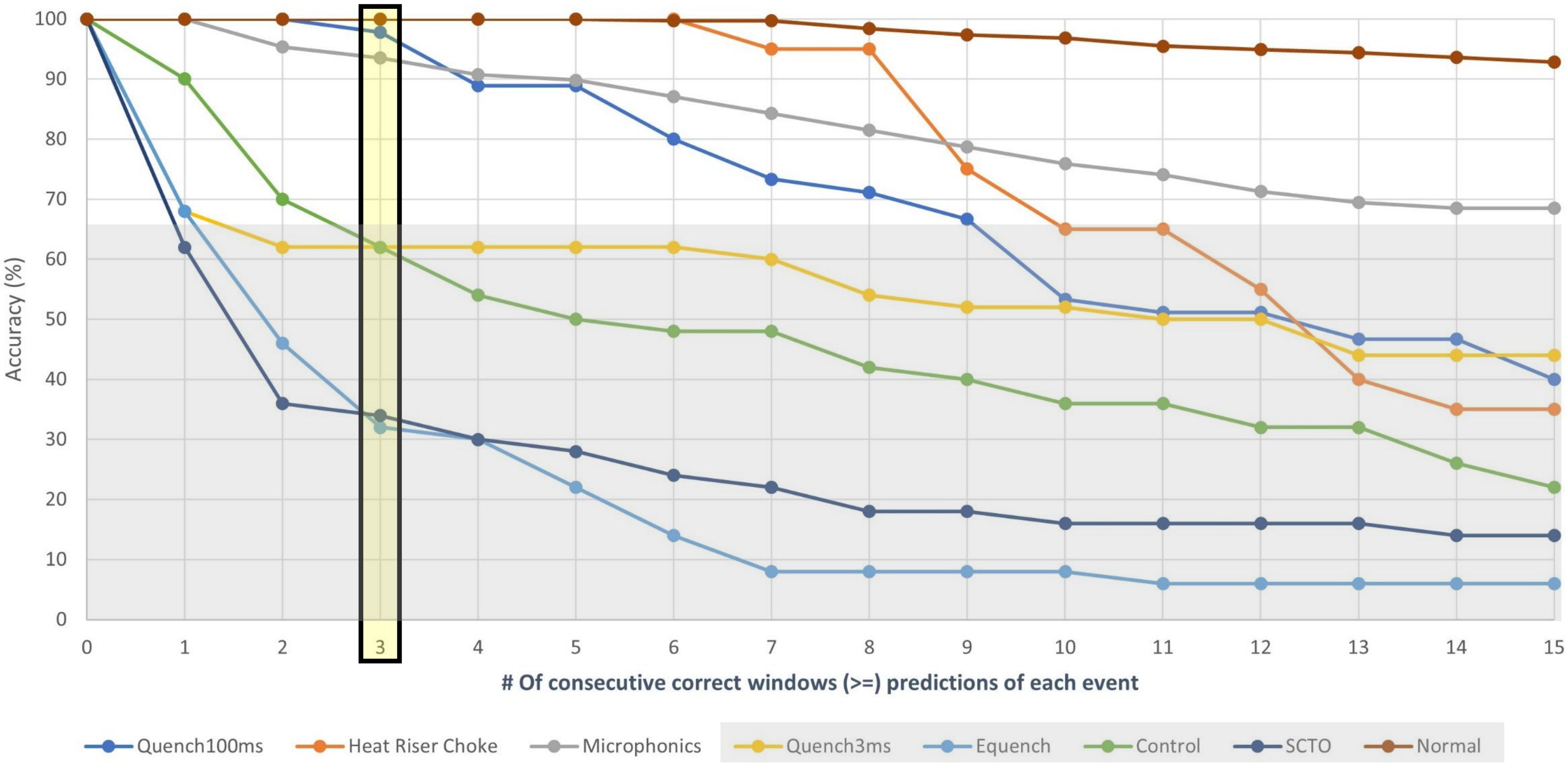
Binary Classifier Results for Prediction

