

EUROPEAN SPALLATION SOURCE



Fast Machine Learning for Accelerator Controls

FastML for Science workshop Imperial College London, 25-28 September 2023









The ESS Machine







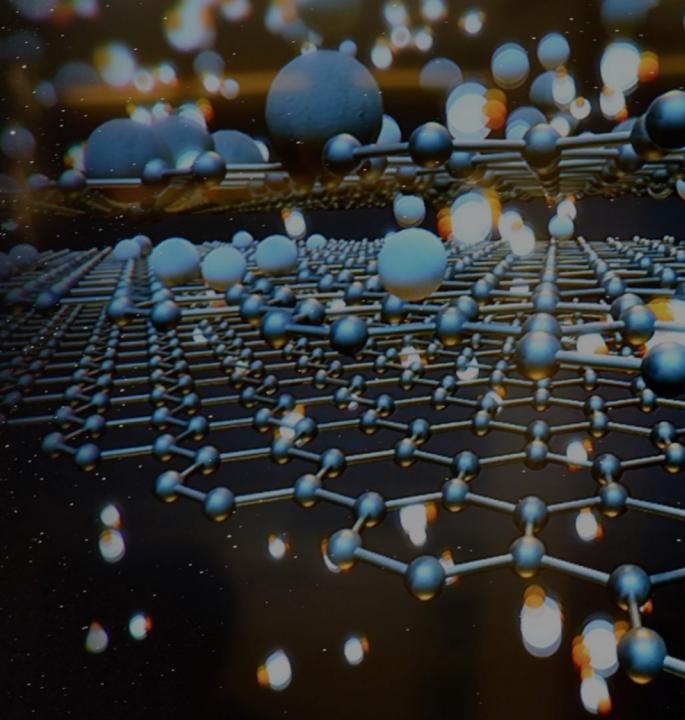
m e sc ie

ESS is a user facility.

Scientists from all over the world will be welcomed to ESS with their specimens to do experiments.

Expectations:

- 800 experiments per year
- 3 000 guest scientists per year



Challenges



- Accelerator based facilities are some of the worlds most complex systems
- ESS is a user facility with a 95% availability goal
 - High availability requirements on equipment
 - The control system plays a key role for the availability of the facility



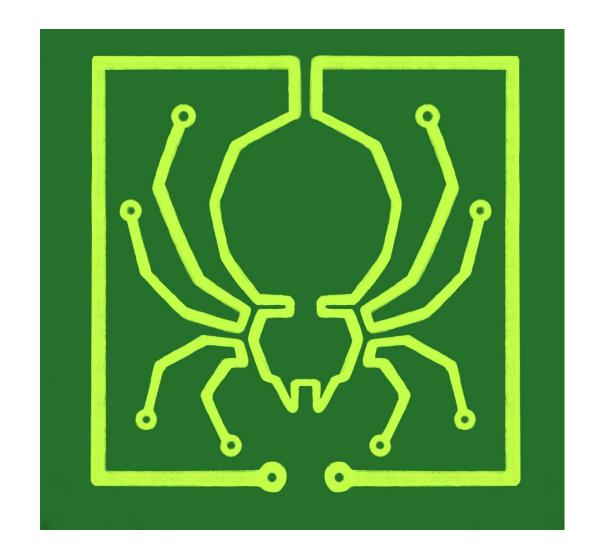
Control System Machine Learning Project



- Explore if machine learning can be used to:
- Increase facility availability.

