Status of Data-Driven Beam Trajectory Anomaly Detection at European XFEL

3rd ICFA Beam Dynamics Mini-Workshop on Machine Learning Applications for Particle Accelerators

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Chicago, IL, 2 Nov 2022

DESY.

European XFEL

The European XFEL:

- Consists of superconducting cavities that boost electrons.
- The electrons are then directed through specially arranged magnets (undulators).
- Then they emit extremely short and intense X-ray flashes.
- These X-ray flashes are then distributed to three beamlines (SASE).

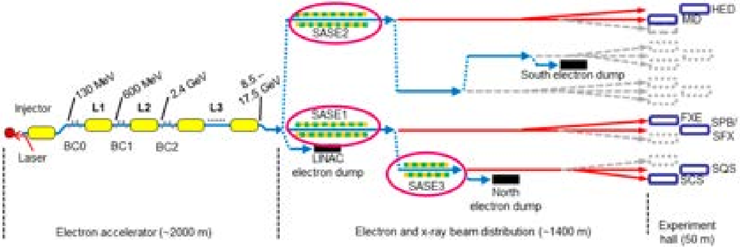
Data-Driven Predictive Maintenance on European XFEL

- Thousands of devices are involved in EuXFEL.
- Many components are operating in **extreme conditions** (radiation, heat...).
- At any moment, any component can **fail**.
- When a component fails, it can lead to undesired **downtime**.

Examples

Orbit Monitoring

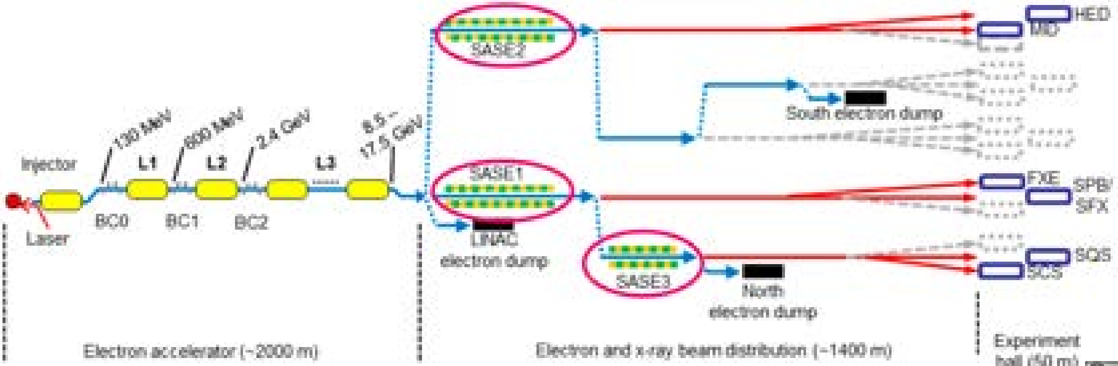
- Analyzing electron orbits in undulator SASEs.
- Various types of problems are indicated by variations in orbits.



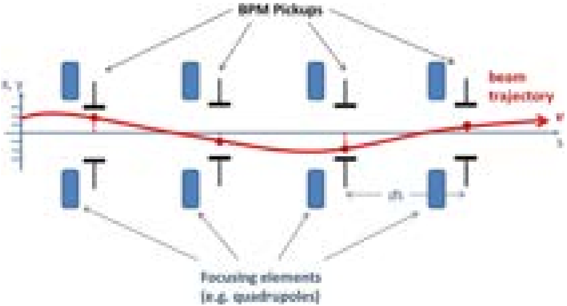
Orbit Monitoring

Assumption

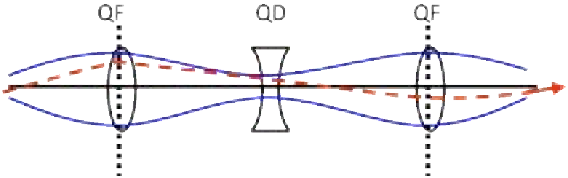
There is a systematic pattern shown in orbits given by the physical construction of EuXFEL.



