# Machine Learning for Accelerator(s) R&D

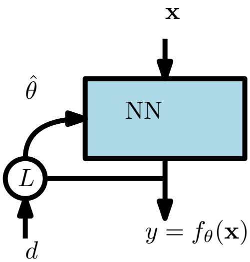
**Antonin Sulc**
Hamburg,

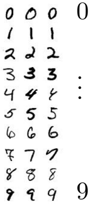
HELMHOLTZ

# Rule 1: Don’t talk about Machine Learning (when it is not necessary)

# Learning - Taxonomy

Mapping (data with labels $d$)




Data without labels




States, actions




$$
\begin{aligned}
\hat{\theta} &= \arg\min L(\theta) & \\
&= \arg\min_\theta \|y - d\|_2 & \text{regression} \\
&= \arg\min_\theta d \log y & \text{classification}
\end{aligned}
$$

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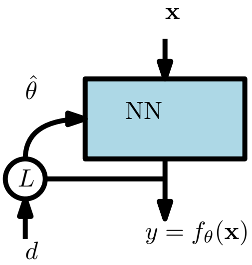
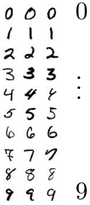
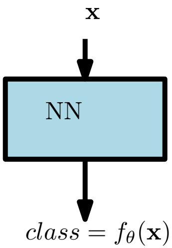



Data without labels

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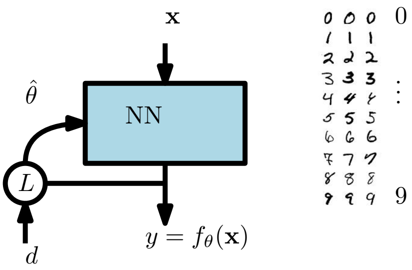


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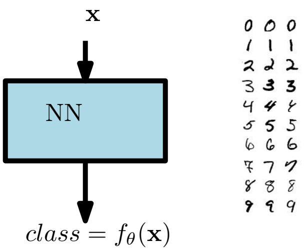


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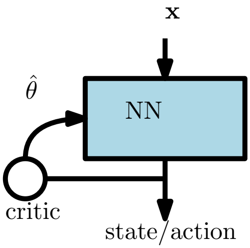


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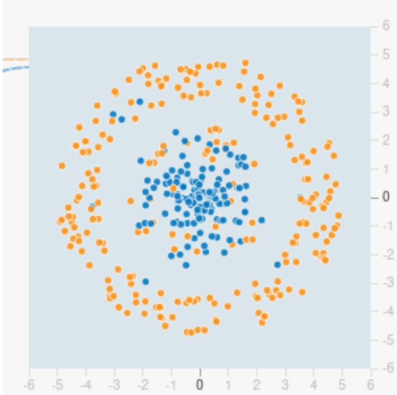
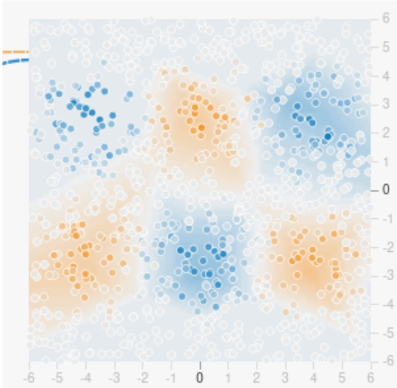
# Neural Networks and Training

## Classification




https://shorturl.at/jlO35

## Regression




https://shorturl.at/mxyP6

# Neural Network - Example

```
import torch
import torch.nn as nn
import torch.optim as optim

x = torch.randn(1000,2)
d = torch.randint(2,(1000,1)).float()

model = nn.Sequential(nn.Linear(2,4),
                      nn.ReLU(),
                      nn.Linear(4,1))

crit = nn.BCEWithLogitsLoss()
optimizer = optim.AdamW(model.parameters())
for i in range(1000):
    y = model(x)
    loss_ = crit(y, d)
    # optimisation
    optimizer.zero_grad()
    loss_.backward()
    optimizer.step()

    print(loss_.item())
```

# Overview - MCS & MSK

- Language

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- Language
- Anomaly Detection

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- Language
- Anomaly Detection
- Control

# Developing a LLM for Particle Accelerators

> Source **books, conference proceedings, and arxiv** preprints as PDFs.