2019 - 2023

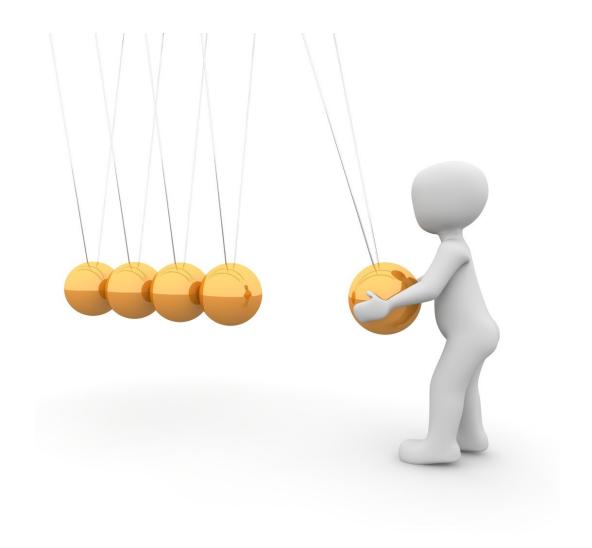
- Increase efficiency of operation
- Enhance process understanding
- Lower operational and maintenance costs
- Decrease commissioning time



Resources



- 100 % me
- Overwhelming interest from
 - Colleagues
 - Students
 - Academia
 - Companies



ESS Control System Data Lab









- NEWS

A big machine with lots of data – WASP researchers in a pilot study with ESS

April 28th, 2021



When finished, the European Spallation Source (ESS) in Lund will have the most complex control system in Sweden, and AI, especially machine learning, is crucial for optimizing its operation. WASP associated researchers Per Runeson and Emma Söderberg, both from Lund University, recently contributed to a pilot study on data sharing for machine learning research from ESS.

In their contribution, they have investigated several issues regarding data sharing. How can data be shared between organizations in order to achieve more and better training data for machine learning models? One useful solution is sharing through data ecosystems with various degrees of openness, where one company shares data, and another annotates it. This could be beneficial in terms of increased knowledge and better prediction models.

"We conclude in our report that by sharing data, ESS can function as a catalyst for Industry 4.0 digitalisation, both in industry and other research facilities," explains Per Runeson, Professor in Software Engineering. "Data sharing fulfills the function of sharing knowledge, and our project shows that it is possible for ESS to be a role model and share relevant data with industry," he adds.

Another topic addressed was how to build long-term reliable data pipelines. They found that agile tools and approaches are needed in order to collect, process and maintain data. Also, data traceability and handling of meta data are important quality factors that needs attention when working with machine learning.

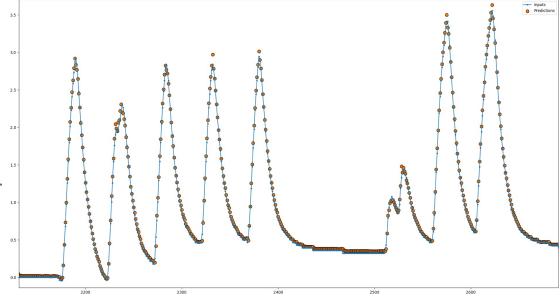
"We found that a lot of the literature cover challenges with Big Data, but in practice for companies in this space the data sets may many times be smaller and there are challenges in how to trace data versions and how to share understanding of the data between developers. We see a potential in further exploring how agile methods and tools from software development can be utilized in management of data," says Emma Söderberg.

Klystron oil temperature

ess

https://www.dvel.se/news/new-collaboration-with-ess-within-vinova-project-regarding-machine-learning-and-ai/





Use case:

Warn before temperatures gets too high.

time

- Warn about fault sensors or calibration issues.
- Apply feedback loop to keep the temperature within limit.

Student Project: Tuning the DTL



Developing an ML-based model for RF tuning of DTL machine at ESS

Student: Amin Hosseini Nejad.

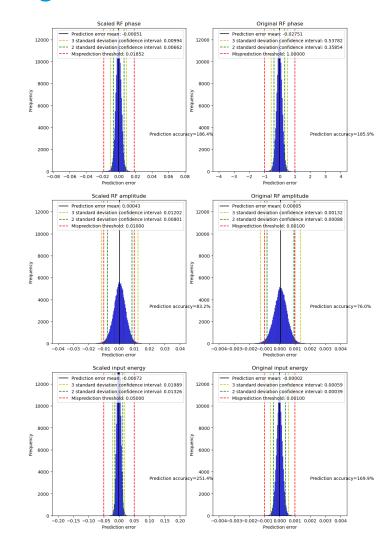
Institute: Automatic Controls LU

Course: Master's Program in Machine

Learning, Systems and Control

ESS Supervisor: Natalia Milas (accelerator)





