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Detection and Forecasting of Particle Accelerator Interlocks

Zurich PhD Seminar, January 27, 2023

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Outline

- Introduction and problem formulation
- Model 1: Recurrence Plot - Convolutional Neural Network model
- Model 2: Logistic Lasso regression model
- Model comparison in classification and real-time metrics
- Conclusion and outlook

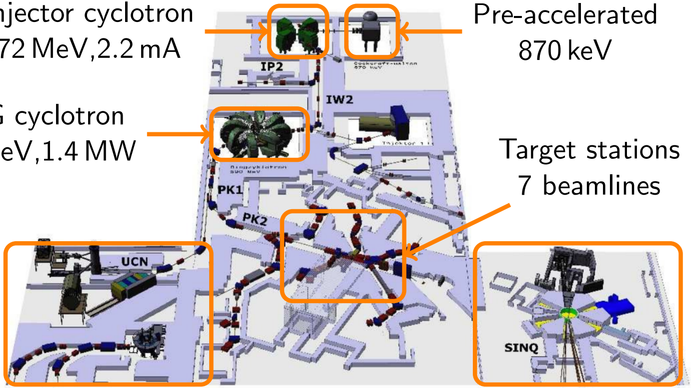
Introduction - High Intensity Proton Accelerators

Injector cyclotron
72 MeV, 2.2 mA

Pre-accelerated
870 keV

RING cyclotron
590 MeV, 1.4 MW

Target stations
7 beamlines

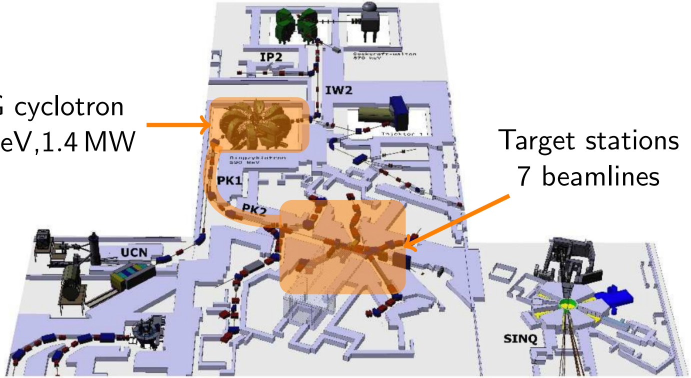


Ultra cold
neutron source

Spallation
neutron source

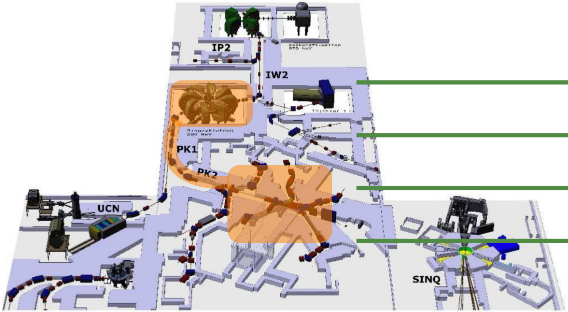
Introduction - Focus region

RING cyclotron
590 MeV,1.4 MW



Target stations
7 beamlines

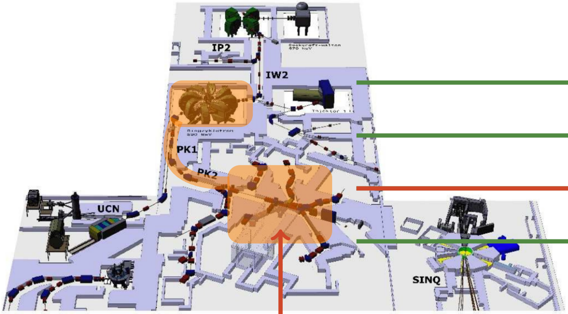
Introduction - Interlock system



- Temperature monitors
- Magnet currents
- Beam loss monitors
- Beam position monitors