## PACuna: Automated Fine-Tuning of Language Models for Particle Accelerators

**Antonin Sulc**[*]
DESY,
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DESY,
Hamburg, Germany

**Annika Eichler**
DESY,
Hamburg, Germany

**Tim Wilksen**
DESY,
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### Abstract

Navigating the landscape of particle accelerators has become increasingly challenging with recent surges in contributions. These intricate devices challenge comprehension, even within individual facilities. To address this, we introduce PACuna, a fine-tuned language model refined through publicly available accelerator resources like conferences, pre-prints, and books. We automated data collection and question generation to minimize expert involvement and make the data publicly available. PACuna demonstrates proficiency in addressing accelerator questions, validated by experts. Our approach shows adapting language models to scientific domains by fine-tuning technical texts and auto-generated corpora capturing the latest developments can further produce pre-trained models to answer some specific questions that commercially available assistants cannot and can serve as intelligent assistants for individual facilities.

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- Showing improved performance over general chatbots like ChatGPT and Falcon.

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- Use: Search, Validation, Checking

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ChatGPT: As of my last knowledge update in September 2021, the European XFEL (X-ray Free-Electron Laser) facility had a total of 100 superconducting radiofrequency (SRF) cavities. wrong

# LLM - Future - Multimodality

**Human** How should I make something like this?

# LLM - Future - Multimodality

**Human** How should I make something like this?

**MiniGPT-4 No Q-Former** To make this dish, you will need the following ingredients:

* 4 large live lobsters
* 2 tablespoons olive oil
* Salt and pepper
* 2 cloves garlic, minced
* 1 lemon, juiced
* 1 tablespoon chopped fresh parsley

Here's how to make it:
1. Preheat your oven to 425°F (220°C).

# Log Anomaly Detection

> Log anomaly detection using word embeddings and Hidden Markov Models.

## LOG ANOMALY DETECTION ON EUXFEL NODES

A. Sulc*, A. Eichler, T. Wilksen, DESY, Hamburg, Germany

*Abstract*

This article introduces a method to detect anomalies in the log data generated by control system nodes at the European XFEL accelerator. The primary aim of this proposed method is to provide operators a comprehensive understanding of the availability, status, and problems specific to each node. This information is vital for ensuring the smooth operation. The sequential nature of logs and the absence of a rich text corpus that is specific to our nodes poses significant limitations for traditional and learning-based approaches for anomaly detection. To overcome this limitation, we propose a method that uses word embedding and models individual nodes as a sequence of these vectors that commonly co-occur, using a Hidden Markov Model (HMM). We score individual log entries by computing a probability ratio between the proba-

to mitigate potential problems from arising. Monitoring the logs of the watchdog nodes by textual analysis of their logs not only provides an automated means of comprehending the European XFEL accelerator system conditions but also enables early detection and resolution of issues that would otherwise only gain significance in the event of a specific node failure.

The structure of the paper is the following: First, we summarize the related work in log anomaly detection. In the next section, we show four main steps of our approach with important justifications and examples. Lastly, we show several examples and sketch a potential future work in this field.

### RELATED WORK

# Log Anomaly Detection

- Log anomaly detection using word embeddings and Hidden Markov Models.
- Represents logs as vectors (Word2Vec), and models their representations as HMMs.

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- Log anomaly detection using word embeddings and Hidden Markov Models.
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- Scores entries by probability ratio to detect anomalies (how well is the message fitting to the sequence).

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- Tested on EuXFEL logs, identifies score spikes corresponding to errors.

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**RELATED WORK**

# Log Anomaly Detection

(TEST,OK, )

# Log Anomaly Detection

(TEST,OK,TEST,OK, )