- each fault example contains 15 100 ms windows of pre-fault data (1.5 sec)
- plot shows the number of *consecutive windows* correctly predicted as a fault by the model



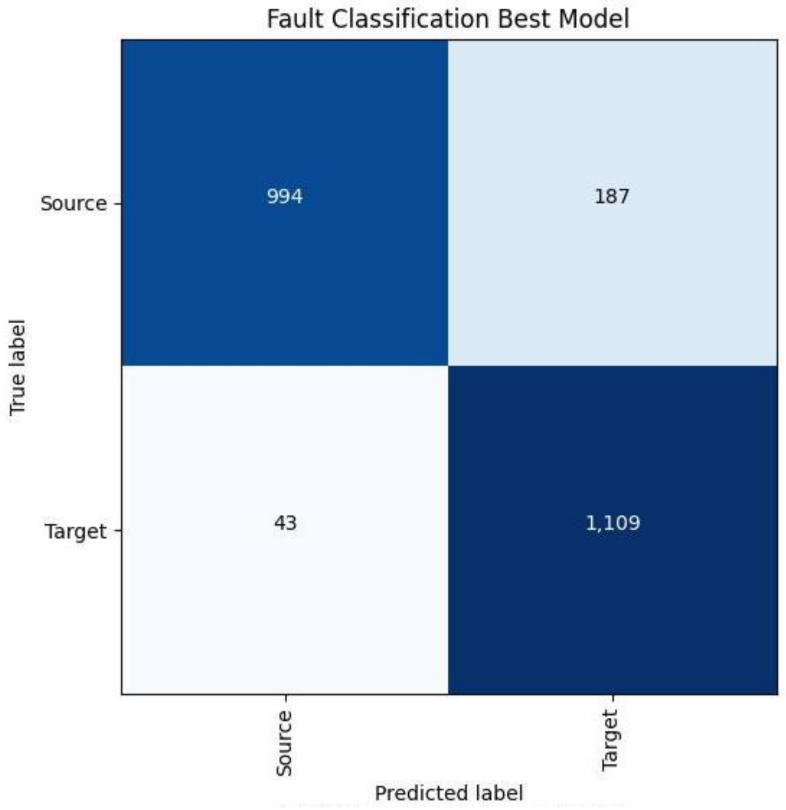
(courtesy Md. M Rahman)

Data Quality Management

- DAQ Configuration Control (or lack thereof)
  - ✓the system is the foundation of the fault identification and fault prediction work
  - ✓different groups can, and will, leverage the system for a variety of uses
  - ✓the flexibility of the system (i.e. sampling rate, when and how it is triggered) is both powerful and, in the absence of configuration control, detrimental
- Low Level RF (LLRF) Upgrade
  - ✓the LLRF system controls cavities, and in particular how they respond during a fault event
  - ✓the upgrade system creates very different fault signatures in the data
  - ✓several years – and many thousands of labeled examples – can no longer be used for training models
- Data Drift
  - ✓in ML applications for accelerators, addressing data drift is critical (seasonal changes, changes between operational runs, changes due to software/firmware modifications, etc.)
  - ✓this remains a work in progress for us

Example of Data Drift

- compare signals from "normal"/stable SRF cavity operation from Fall 2022 and March 2023
  - ✓ label data from Fall 2022 as "0"
  - ✓ label data from March 2023 as "1"
  - ✓ train a classifier to distinguish between the two



accuracy 90.14%

if the data was indistinguishable, the model would be "confused" and be reflected in the accuracy

(courtesy Md. M Rahman)

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Summary

- detecting, localizing (isolation) and classifying (identification) faults represent areas ripe for ML application
- the transition to fault prediction represents an ultimate goal
- in general, higher fidelity data is needed as you move along the spectrum from detection to isolation to identification to prediction
- more and more sources of information-rich data are becoming available, however data quality management remains a challenge
    - ✓hardware configuration control, documentation, and ownership, data formats and storage, ease of access, etc.

Thank You.

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