Student Project: Alarm Cascades

https://drops.dagstuhl.de/opus/volltexte/2023/19098/

Common Alarm Problems

- Many alarms are unnecessary
- Some alarms are missing
- Many alarms have badly tuned parameters
- Some alarms has a higher priority than others.
- Many alarms are only relevant in certain operational states
- A fault often leads to several consequences

Analyzing Complex Systems with Cascades Using Continuous-Time Bayesian Networks

Alexsandro Bregon & Department of Informatics, Systems and Communication, University of Milano-Bicocca, Italy Karin Rathsman ⊠∰ 0 European Spallation Source ERIC, Lund, Sweden

Marco Scutari ⊠ 😭 🙃

Søren Wengel Mogensen ☆◎ Department of Automatic Control, Lund University, Sweden

ADSTRUCT

Interacting systems of events may exhibit cascading behavior where events tend to be temporally transfer to the systems of events may exhibit cascading behavior where events tend to be temporally transfer to the system of the syst interacting systems of events may exhibit casening denavior where events tend to be temporary clustered. While the cascades themselves may be obvious from the data, it is important to understand child, and the case of the clustered. While the cascades themselves may be obvious from the data, it is important to understand which states of the system trigger them. For this purpose, we propose a modeling framework based over the contract of the purpose es of the system trigger them. For tims purpose, we propose a modeling trainework based sous-time Bayesian networks (CTBNs) to analyze cascading behavior in complex systems. on continuous-time Bayesian networks (CTBNs) to analyze cascading behavior in complex systems.

This framework allows us to describe how events propagate through the system and to identify I has transework allows us to describe how events propagate through the system and to men likely scaling states, that is, system states that may lead to imminent cascading behavior. More likely sentry states, that is, system states that may lead to imminent cascading behavior. Moreover, CTBNs have a simple graphical representation and provide interpretable outputs, both of which are the context of th important when communicating with domain experts, we also develop new methods for knowledge extraction from CTBNs and we apply the proposed methodology to a data set of alarms in a large

2012 ACM Subject Classification Mathematics of computing → Markov processes; Mathematics of

Keywords and phrases event model, continuous-time Bayesian network, alarm network, graphical Digital Object Identifier 10.4230/LIPIcs.TIME.2023.8

Funding Søren Wengel Magensen: The work of SWM was funded by a DFF-International Postdoc-Funding Søren Wengel Megensen: The work of SWM was funded by a DFF-International Postdoc-toral Grant (0164-00023B) from Independent Research Fund Denmark. SWM is a member of the

Acknowledgements The authors would like to thank Per Nilsson for sharing his knowledge about Acknowledgements the authors would like to thank Per Nisson for sharing his knowledge ab the cryogenics plant and for providing valuable feedback on the work presented in this paper.

Many real-world phenomena can be modeled as interacting sequences of events of different Many real-world phenomena can be modeled as interacting sequences of events of different types. This includes social networks where user activity influences the activity of other types. Ans includes social networks where user activity influences the activity of other states [11]. In healthcare, patient history may be modeled as a sequence of events [46]. In the state of the st users [11]. In neathrcare, patient instory may be modeled as a sequence of events [46]. In this paper, we focus on an industrial application in which the events are alarm signals of a tan paper, we notes on an industrial application in which the events are alarm signals of a complex engineered system. As an illustration, consider Figure 1. Three different alarms of the complex engineers of the complex engineers of the complex engineers. complex engineered system. As an illustration, consider Figure 1. Three different alarms

(A, B, and C) monitor a process each within an industrial system. These processes may, for (c), p, and (c) monitor a process each warm an industrial system. These processes may, or instance, represent measured temperatures or pressures. An alarm transitions to on when its assumer, represent measured temperatures or pressures. An atarm transitions to on when its the process it monitors leaves a prespecified range of values and transitions to off when the

