Training and Detection of Anomalies at European XFEL

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CDCS
CENTER FOR DATA AND COMPUTING
IN NATURAL SCIENCES

DESY.

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DER FORSCHUNG | DER LEHRE | DER BILDUNG

What's an Anomaly

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- ...
- A person with no perceptible faults, who consistently fails at achieving matches thru all forms of social media [Urban Dictionary]

Overview

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- **Example:** Anomaly detection on beam position monitors.

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- These X-ray flashes are then distributed to three beamlines (SASE).

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- At any moment, any component can **fail**.
- When a component fails, it can lead to undesired **downtime**.

Examples

(1) LLRF Cavities

- Monitoring signals from cavities.
- Detecting quenches and other faults.

(2) Orbit Monitoring

- Analyzing electron orbits in SASEs.
- Various types of problems are indicated by variations on orbits.

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- Very low temperatures (near absolute zero) are needed for superconductivity.

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- We record an envelope (phase, amplitude) of three signals - probe, forward and reflected signals.
- Each signal consists of a pair of 1820 values (amplitude, phase) per pulse.
- Quench (right) means a loss of superconductivity in a cavity, which has a significant effect on the quality factor.

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- Semi-supervised anomaly loss [Ruff(2019)]

$$L(\theta) = \|f_\theta(\mathbf{x}) - \mathbf{c}\|_2^y + \|f_\theta(\mathbf{x}) - \mathbf{c}\|_2 \text{ where } y \in \{-1, 1\}.$$

(1) Semi-Supervised Anomaly Loss

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(1) Results - Quenches

(1) Feature Space - TSNE of $f_\theta(\mathbf{x})$

Healthy / Faulty

Healthy / Healthy

(2) Orbit Monitoring

Assumption

There is a systematic pattern shown in orbits given by the physical construction of EuXFEL.

Orbit Monitoring - FODO Lattice

[Wendt(2011)]

[Holzer(2006)]

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(2) Data-Driven Orbit Monitoring

Model-Based Orbit Monitoring

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- Fit a sine and measure residual.
- **Pros** It is **fast** and **intuitive**.
- **Cons** No intra-bunching instabilities.

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Model-Free Orbit Monitoring

- Series of BPM read-outs.
- Train a model with the anomaly loss.
- **Pros** Takes into consideration intra-bunching instabilities.

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- **Unsupervised one-class anomaly** loss [Ruff et al.(2018)Ruff, Vandermeulen, Goernitz, Deecke, Siddiqui, Binder, Müller, an

$$L(\theta) = \|f(\mathbf{x};\theta) - \mathbf{c}\|_2$$

Beam is O.K.

Anomaly score s

TSNE Embedding of $f(\mathbf{x})$

Lowest score orbits

Highest scores orbits

PSM Board Failture

Anomaly score s

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Undulator Crash

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Phase Shifter Crash

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Thank you!

This is the joint work of A. Eichler, R. Kammering and T. Wilksen!

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