Orbit Monitoring - FODO Lattice



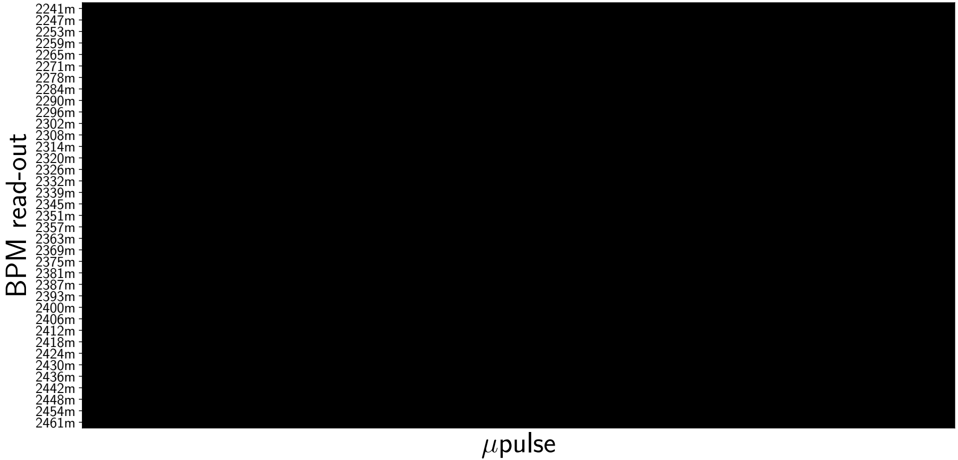
Source: [Wendt(2011)]



Source: [Holzer(2006)]

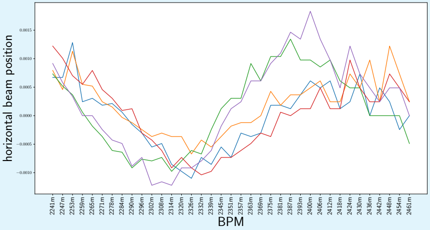
Orbit Monitoring

Orbit Monitoring



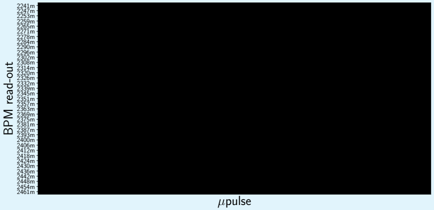
Data-Driven Orbit Monitoring

Model-Based Orbit Monitoring



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

Model-Free Orbit Monitoring

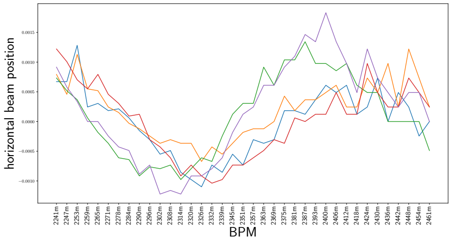


- Series of BPM read-outs.
- Train a model with the anomaly loss.
- **Pros** Takes into consideration intra-bunching instabilities.

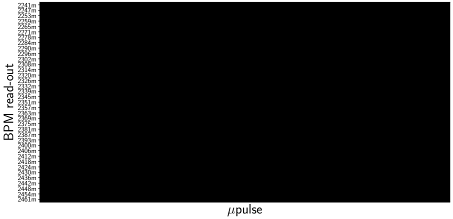
Data

- **No labels**, just logbook records.
- We rarely have an **interpretation** how a failure is propagated to orbit (if so).
- We have 84351 minutes which spans from **Feb 25 2022** to **May 19 2022**.
- Each minute record has ≈600 macro-pulses (1 minute, 10 Hz) ordered sequentially.
- Only **first bunch** in the bunch train is considered!

BPM/position (each line is one bunch)



μ-pulse vs BPM (stack of bunches)



Model-Free Data-Driven Orbit Monitoring

$$\underbrace{\underset{\text{input}=2|\text{BPM}|}{\mathbf{h}_1 = \text{A Layer}(\mathbf{x})} \longrightarrow \cdots \longrightarrow \phi = \text{Linear}(\mathbf{h})}_{f_\theta(\mathbf{x})} \longrightarrow \underset{\text{input}=16,\ \text{output}=1}{s(\phi) := \|\phi - \mathbf{c}\|_2^2}$$

- Units that are scoring a series of BPM read-outs.
- Each input is stacked in horizontal and vertical positions from all beamlines.
- We **do not** have any **faulty labels**.
- **Unsupervised one-class anomaly** loss [Ruff(2018)]:

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

- Trained features f_θ can be used for further analysis, e.g. TSNE embedding.

