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Jochem Snuverink :: Paul Scherrer Institut

Machine Learning an den PSI-Beschleunigern

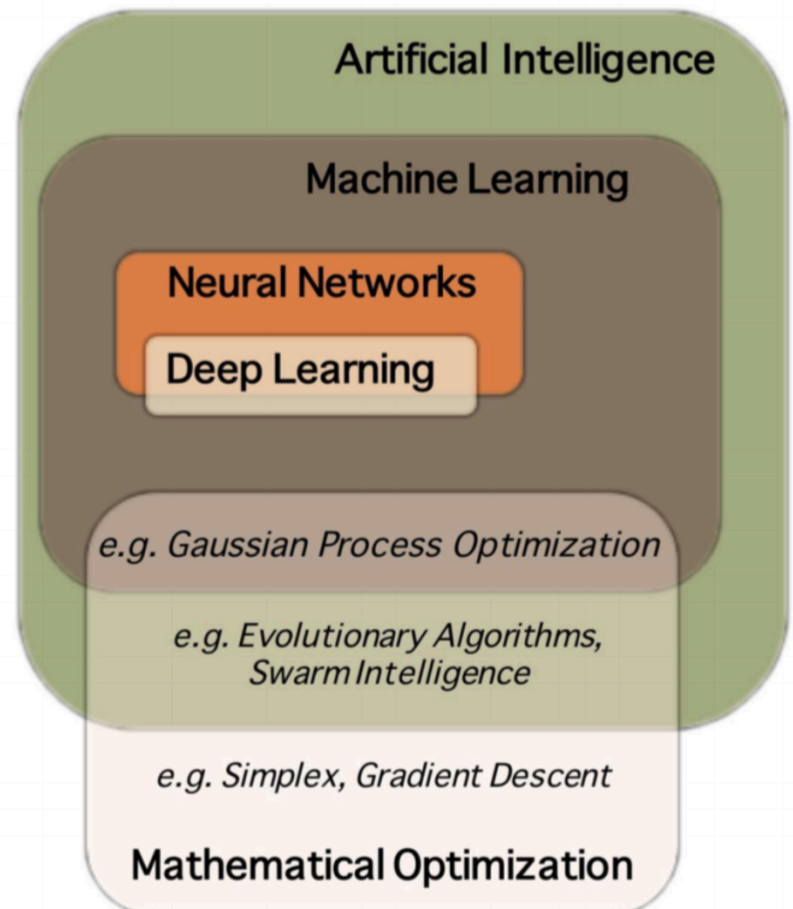
5. LAB – 06.11.2020

Outline

- What is Machine Learning?
- Possibilities to use Machine Learning in Accelerator Physics
- GFA examples
- Further Links & Conclusions

What is Machine Learning?

- Artificial Intelligence (AI)
  - enabling machines to exhibit aspects of human intelligence
- Machine Learning (ML)
  - enables machines to fulfill tasks without explicitly programmed
- Neural Networks (NNs or ANNs)
  - one approach within ML
- Deep Learning (DL)
  - synonymous with deep (many-layered) NNs



A.L. Edelen

New AI Research Centre at ETH

- The “hype” is not yet over:
  - https://ethz.ch/de/news-und-veranstaltungen/eth-news/news/2020/10/mm-neues-zentrum-fuer-ki-forschung.html
  - 29 new professorships

Das neu eröffnete ETH AI Center intensiviert den Dialog mit Wirtschaft, Politik und Gesellschaft über eine innovative und vertrauensfördernde Weiterentwicklung der künstlichen Intelligenz.
(Bild: ETH Zürich / ETH AI Center)

Machine Learning for Accelerator Physics

- Possible Applications of Machine Learning in Accelerator Physics:

1. Tuning, Optimisation and Control
   → Optimise or control accelerator parameters
2. Virtual Diagnostics
   → Surrogate model of destructive, imprecise, slow or broken diagnostic
3. Online modelling / Simulations
   → Fast beam transport model
4. Anomaly detection and machine protection
   → Preventive maintenance, interlock prediction
5. Advanced data analysis
   → Enhanced phase space measurements

PACMAN
Particle Accelerators & Machine Learning

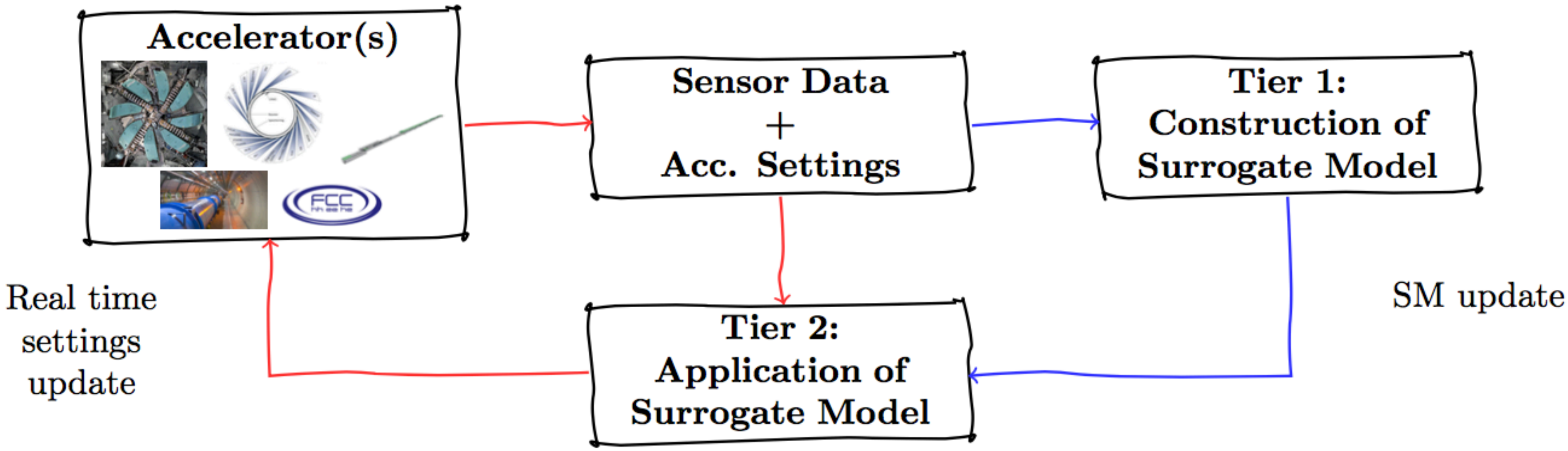


Figure 1: Sketch of the application of a Surrogate Model (SM) for particle accelerators. Red lines indicate real time data transfer.

Collaboration PSI, EPFL and Swiss Data Science Center (SDSC)

- Research goals:

1. Minimise beam losses (HIPA and LHC)
2. Better control of accelerator parameters (HIPA and LHC)
3. Prevent unnecessary machine interruptions (HIPA)
4. Neural networks instead of particle tracking (LHC)
5. Anomaly Detection on streaming data (HIPA)

1. Tuning, Optimisation and Control

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Why Bayesian Optimisation?

Human Optimisation ≠ Numerical Optimisation

Human Optimisation

- Life-long learning
- Experience
- Limited working memory
- (relatively) Slow decisions

Numerical Optimisation

- Bulk learning
- Cannot estimate uncertainty
- Juggle many things at once
- Fast decisions