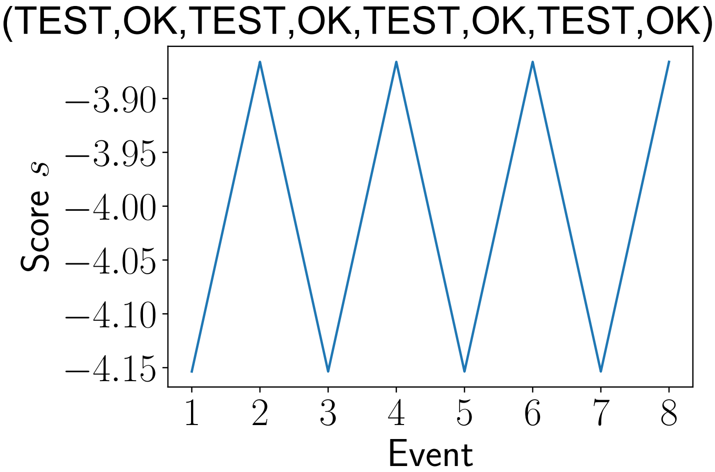
# Log Anomaly Detection

(TEST,OK,TEST,OK,TEST,OK, )

# Log Anomaly Detection

(TEST,OK,TEST,OK,TEST,OK,TEST,OK)

# Log Anomaly Detection



# Log Anomaly Detection - Sequential Anomaly

(TEST,OK,                                                            )

# Log Anomaly Detection - Sequential Anomaly

(TEST,OK,TEST,OK, )

# Log Anomaly Detection - Sequential Anomaly

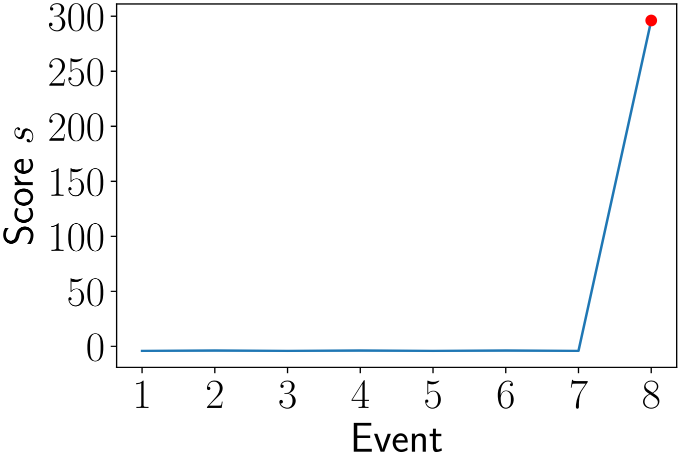
(TEST,OK,TEST,OK,TEST,OK, )

# Log Anomaly Detection - Sequential Anomaly

(TEST,OK,TEST,OK,TEST,OK,TEST,**TEST**)

# Log Anomaly Detection - Sequential Anomaly

(TEST,OK,TEST,OK,TEST,OK,TEST,**TEST**)



# Log Anomaly Detection - Unexpected Message Anomaly

(TEST,OK, )

# Log Anomaly Detection - Unexpected Message Anomaly

(TEST,OK,TEST,OK, )

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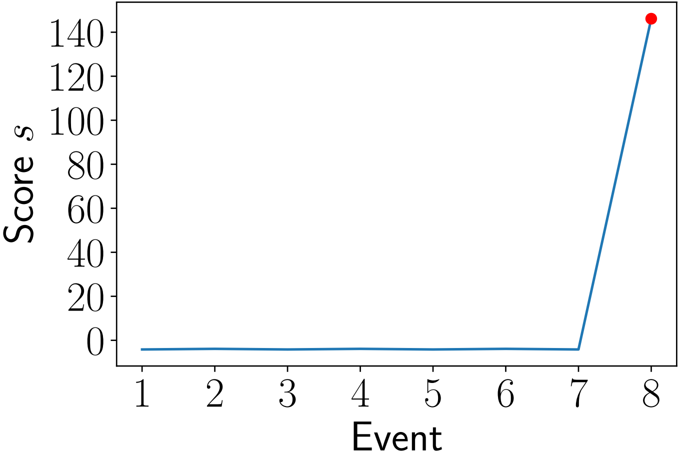
(TEST,OK,TEST,OK,TEST,OK, )

# Log Anomaly Detection - Unexpected Message Anomaly

(TEST,OK,TEST,OK,TEST,OK,TEST,**ERROR**)

# Log Anomaly Detection - Unexpected Message Anomaly

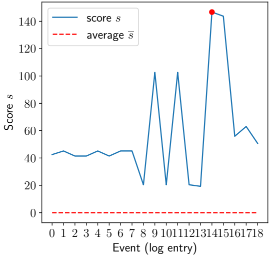
(TEST,OK,TEST,OK,TEST,OK,TEST,**ERROR**)