Models

Linear - The Simplest

Bunches **scored independently**, i. e. no correlations of adjacent bunches are taken into consideration.

Recurrent - The Classics for Sequences

Has an **”internal state”** and takes into consideration other bunches and their order

Convolutional - Translation Invariant

Does not have an internal state, but is **translation invariant**. It still considers the order.

Transformers - Permutation Invariant

Takes co-occurrences of some bunches into consideration (if the positional encoding is not used) - i. e. **permutation invariant**.

Linear Units

$$\underbrace{\underset{\text{input}=|\text{BPM}|,\ \text{output}=|\text{BPM}|}{\mathbf{h}_1 = \text{Linear}(\mathbf{x})} \longrightarrow \underset{\text{input}=|\text{BPM}|,\ \text{output}=|\text{BPM}|}{\mathbf{h}_1 = \text{Linear}(\mathbf{x})} \longrightarrow \underset{\text{input}=|\text{BPM}|,\ \text{output}=16}{\phi = \text{Linear}(\mathbf{h}_2)}}_{f_\theta(\mathbf{x})} \longrightarrow \underset{\text{input}=16,\ \text{output}=1}{s(\phi) := \|\phi - \mathbf{c}\|_2^2}$$

- The **simplest**.
- Individual bunches are **independent**.
- Surprisingly **powerful** already.
- Very **hard to interpret** (in general).

Recurrent Neural Networks - Old Classics

$$\underbrace{\underset{\text{input=|BPM|, output=|BPM|}}{\mathbf{h}_1 = \mathrm{LSTM}(\mathbf{x})} \longrightarrow \underset{\text{input=|BPM|, output=|BPM|}}{\mathbf{h}_1 = \mathrm{LSTM}(\mathbf{x})} \longrightarrow \underset{\text{input=|BPM|, output=16}}{\phi = \mathrm{Linear}(\mathbf{h}_2)}}_{f_\theta(\mathbf{x})} \longrightarrow \underset{\text{input=16, output=1}}{s(\phi) := \|\phi - \mathbf{c}\|_2^2}$$

- A **classic way to handle sequences**, literally a few lines of code to make a model.
- **Slow** (very inefficient on GPUs).
- Results are **similar** to the purely **linear** model.

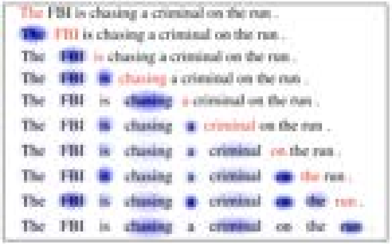
Transformers

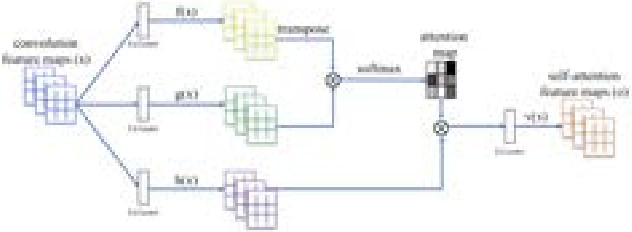
$\mathbf{h}_1 = \text{Transformer}(\mathbf{x})$ → $\phi = \text{Linear}(\mathbf{h}_1)$ → $s(\phi) := \|\phi - \mathbf{c}\|_2^2$

input=|BPM|, output=128 | input=128, output=16 | input=64, output=1

$$\underbrace{\mathbf{h}_1 = \text{Transformer}(\mathbf{x}) \rightarrow \phi = \text{Linear}(\mathbf{h}_1)}_{f_\theta(\mathbf{x})}$$

- Transformers have self-attention mechanism, puts other inputs into a **”context”**
- **Permutation invariant**, scores all bunches in correlation with other bunches (if no positional encoding is used).