ETH zürich

Learning & Adaptive Systems

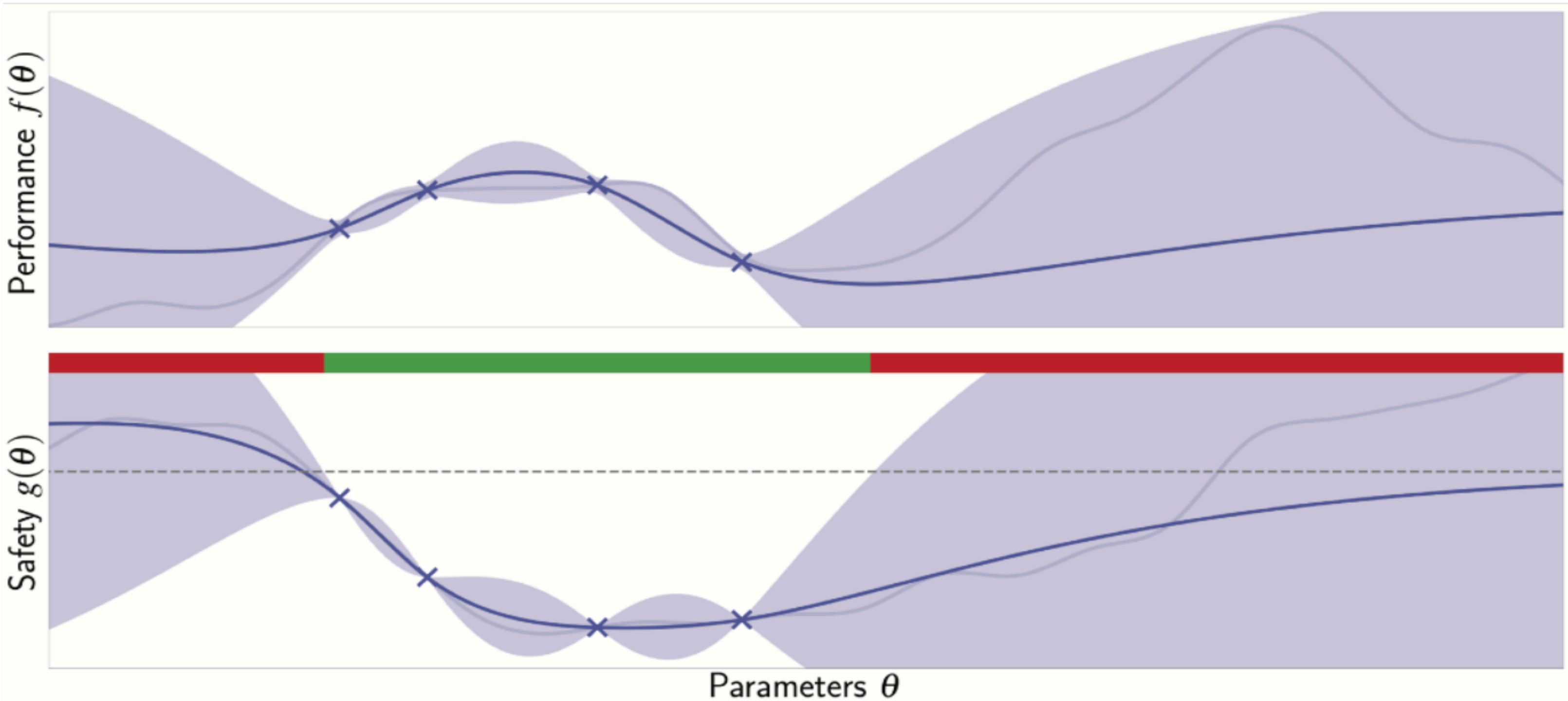
Why Bayesian Optimisation?

Bayesian Optimisation

- ~~Life-long~~ learning
- Experience
- ~~Limited working memory~~
- ~~(relatively) Slow decisions~~

- ~~Bulk learning~~
- ~~Cannot estimate uncertainty~~
- Juggle many things at once
- Fast decisions

Safe Bayesian Optimisation



- X are evaluation points, for each evaluation point the performance (e.g. FEL pulse energy) is measured and the model is updated
- Additionally, the safety function (e.g. losses recorded by various detectors) is evaluated and its model is also updated ➜ taking into account the uncertainties of the safety function this defines the safe-set marked in green

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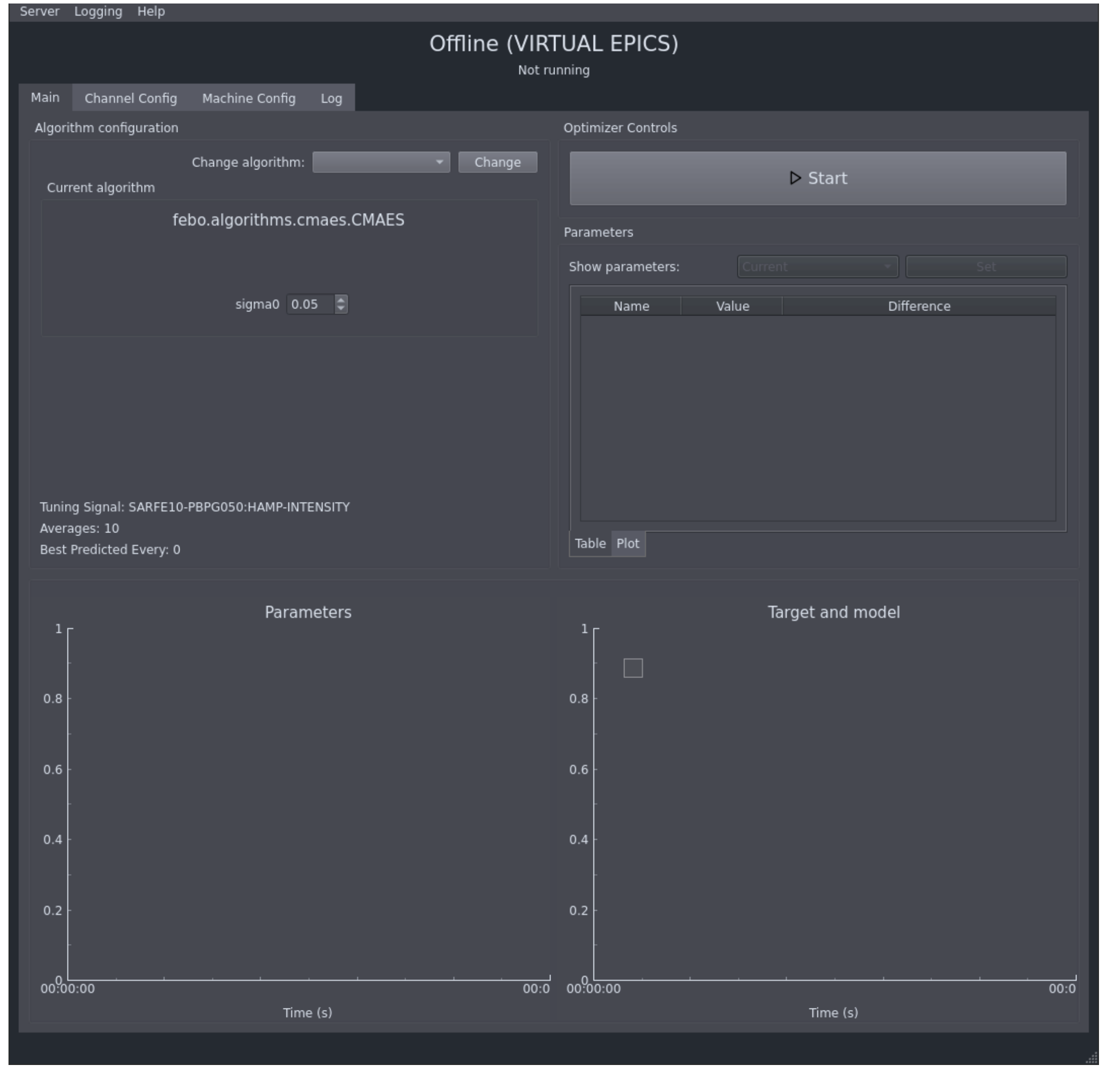
Optimisation GUI

- Server application
  - Optimiser runs on a server
  - client GUI through REST API
- Status data in EPICS
- Additional algorithms
  - Extremum seeking
  - Nelder Mead (Simplex)
- Very few settings
- Machine related beam checks (e.g. good-flags from the feedbacks, beam detection)
- Live plotting & analysis
- Accelerator independent
  - used at both SwissFEL & HIPA



2. Virtual Diagnostics

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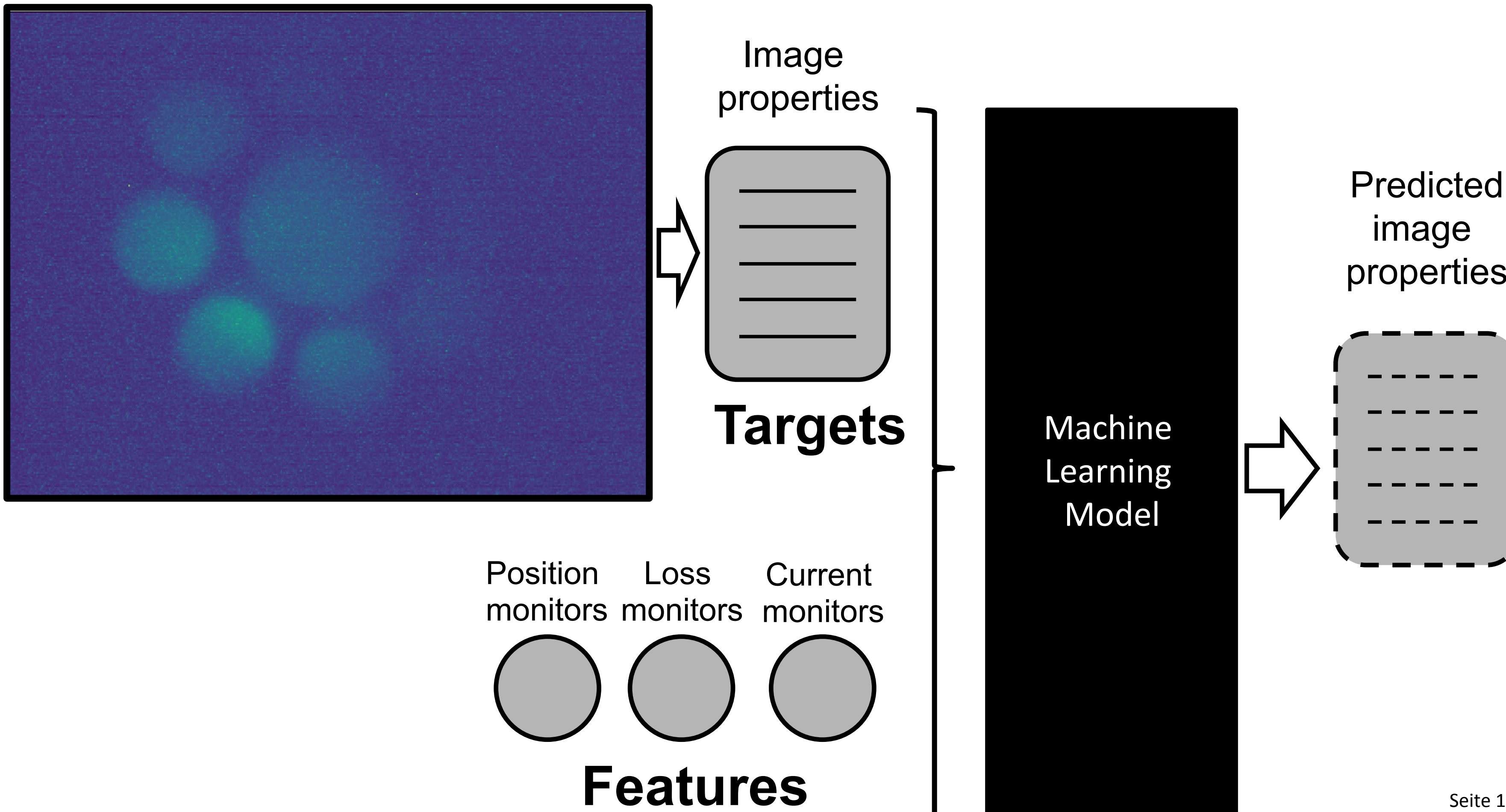
VIMOS SINQ: Virtual diagnostics