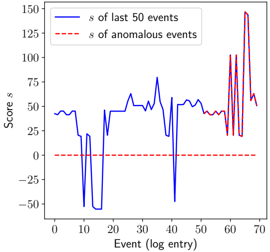


# Log Anomaly Detection - Real Example

⋮

```
0   getpid no process
1   no process try start
2   getpid no process
3   getpid no process
4   no process try start
5   getpid no process
6   no process try start
7   no process try start
8   pid change $nz $nz
9   getpid pid not match process name
10  pid change $nz $nz
11  getpid pid not match process name
12  pid change $nz $nz
13  pid change $nz $nz
14  pid not match process name toggled $nz times $nz min
15  pid not match process name toggled $nz times $nz min
16  signal term received
17  terminating threads closing files
18  writer thread terminated
19  interrupt thread terminated
```



# Log Anomaly Detection

```
from hmmlearn import hmm
import numpy as np

x = np.stack([[0,1],[1,0],[0,1],[1,0],[0,1],[1,0],[0,1],[1,0]])
model = hmm.GaussianHMM(n_components=2, covariance_type="diag")
model.fit(x[:-1,:])
logp = []
for i in range(1,x.shape[0]+1):
    logp.append(model.score(x[:i]))

logp = np.array(logp)
score = logp[:-1] - logp[1:]
```

# Anomaly Detection on BPMs

> Use **data-driven approaches** to analyze beam trajectories at European XFEL.

A DATA-DRIVEN BEAM TRAJECTORY MONITORING AT THE EUROPEAN XFEL

A. Sulc*, R. Kammering, T. Wilksen, DESY, Hamburg, Germany

*Abstract*

Interpretation of data from beam position monitors is a crucial part of the reliable operation of European XFEL. The interpretation of beam positions is often handled by a physical model, which can be prone to modeling errors or can lead to the high complexity of the computational model. In this paper, we show two data-driven approaches that provide insights into the operation of the SASE beamlines at European XFEL. We handle the analysis as a data-driven problem, separate it from physical peculiarities and experiment with available data based only on our empirical evidence and the

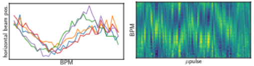



Figure 1: An example input to our methods. The left figure shows a series of the first five bunch trajectories at the SASE1 beamline after the mean of 600 bunches is subtracted. The right figure shows a series of bunches after substraction of mean. Each column is one $\mu$pulse.

# Anomaly Detection on BPMs

- Use **data-driven approaches** to analyze beam trajectories at European XFEL.
- Fit trajectories to **sine function** based on periodicity from beam optics.

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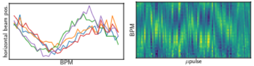


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- **Train transformer** model to map inputs to common mode for anomaly detection.

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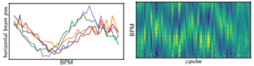


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- Fit trajectories to **sine function** based on periodicity from beam optics.
- **Train transformer** model to map inputs to common mode for anomaly detection.
- **Identify some faults** from beam data recorded prior to issue reports.

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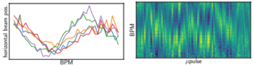


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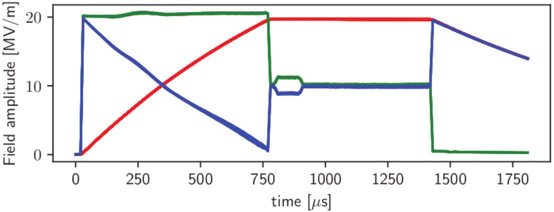
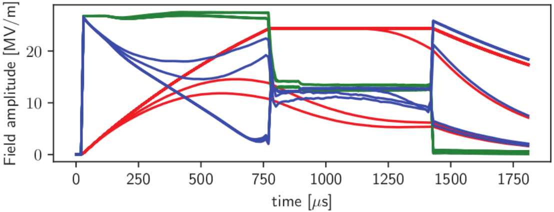
# Anomaly Detection on RF Cavities



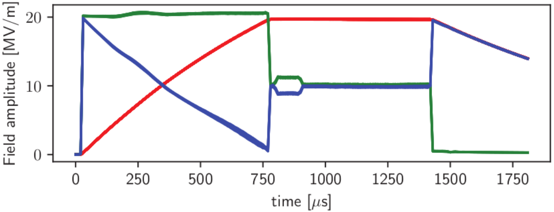

> RNN model for fault prediction on XFEL SRF cavities.