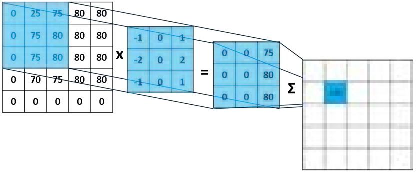


Source: https://lilianweng.github.io/posts/2018-06-24-attention/

Convolutional Neural Networks

$$\underbrace{\underset{\text{input}=|\text{BPM}|}{\mathbf{h}_1 = \text{Conv2d}(\mathbf{x})} \longrightarrow \mathbf{h}_2 = \text{Conv2d}(\mathbf{h}_1) \longrightarrow \underset{\text{output}=16}{\phi = \text{Linear}(\mathbf{h}_2)}}_{f_\theta(\mathbf{x})} \longrightarrow \underset{\text{input}=16,\ \text{output}=1}{s(\phi) := \|\phi - \mathbf{c}\|_2^2}$$

- **Translation** invariant.
- Unlike RNNs very **fast** on GPUs!
- The dynamic number of bunches was eliminated via calculating maximum over features along bunch dimensions.
- Therefore a single number for an arbitrarily long sequence.



Source: https://mlnotebook.github.io/post/CNN1/

CNN + Transformers

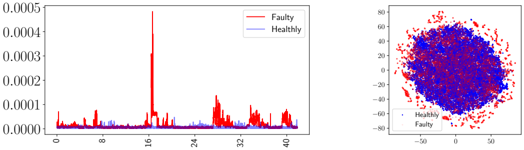
$$\underbrace{\underset{\text{input}=|\text{BPM}|}{\mathbf{h}_1 = \text{Conv2d}(\mathbf{x})} \longrightarrow \mathbf{h}_2 = \text{Transformer}(\mathbf{h}_1) \longrightarrow \underset{\text{output}=16}{\phi = \text{Linear}(\mathbf{h}_2)}}_{f_\theta(\mathbf{x})} \longrightarrow \underset{\text{input}=16,\ \text{output}=1}{s(\phi) := \|\phi - \mathbf{c}\|_2^2}$$

- **Translation and permutation** invariant.
- Still fast on the GPU.
- Fixes the problem with the dynamic number of bunches, each bunch is like a token after being processed by CNN.

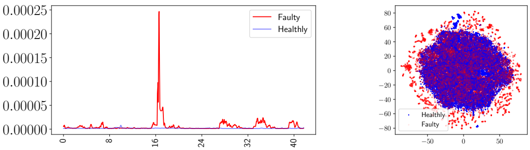
Example 1

The undulator server crashed after an unusual selection of colors for individual cells