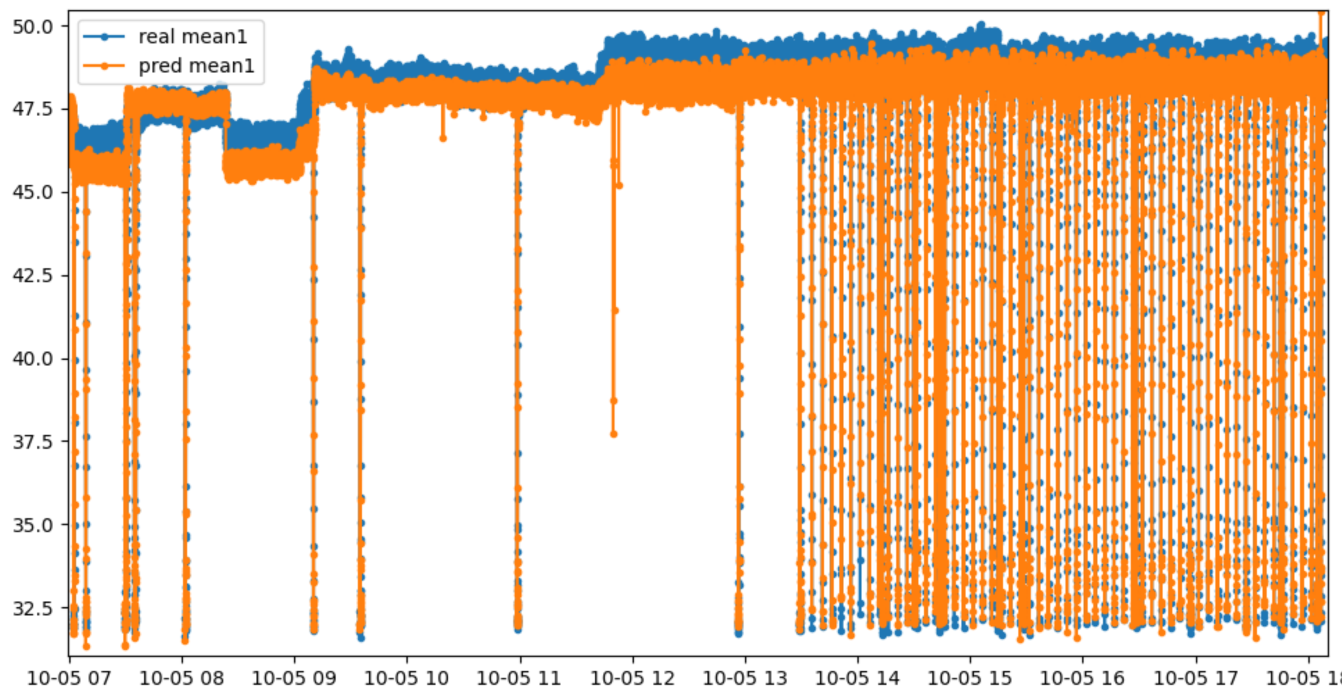
Jaime Coello de Portugal

- The VIMOS system monitors the SINQ target beam spot with a metal grid.
- If the beam is focussed too much or changes too fast interlocks are triggered.
- This grid is degrading over time and cannot be replaced
- **Can we use other sensors to predict the images?**