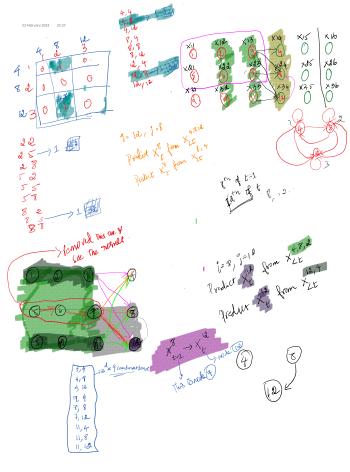
Johnsandre, Bregelt, Karin Rathaman, Marco Scutari, Fabio Stella, and Søren W Johnson and Marco Marco Marco Marco Scutari, Fabio Stella, and Søren W Johnson and Johnson and Representation of Control of Contr

Student project: Alarms

Causal event processes and alarm analysis at ESS

- Student: Vishnu Pradheep Raveendran
- Department: Automatic controls, Lund University.
- Degree: MsC in Machine Learning,
 Systems and Control





Student project: Anomaly detection

https://gupea.ub.gu.se/handle/2077/78206



Student: Vernita Gouws

Title: A Software Process Workflow for

Smart Anomaly Detection Systems

Degree: BSc Software Engineering and

Management

ESS Supervisor: Target division

University: Chalmers and Göteborg University



Data

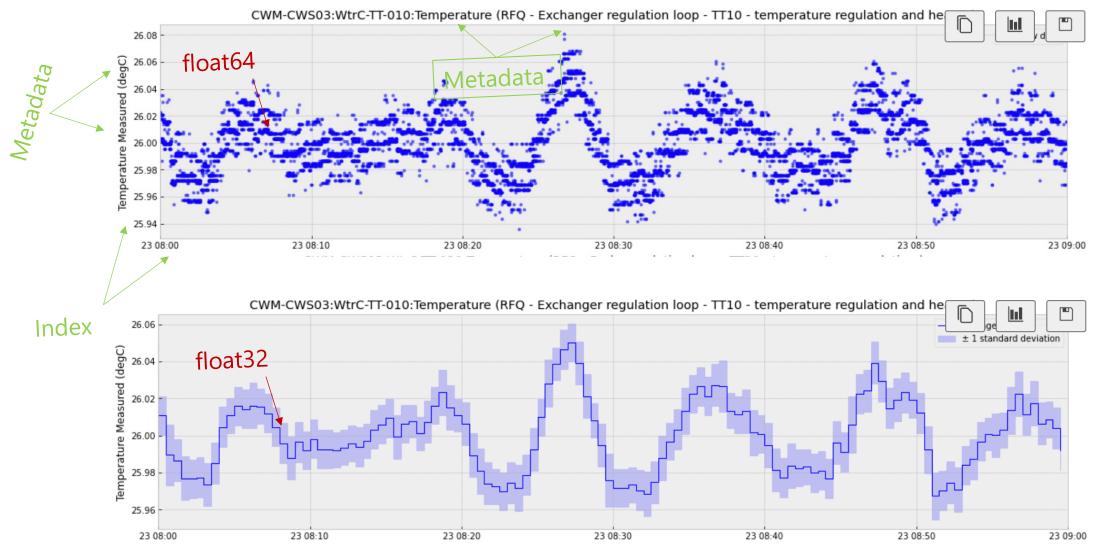


Machine learning models can never perform better than the data they were trained on.

- Reduce volume of data to mitigate network problems, reduce time to retrieve data, reduce costs to store data and reduce costs to pre-process data.
- Enhance information in control system data: Set alarm limits, description, units, operational limits, dead bands, calibration parameters...
- Develop data model and control system data protocol to minimize need of complicated interfaces.
- Make control system data easier to understand for non-experts in control systems (compare with data model in e.g. Numpy, Pandas, Tensorflow, Pytorch, Spark)

More metadata and less data







EUROPEAN SPALLATION SOURCE