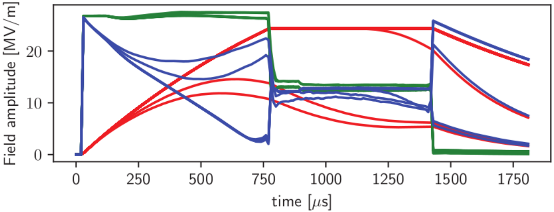
**A data-driven anomaly detection on SRF cavities at the European XFEL**

**A Sulc, A Eichler and T Wilsken**
Deutsches Elektronen-Synchrotron DESY, Notkestr. 85, 22607 Hamburg, Germany
E-mail: `sulcan@desy.de`

**Abstract.** The European XFEL is currently operating with hundreds of superconducting radio frequency cavities. To be able to minimize the downtimes, prevention of failures on the SRF cavities is crucial. In this paper, we propose an anomaly detection approach based on a neural network model to predict occurrences of breakdowns on the SRF cavities based on a model trained on historical data. We used our existing anomaly detection infrastructure to get a subset of the stored data labeled as faulty. We experimented with different training losses to maximally profit from the available data and trained a recurrent neural network that can predict a failure from a series of pulses. The proposed model is using a tailored architecture with recurrent neural units and takes into account the sequential nature of the problem which can generalize and predict a variety of failures that we have been experiencing in operation.

# Anomaly Detection on RF Cavities




- RNN model for fault prediction on XFEL SRF cavities.
- Model inputs: preprocessed cavity waveform time series.

### A data-driven anomaly detection on SRF cavities at the European XFEL


**A Sulc, A Eichler and T Wilsken**

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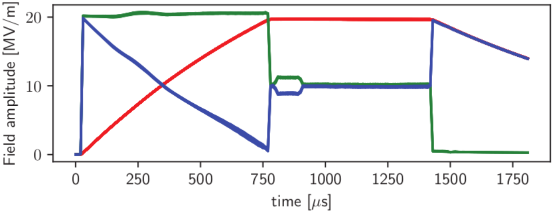


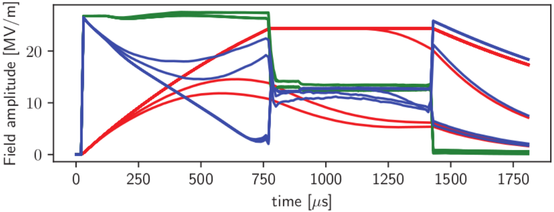


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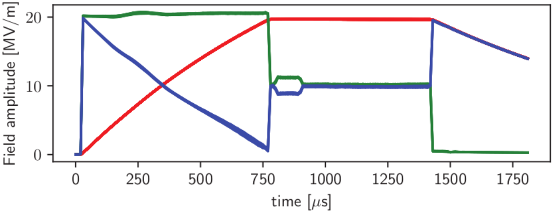


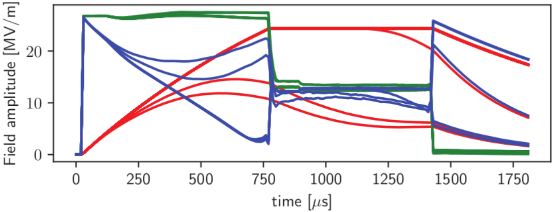


- RNN model for fault prediction on XFEL SRF cavities.
- Model inputs: preprocessed cavity waveform time series.
- Good test performance detecting faults; low false positives
- Future work: distinguish fault types; generative models