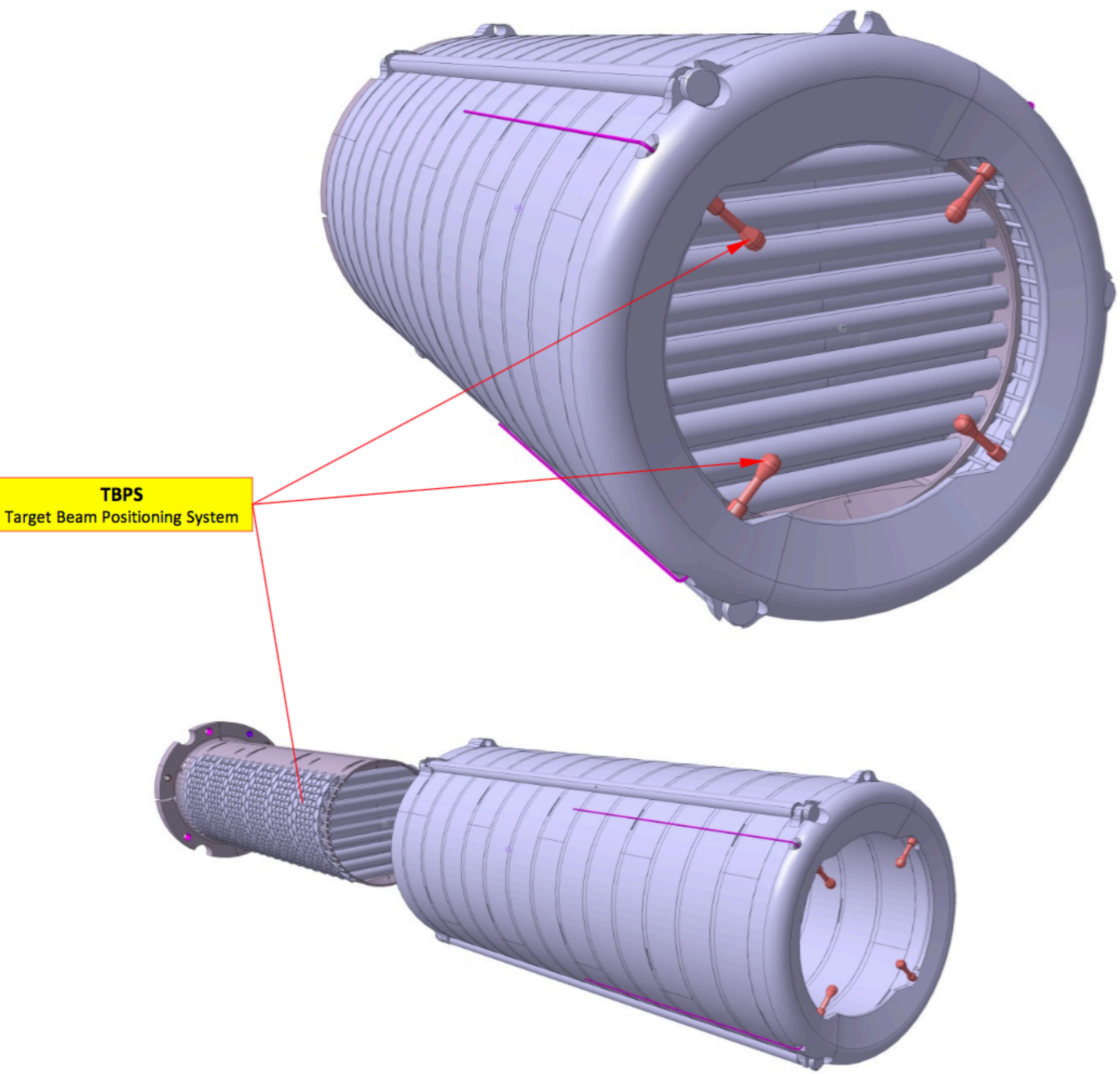
Preliminary results: VIMOS images

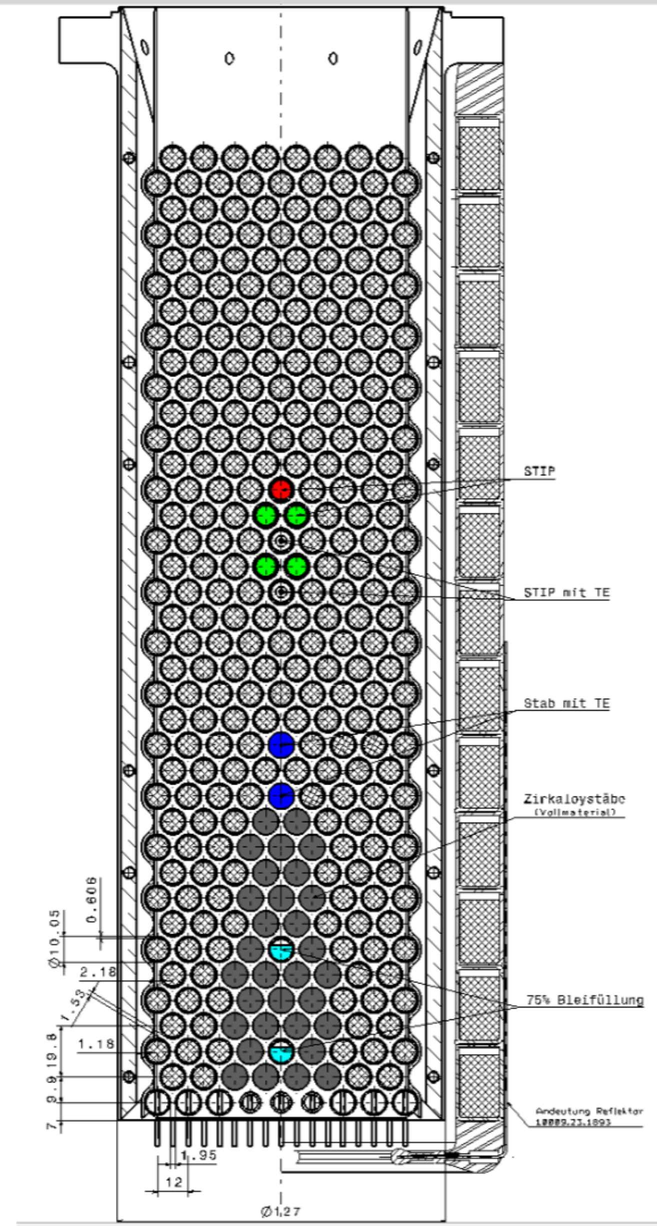
- Model: CatBoost -> Gradient boosting over decision trees.
- Trained on 2020 data.
- Mean1: Average brightness of the central circle of the picture:



SINQ: Target-13

Alternative? TBPS (Target Beam Positioning System)



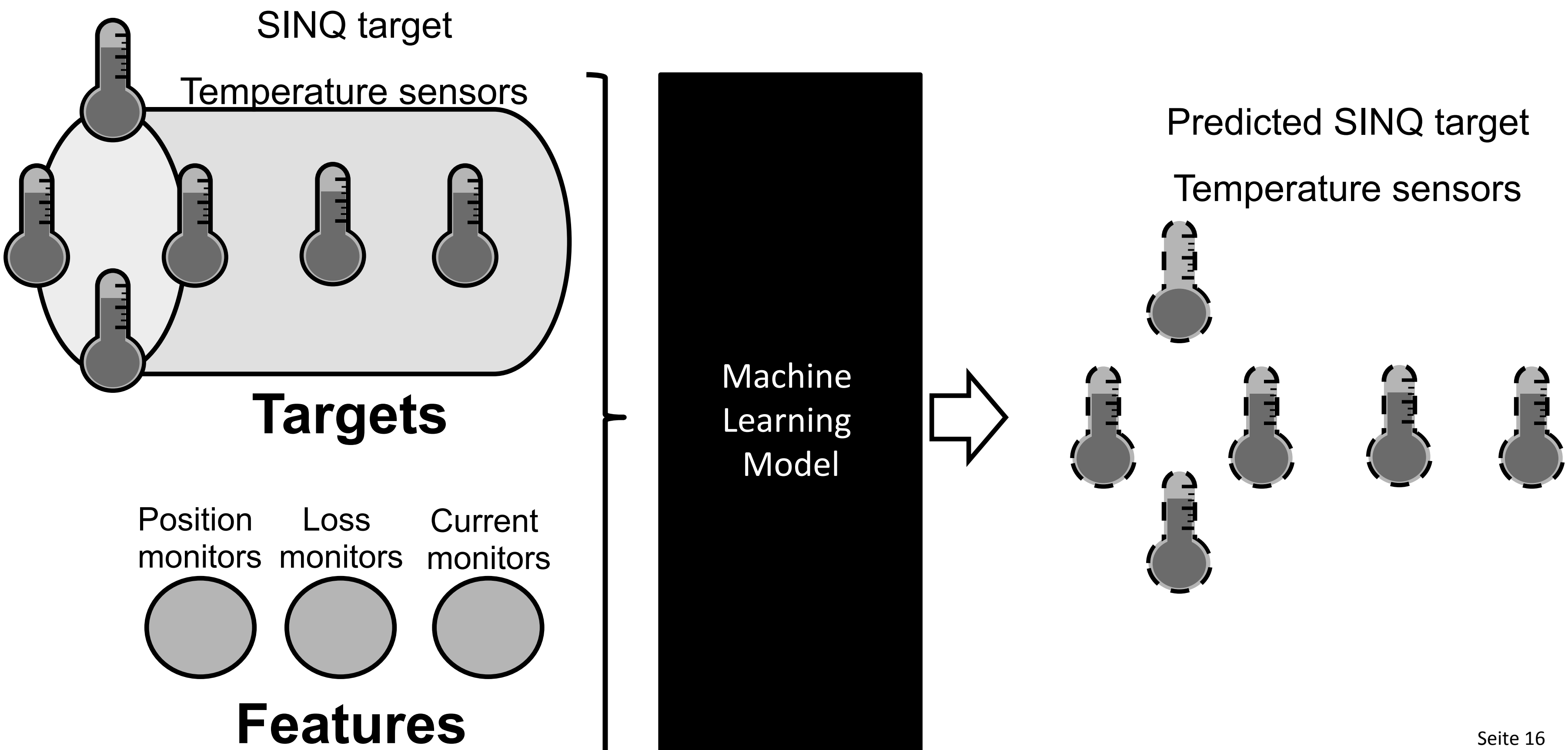


2018-08-22, J. Welte

SINQ temp. sensors: Virtual diagnostics

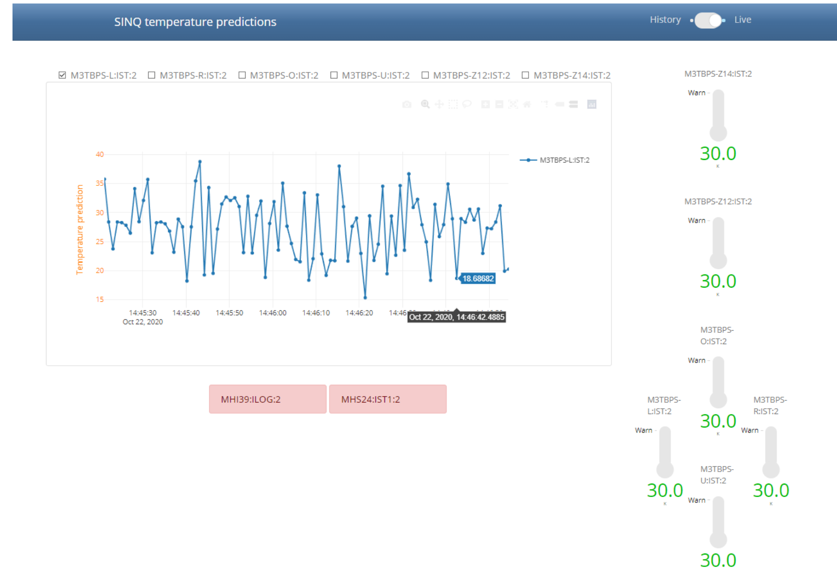
Jaime Coello de Portugal

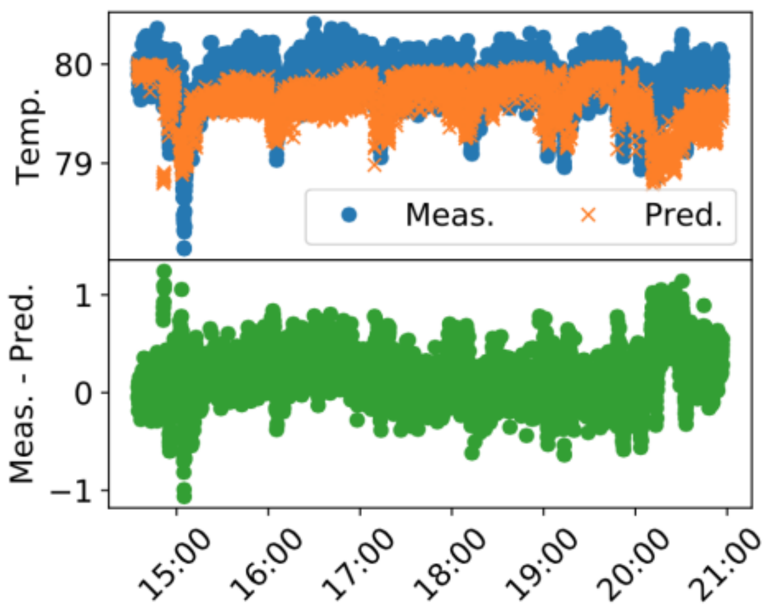
- Similarly, SINQ target has 6 temperature sensors: 4 at the entrance and 2 inside.
- These temperature sensors might degrade over time and are critical for the safety of the target.
- Once again: **Can we use other sensors to predict these temperatures?**

