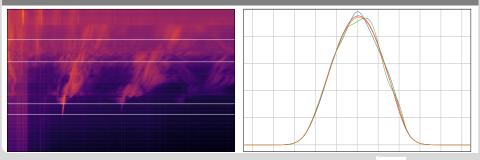




Machine Learning Applications at a Storage Ring

Tobias Boltz, Miriam Brosi, Erik Bründermann, Florian Rämisch, Patrik Schönfeldt, Markus Schwarz, Minjie Yan and Anke-Susanne Müller | July 20, 2017

Laboratory for Applications of Synchrotron Radiation (LAS)



KIT - The Research University in the Helmholtz Association



Motivation Why use Machine Learning Techniques?



- increasing data rates at particle accelerators (reaching TB per day)
- data reduction \Rightarrow information loss?
- a fast (maybe even online), but precise data analysis required
- make use of large statistics to get higher precision
- machine learning offers options to process large data rates
- can model multivariate and non-linear dependencies

Machine Learning

Karbruhe Institute of Technology

Overview

- emerged as a sub-field of computer science in the 1950s
- explores algorithms that enable computers to learn from data without being explicitly programmed¹
- separated into two main categories: supervised learning and unsupervised learning
- variety of different methods for both categories exists
- typical examples are classification (supervised) and clustering (unsupervised) methods

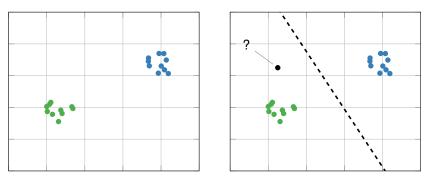
¹Samuel, A. L. Some Studies in Machine Learning Using the Game of Checkers. *IBM Journal of research and development*, 206–226 (1959)

Supervised Learning

initial data set



Classification: Autom. Identification of New Object's Category



classification of new objects

 \Rightarrow e.g. neural networks, decision trees, support vector machines, . . . \Rightarrow simple evaluation measures, e.g. accuracy score

Unsupervised Learning



Clustering: Exploratory Tool of Data Analysis

initial data set





- \Rightarrow e.g. k-means, DBSCAN, gaussian mixture models, ...
- \Rightarrow evaluation generally requires more effort

Machine Learning Applications at ANKA

CSR and Micro-Bunching Instability



Studies at ANKA

- operation of synchrotron light sources with short electron bunches increases coherent synchrotron radiation (CSR) power
- leads to complex dynamics in the longitudinal phase space and the formation of micro-structures within the bunch
- indirect measurement: resulting fluctuations in the emitted CSR power
- direct measurement: electron distribution, difficult due to the small scale of the micro-structures
- \Rightarrow See posters by M. Brosi and B. Kehrer this afternoon!

ML Applications at ANKA



Master's Thesis: Spectrogram Classification

- Title: Analysis of Bursting Spectrograms using Machine Learning Techniques
- Author: Florian Rämisch
- Date: January 2017
- Processed data: order of TB, measured at ANKA

ML Applications at ANKA



Master's Thesis: Spectrogram Classification

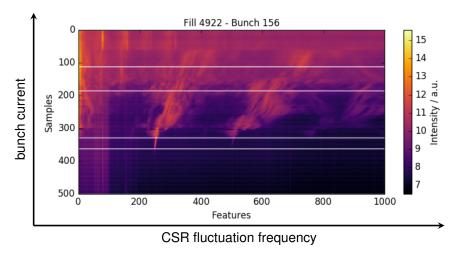
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Bursting Spectrogram Classification



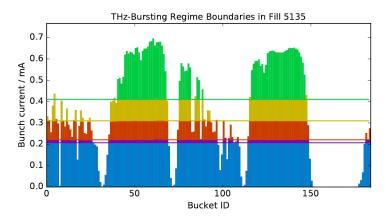
Automated Identification of Marked Bursting Regimes



Bursting Spectrogram Classification



Potential Tool for Multi-Bunch Studies



Brosi, M. et al. Studies of the Micro-Bunching Instability in Multi-Bunch Operation at the ANKA Storage Ring in Proc. of IPAC (2017). doi:https://doi.org/10.18429/JACoW-IPAC2017-THOBA1