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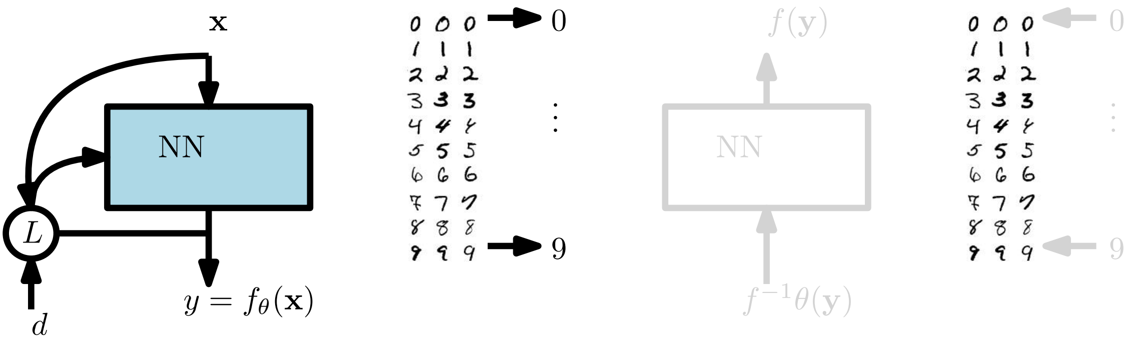
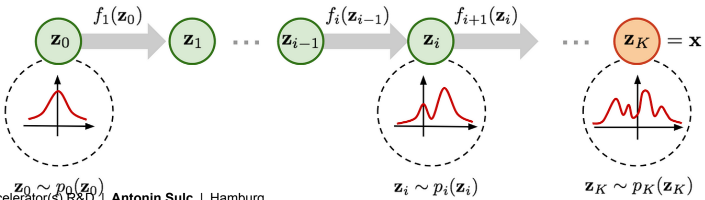
# Normalizing Flow - Invertible Models



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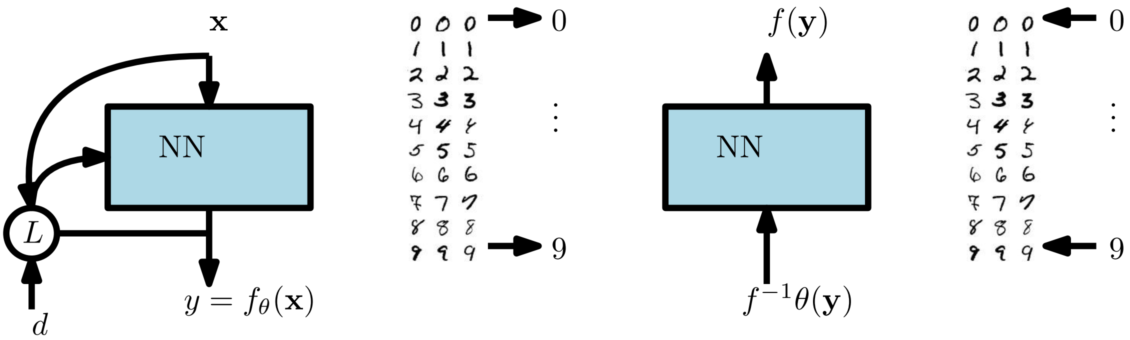
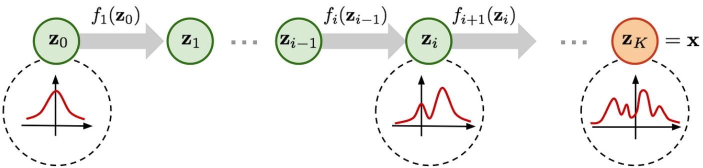
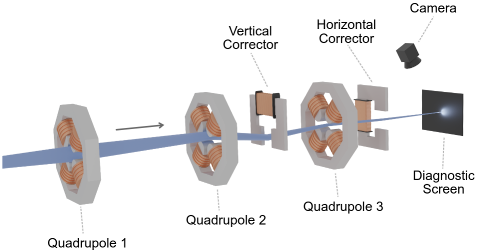