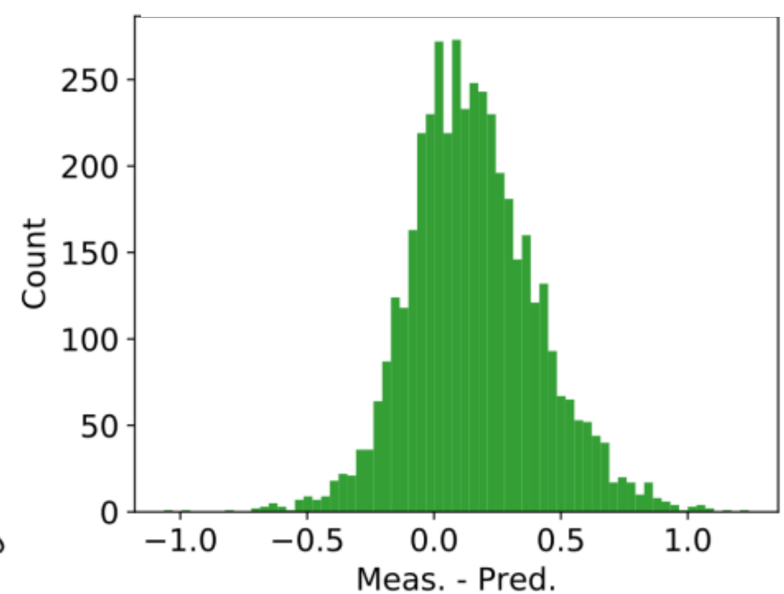


Preliminary results: SINQ temperature

- Model: Random Forest
- Trained on 2018 data.
- The prediction is in general within 1 Kelvin of the real value.
- How robust is it?

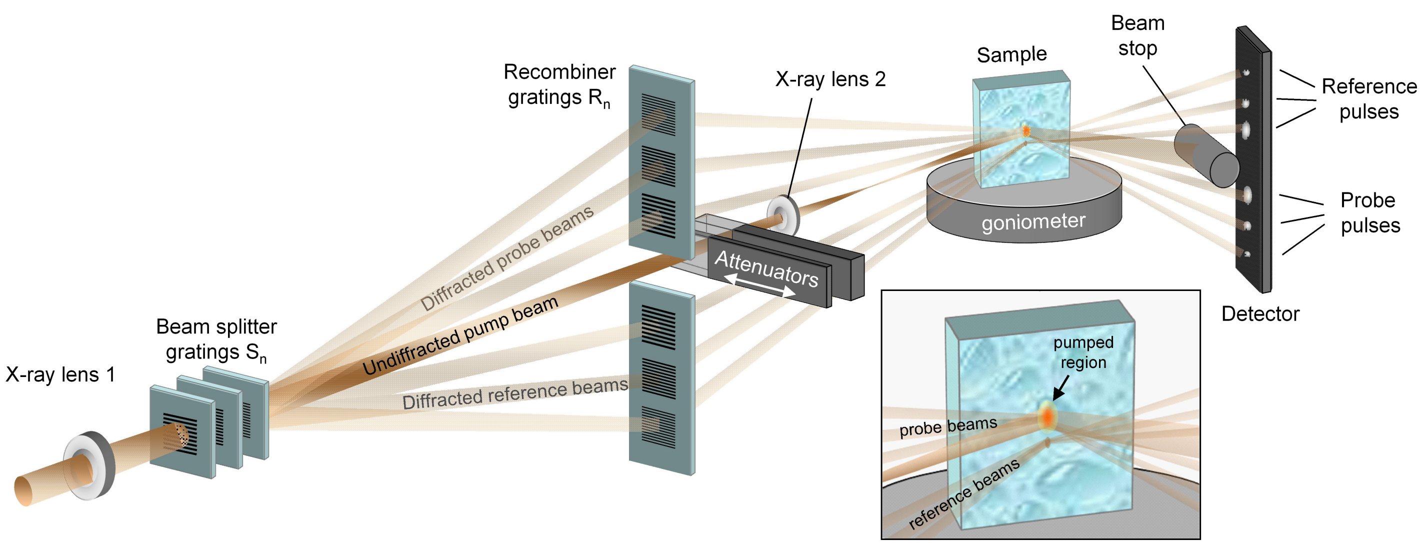






Ultra-Fast Pump-Probe Experiments

- XFELs are successfully used for the investigation of ultrafast phenomena
- Pump-probe experiment:
  - excited by a a short „pump“ pulse
  - probed by a second „probe“ pulse after a certain delay time.
  - full dynamics obtained by repeating at different delay times.
  - important to know delay time precisely

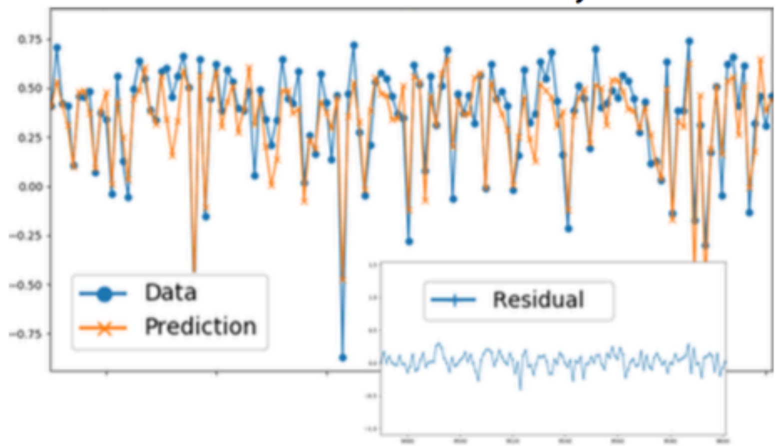


https://www.psi.ch/de/lmn/ultra-fast-pump-probe-experiments

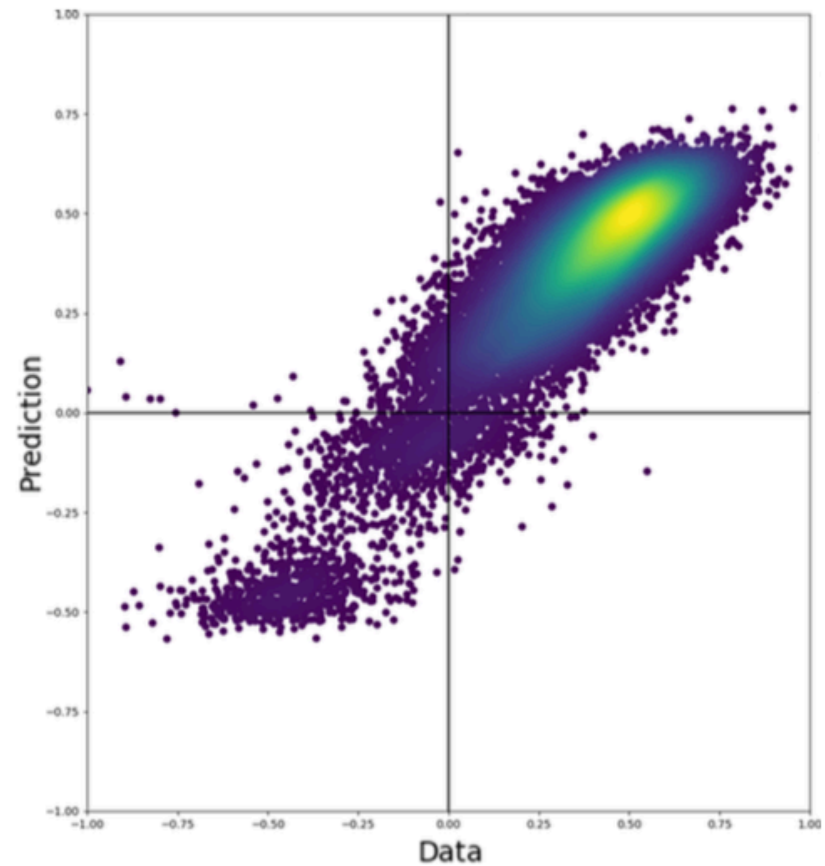
SwissFEL Pump-Probe Delay Prediction using ML

Sven Augustin – PSI Fellow (LSF)