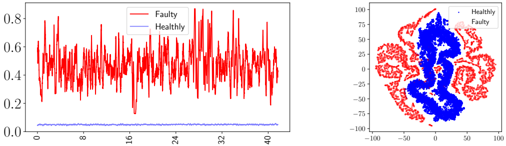
Linear



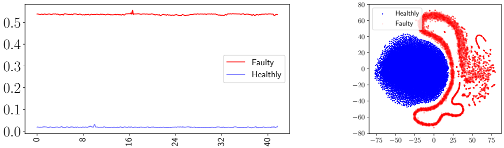
RNN



Transformer



CNN+Transformers



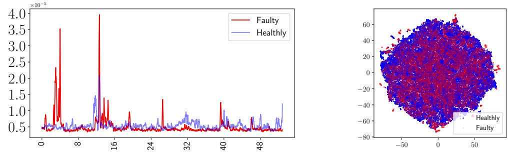
CNN

$s_{faulty} = \mathbf{0.0639}$ $s_{healthly} = 0.003$

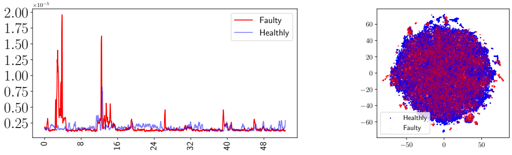
Example 2

An issue with a cold quadrupole in A6

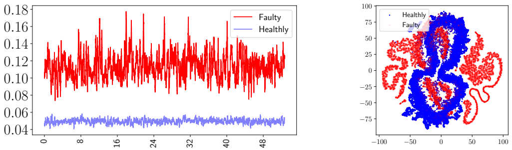
Linear



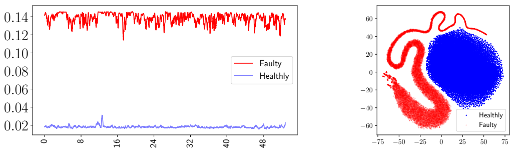
RNN



Transformer



CNN+Transformers



CNN

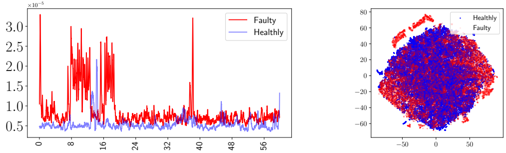
$s_{faulty} = \mathbf{0.0086}$

$s_{healthly} = 0.003$

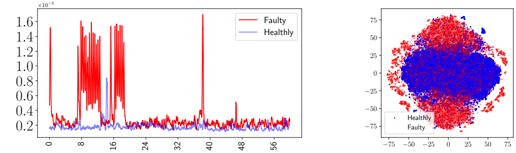
Example 3

A CPU failure on one of the control boards

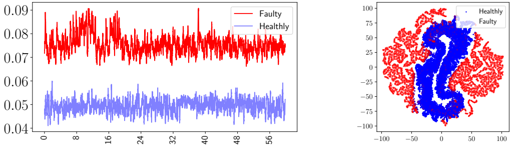
Linear



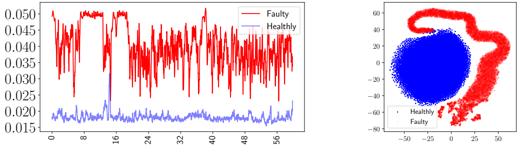
RNN



Transformer



CNN+Transformers



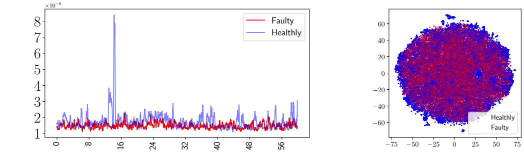
CNN

$s_{faulty} =$ **0.005** $s_{healthly} = 0.003$

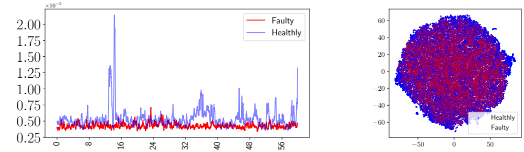
Example 4

Safety magnet at SA1/SA3

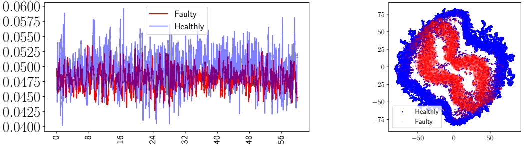
Linear



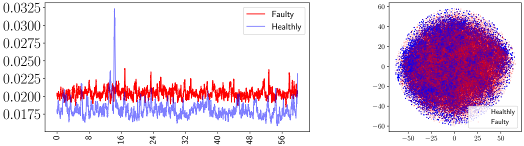
RNN



Transformer



CNN+Transformers



CNN

$s_{faulty} = 0.0003$ $s_{healthly} = \mathbf{0.003}$

Conclusion and Outlook

- We used **classical** ML models including well-established convolution neural nets (image processing) and transformers (language models).
- **Lack of interpretation** makes it **extremely challenging** (labelling, interpreting).
- Linear and RNN have lower recall but higher precision, unlike CNN and transformers.
- Especially transformers, CNN and their combinations show **how a context is important**.
- In the future we would like to try generative models, e. g. normalizing flows, (RNN)-VAE or GANs.

Thank you for your attention!

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

https://github.com/sulcantonin/ICFA-Beam-2022

And I shouldn't forget to mention that we are very eager to collaborate!

Contact

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MLops Repository

We started to collect ideas about what we have talked about towards approaches and unification of MLops operations.

https://github.com/owle-ml/owle-ml

1. Fork the repo.
2. Create a pull request.
3. We (Tia Miceli, me, event. someone else) would approve it (for transparency)