# Reinforcement Learning - SINBAD ARES




**Learning-based Optimisation of Particle Accelerators Under Partial Observability Without Real-World Training**

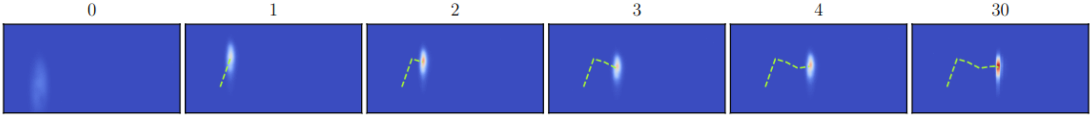

**Jan Kaiser** [* 1] **Oliver Stein** [* 1] **Annika Eichler** [1]



**Abstract**

In recent work, it has been shown that reinforcement learning (RL) is capable of solving a variety of problems at sometimes super-human performance levels. But despite continued advances in the field, applying RL to complex real-world control and optimisation problems has proven difficult. In this contribution, we demonstrate how to successfully apply RL to the optimisation of a highly complex real-world machine – specifically a linear


Particle accelerators are an excellent example of a high-impact real-world application where RL can make a meaningful difference. Among the most advanced machines of our time, particle accelerators find use in many applications such as fundamental physics research, cancer treatment, the development of vaccines and drugs as well as the development and production of novel materials enabling for example for carbon-neutral transportation. These applications place strict requirements on the electron or photon beam delivered by the accelerator. Tuning accelerators to fulfil these requirements has historically been a challenging and diffi-



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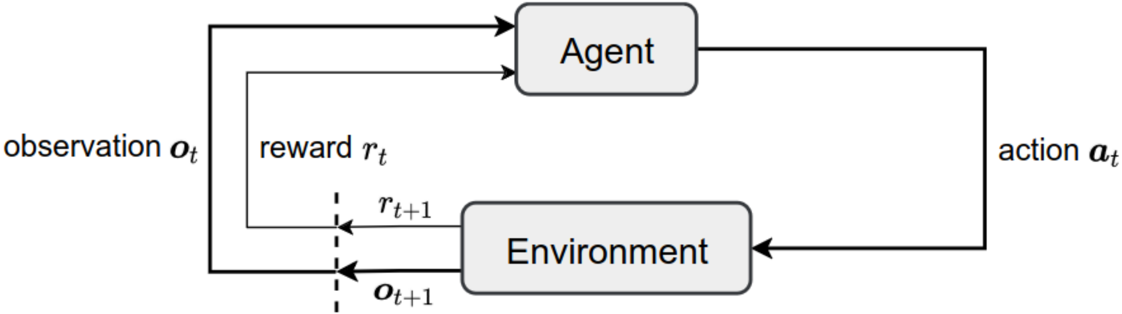

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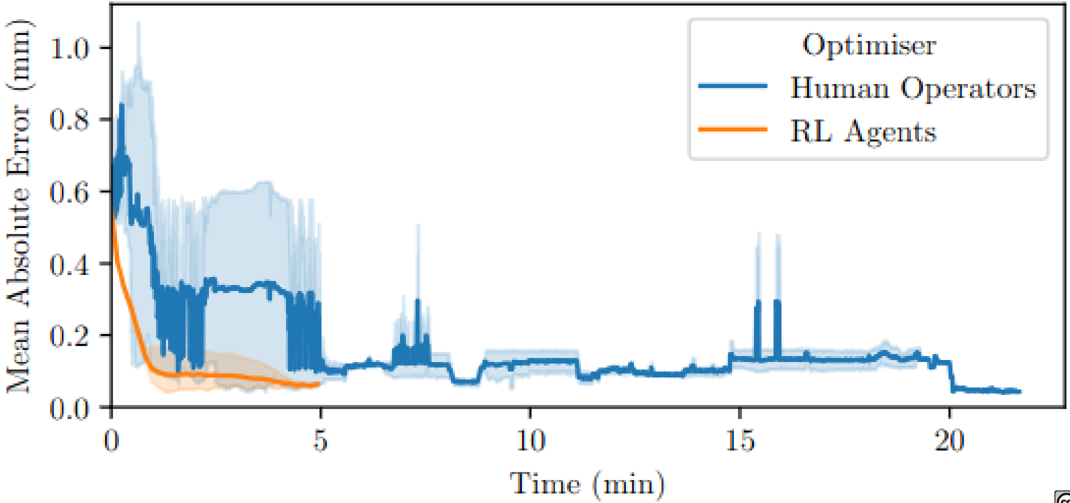
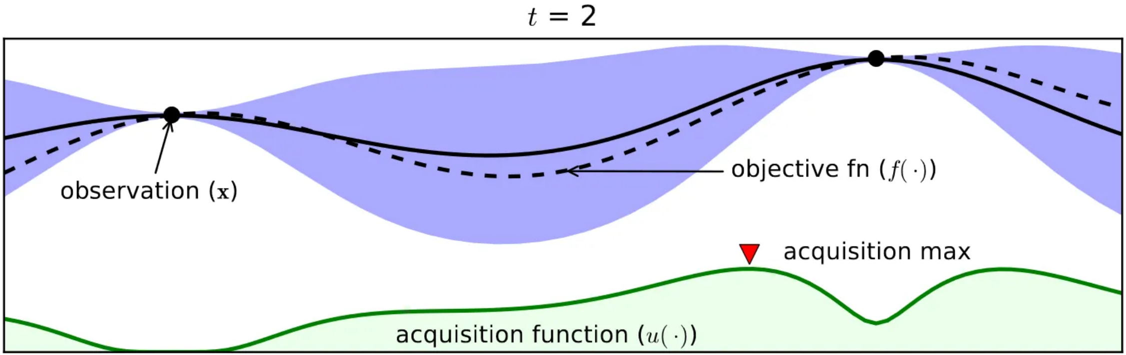