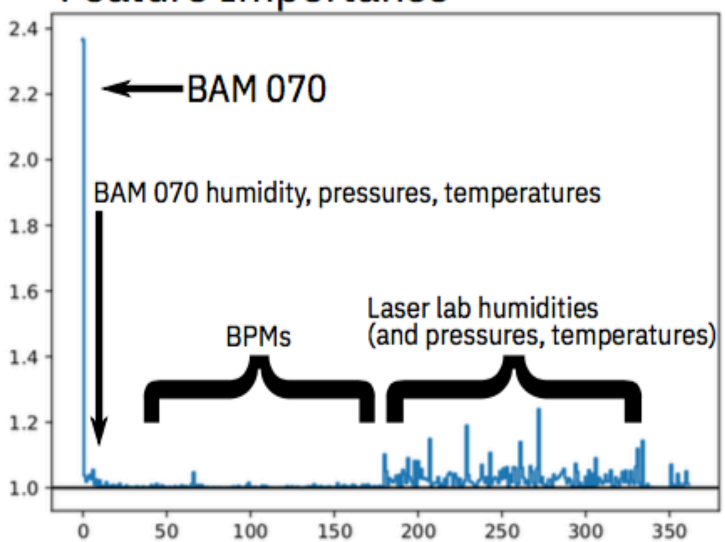
Trends are followed with tiny residual:



Input and output nicely correlated



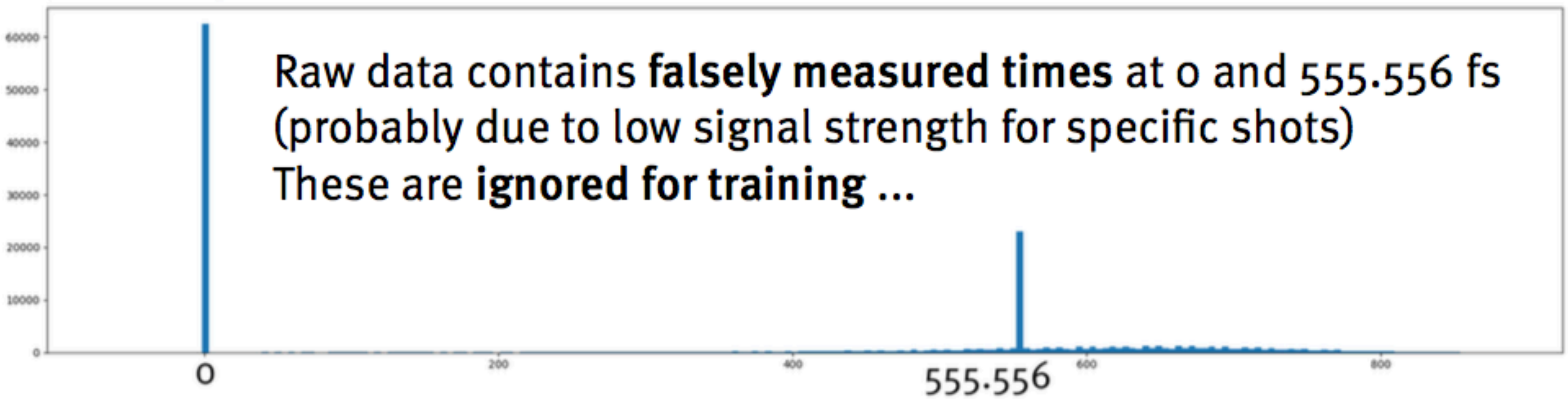
Feature Importance

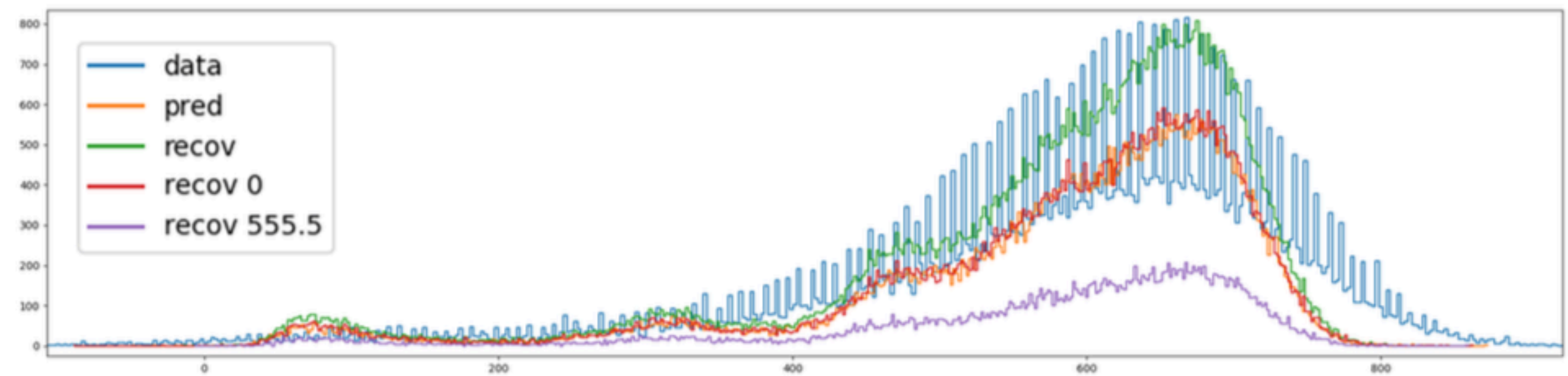


In collaboration with A. Adelmann (LSM) and C. Bostedt (LSF)

SwissFEL Pump-Probe Delay Prediction using ML

Sven Augustin – PSI Fellow (LSF)





... and **predicting for these points** yields distributions similar to the input!

→ Model **recovers** false measurements for low intensity!

(which is about half of the data in this data set)

3. Online modelling / Simulations

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DA optimization for SLS 2.0

(Kranjčević, Riemann, Adelmann, Streun)

Multi-objective optimization with MOGA (`opt-pilot + tracy`):

GOOD: found tens of points with all objective function values better than the design solution (one point shown in Figure, right)

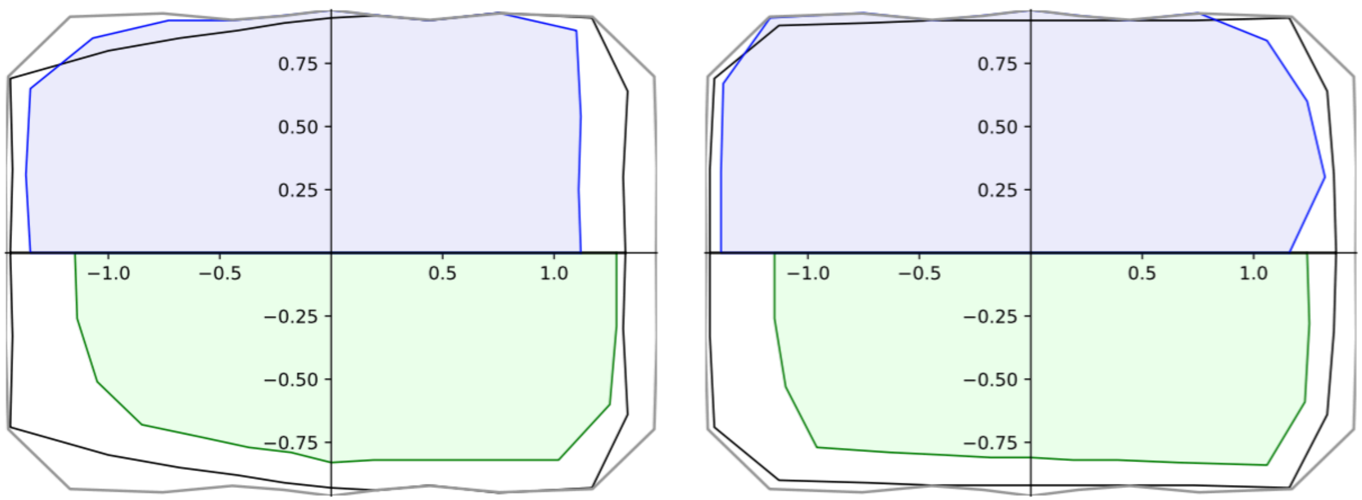

Figure: Left: design solution, right: newfound point. Transverse DAs at $\delta = -0.03$ (green), 0.03 (blue), and 0 (bold black line). For both points chromatic tune footprint and ADTS footprint constrained.