ML Applications at ANKA



Master's Thesis: Clustering of Micro-Structures

- Title: Comprehensive Analysis of Micro-Structure Dynamics in Longitudinal Electron Bunch Profiles
- Author: Tobias Boltz
- Date: March 2017
- Processed data: order of TB, simulated using Inovesa²
- Published in KITopen:

https://publikationen.bibliothek.kit.edu/1000068253

²Schönfeldt, P. *et al.* Parallelized Vlasov-Fokker-Planck solver for desktop personal computers. *Phys. Rev. Accel. Beams* **20** (2017)

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unsupervised learning

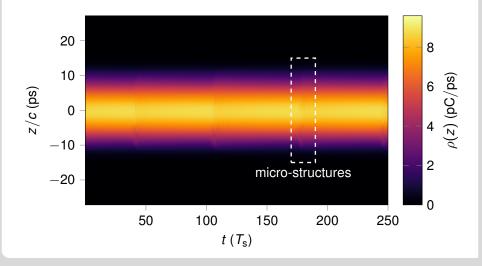


Master's Thesis: Clustering of Micro-Structures



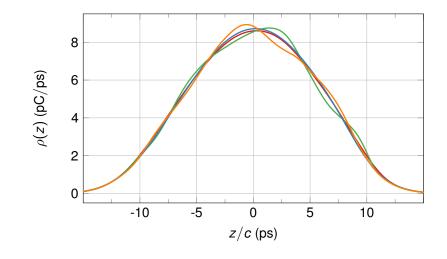


Micro-Structures on the Longitudinal Bunch Profiles



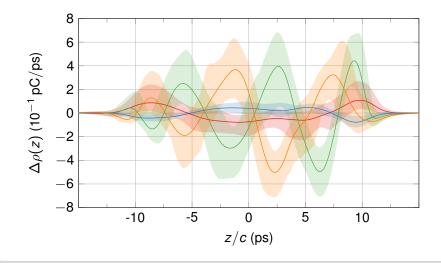


Analysis of Micro-Structures



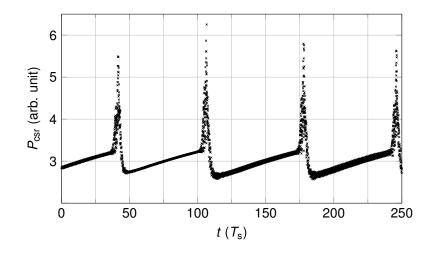


Analysis of Micro-Structures



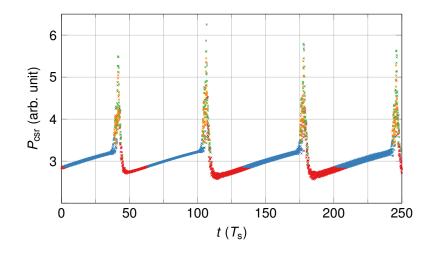


Correlation to CSR Power





Correlation to CSR Power



Summary and Outlook



Machine Learning at a Storage Ring

- machine learning provides tools to handle large data sets, e.g.:
 - classification: automated identification of new object's category
 - clustering: exploratory tool of data analysis
- increasing data rates at particle accelerators yield new possibilities for the application of machine learning techniques
- first applications at ANKA have already proven successful

Thank you for your attention!

Backup

Backup



Clustering of Micro-Structures: Simulation Parameters

Physical parameter	Value
RF voltage U_0	1 MV
revolution frequency frev	9 MHz
synchrotron frequency f_s	30 kHz
damping time $ au_{d}$	5 ms
harmonic number <i>h</i>	50
parallel plates distance g	3.2 cm
initial electron distribution $\varphi(z, E, t_0)$	2-dim. Gaussian
simulation time t	250 <i>T</i> s
bunch current <i>I</i> _{bunch}	0.5 mA to 2.0 mA
Control parameter	Value
grid size n _{grid}	256
time steps n _{steps}	10 000