# Bayesian Optimisation



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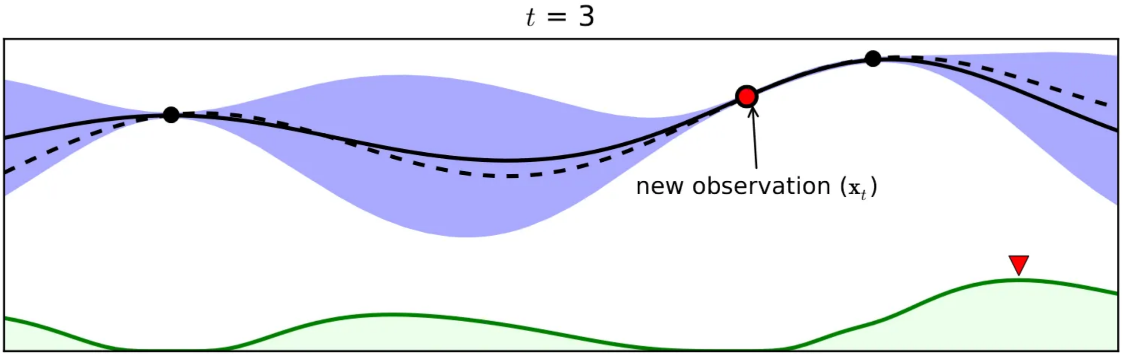

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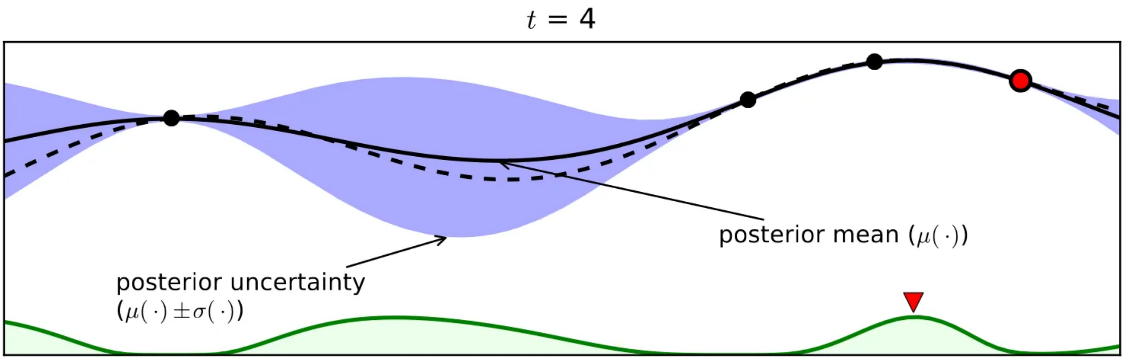

# Conclusion

- Presented overview of machine learning techniques for particle accelerator R&D.
- Custom language model to aid search/validation.
- Anomaly detection on logs, beam instrumentation, RF cavities.
- Identified RF and BPM faults data using data-driven approaches.
- Reinforcement learning for automated control/optimization.

# Thank you!

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