BAD: for detailed lattice models the optimization needs to be faster

DA optimization for SLS 2.0

(Kranjčević, Riemann, Adelmann, Streun)

Speeding it up using an ANN surrogate model (SM):

- the prediction quality is very good (Figure, left; $y = x$ desired)
- straightforward use of the SM $\rightarrow$ prediction quality on the last generation poor (Figure, right) $\rightarrow$ speedup & poor results
- retraining during the optimization $\rightarrow$ better prediction quality on the last gen. (Figure, right) $\rightarrow$ speedup & good results

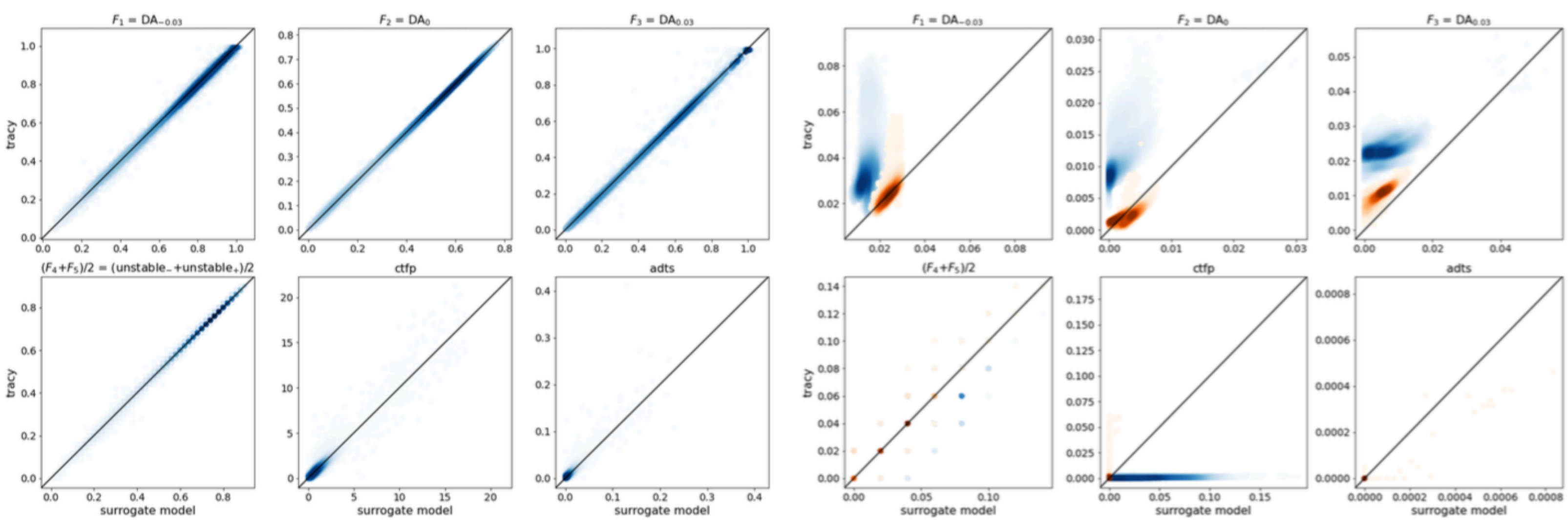

Figure: Sub-plots: considered figures of merit (objectives or constraints).

DA optimization for SLS 2.0
(Kranjčević, Riemann, Adelmann, Streun)

Run time and solution quality comparison for different methods:

	`opt-pilot + tracy`	SM (30k)	SM + re-train (20k)	SM + re-train (5k)
nof pts better	31	0	148	87
run time	48 h	11 h 21 min	8 h 52 min	3 h 10 min
speedup	1.0	4.2	5.4	15.1

Columns: methods (the number in the parentheses is the combined size of the samples used for training)

Rows:

- '`nof pts better`' is the number of design points (magnet configurations) in the last gen. that satisfy the constraints and have all objectives better than the design solution
- run times include: evaluating points used for training, training, optimization and re-eval of 10 % of the points in the last gen.

https://arxiv.org/abs/2008.04151

4. Anomaly detection and machine protection

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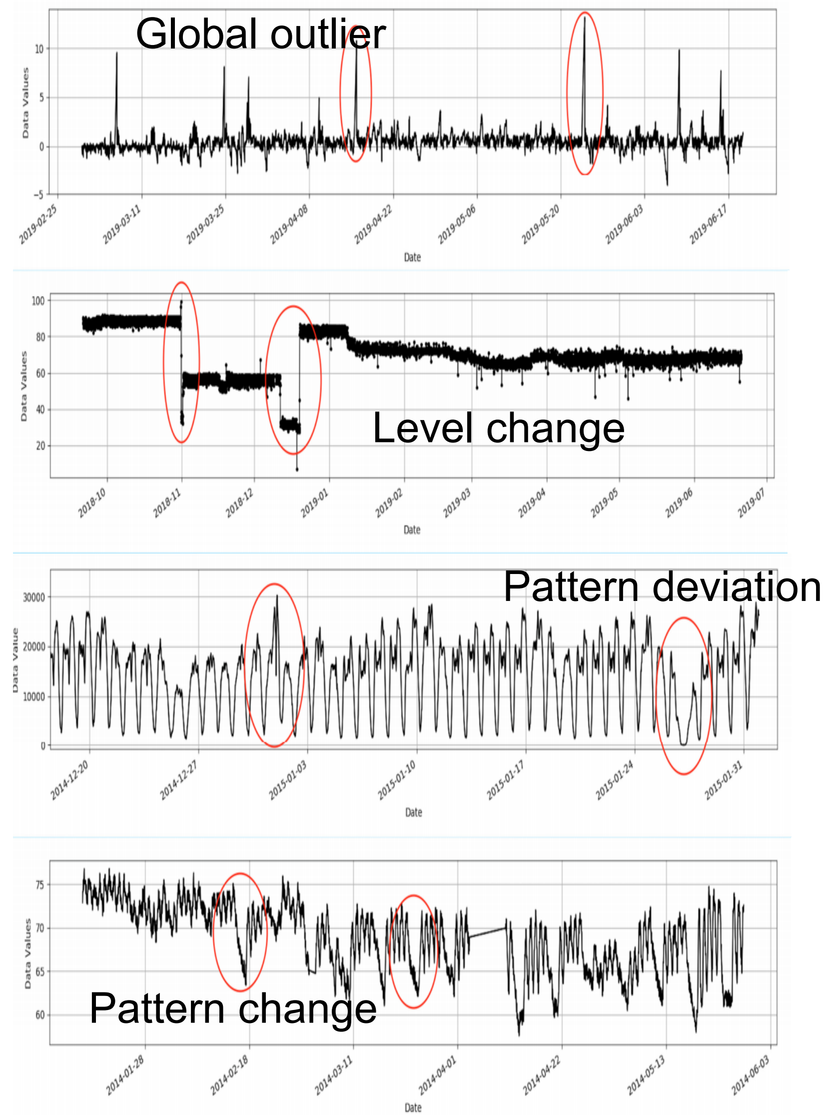
Anomaly Detection

“An observation which deviates so much from other observations as to arouse suspicions that it was generated by a different mechanism."
— Hawkins, 1980

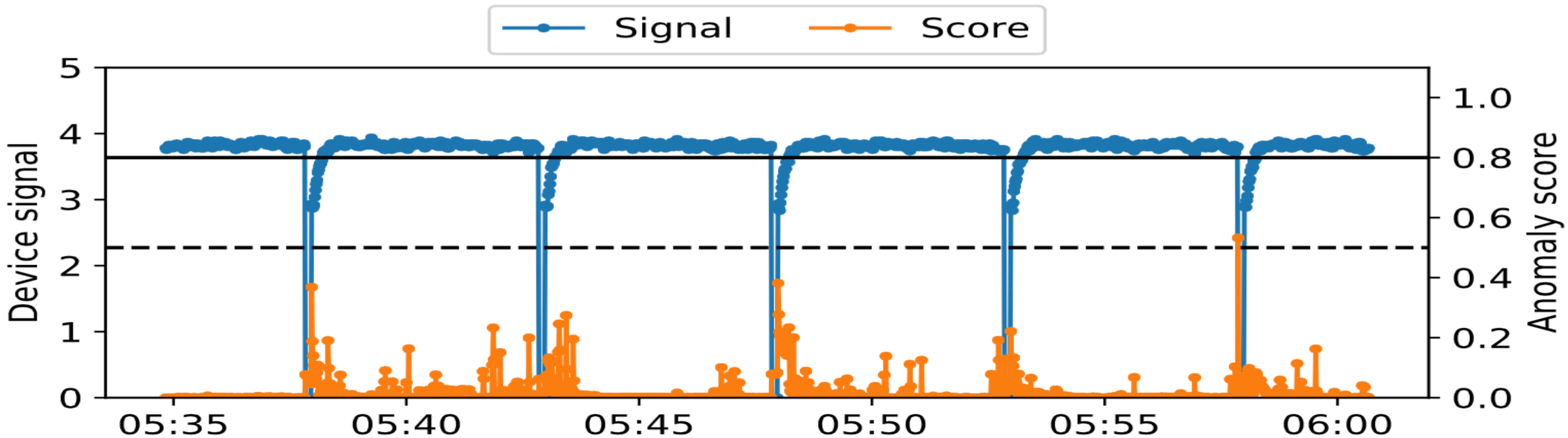
- Try to find observation or sequences that deviate from the “normal behaviour”.
- Experts would recognize these anomalous patterns easily, but cannot be monitoring the huge amount of data some systems produce.
- E.g: Credit card fraud detection, intrusion detection in cybersecurity, or **fault diagnosis in industry**.
- Specific e.g: At HIPA a loss monitor broke down without anyone noticing.

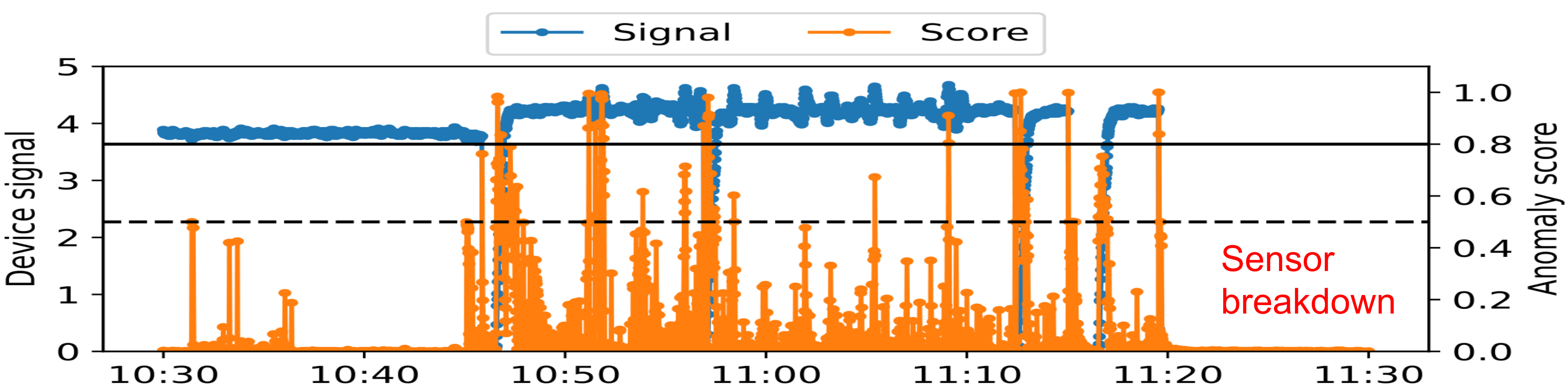


*Plots from: Ted D’Ottavio et al, **Experience Using NuPIC to Detect Anomalies in Controls Data**, ICALEPCS 2019*

Anomaly Detection in HIPA
Jaime Coello de Portugal

- Loss monitor signal HIPA and anomaly score, hours before it broke down (11:20):
  - early warning possible at least half an hour before





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Interlock prediction at HIPA

Mélissa Zacharias, Sichen Li, Fernando Perez

- Every interlock turns off the beam for 25 s
- Around 30-40 interlocks a day
- Some of them could be prevented by lowering the current for a few seconds
- ➜ Can we predict that an interlock is going to happen soon?

- Different approaches with neural networks
  - Approach 1: Classification
  - Approach 2: Time series analysis (Sichen Li)

- 450(!) EPICS channels are analysed

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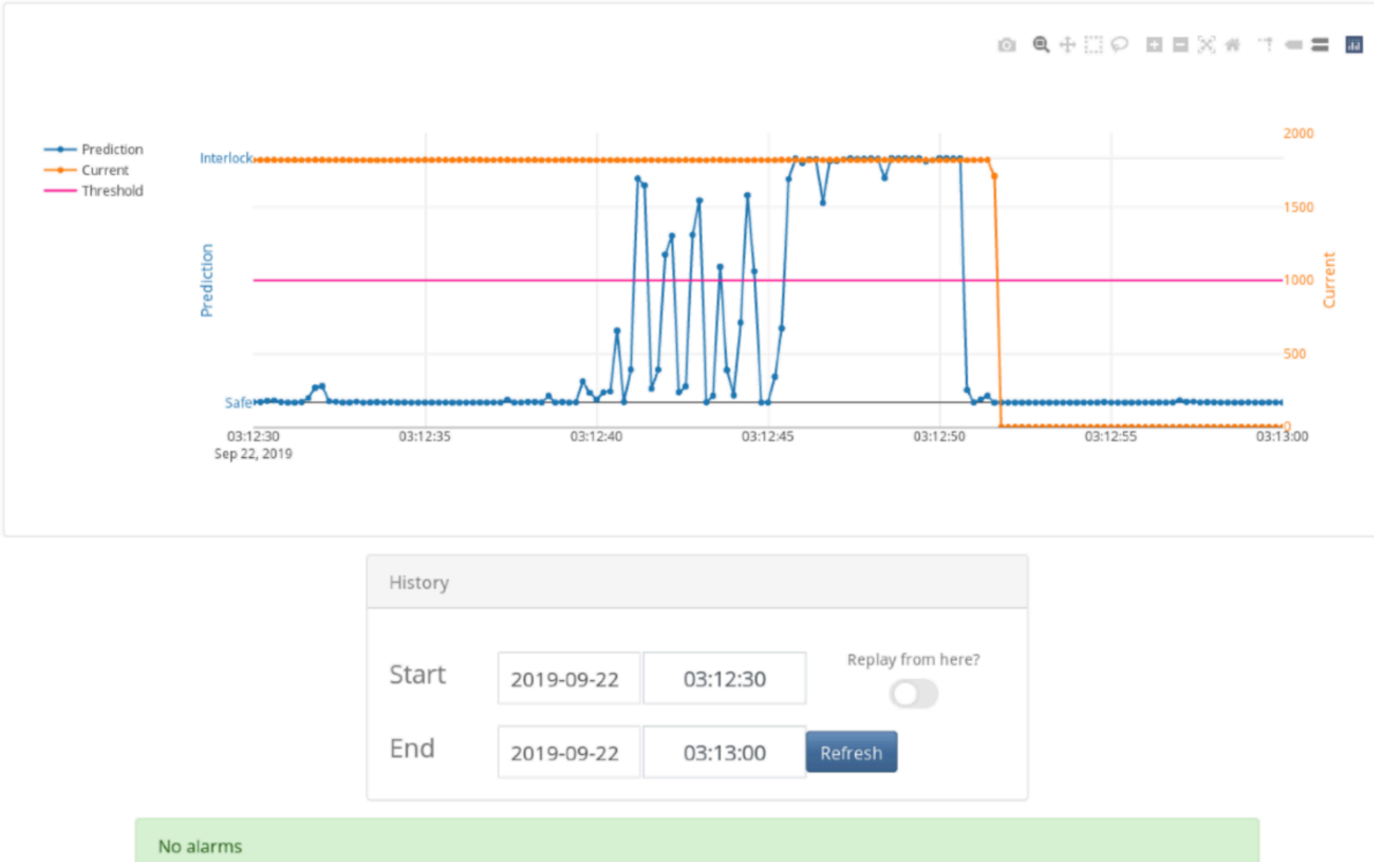
Example from training set



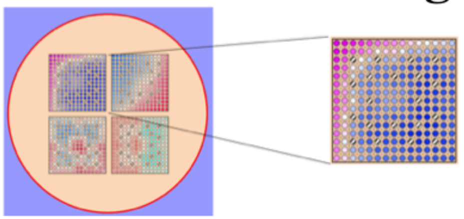
Goal: Live prediction of potential interlocks

material courtesy of Melissa Zacharias

Other projects

COLOSS: COmbined Loading Optimization with Simulations and Surrogates

- Joint project between LRT and LSM
- The project includes a PhD student - A. Albà - at the LSM (started September 1, 2020)
- Strong link with the EU EURAD WP.8 project on "Spent fuel characterization"
- PhD project is funded by Swiss Nuclear



A particular core assembly

Within the CLOSS project: research on ML based (meta)models/surrogate models for quantifying uncertainties and sensitivities w.r.t loading curves. The ultimate goal is to optimise core assemblies

Automated AI Based Proton Therapy Treatment Planning

- Cross project between ZPT and LSM
- The project includes a PhD student - R. Bellotti - (started September 15, 2020)

The goal of the PhD project is to automate the process of treatment planning. This means that planners are relieved of many routine steps they currently have to perform, up to the point where complete plans are generated. The goal is not to replace planners. There are still very difficult cases that cannot be automated in the near future, and the question which organs to damage is to some extent an ethical question. Therefore, the human element cannot be completely eliminated. Current approaches can be divided into two categories: Knowledge-based systems, and machine learning (ML) tools. The knowledge based systems rely on human-crafted rules to select similar cases from a case database, and translate their treatment configurations to the new case. ML tools, on the other hand, try to make data-driven predictions for the planning decisions.

Further information & Links

- ML Luncheons
  - Monthly lunch meetings to discuss Machine Learning in an informal setting
  - Organised by Andreas Adelmann, Nicole Hiller and Jochem Snuverink
  - https://indico.psi.ch/category/346/
- PSI Email list: ml@lists.psi.ch
- Slack channel: psi-ml.slack.com & accelerator-ml.slack.com
- One World Seminars on Tuesday evenings (both ML and non-ML)
  - https://sites.google.com/view/owle/home
  - Nicole Hiller: https://www.youtube.com/watch?v=76ESYcmMWrA
- ICFA workshops:
  - SLAC 2018: https://conf.slac.stanford.edu/icfa-ml-2018/
  - PSI 2019: https://indico.psi.ch/event/6698/
- "Opportunities in Machine Learning for Particle Accelerators" https://arxiv.org/abs/1811.03172

Machine Learning is another useful toolbox to improve operation of our accelerators…

…already in use by many groups

... many different applications and usage

…in different stages of implementation

…feel free to contact and discuss your idea

…more to come!

Mein Dank geht an

- Andreas Adelmann
- Fernando Perez (SDSC)
- Jaime Coello de Portugal
- Johannes Kirschner (ETHZ)
- Nicole Hiller
- Marija Kranjcevic
- Mélissa Zacharias
- Sichen Li
- Sven Augustin