→ Interlock system

Introduction - Interlock system

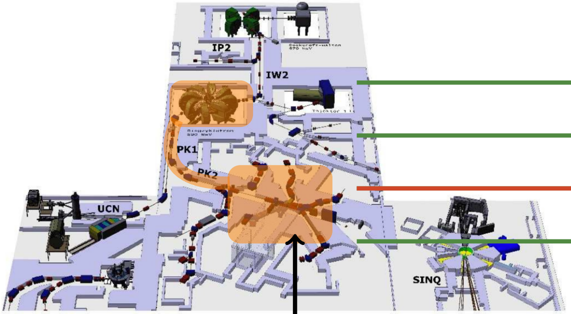


- Temperature monitors
- Magnet currents
- Beam loss monitors
- Beam position monitors

→ **Interlock system** → Shut off the beam

Lose 25 s beam time

Introduction - Interlock system



Temperature monitors

Magnet currents

Beam loss monitors

Beam position monitors

Forecasting model

if interlock

Recover operation

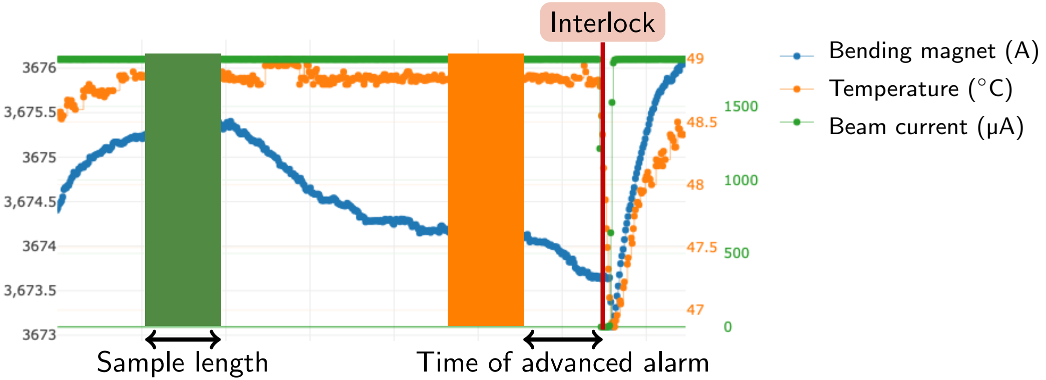
Shut off the beam

Lose 25 s beam time

Interlock system

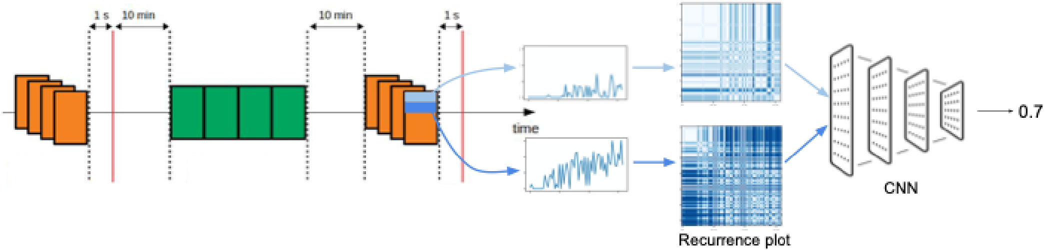
Introduction - Problem formulation

- Binary classification
- **Class Positive (1)**: interlock samples close to interlock
- **Class Negative (0)**: stable samples far from interlock



Model 1 - The RPCNN model

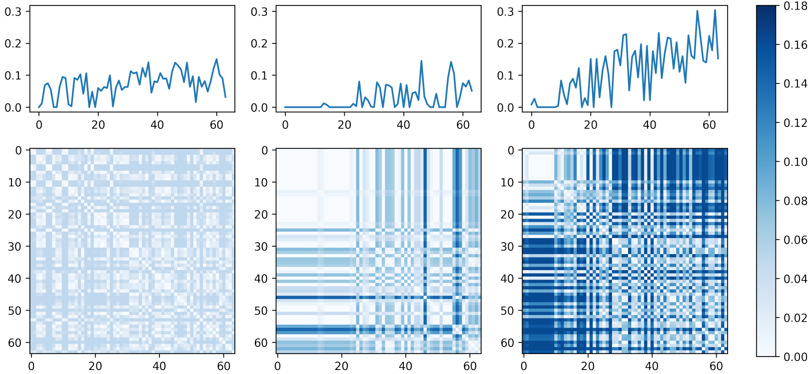
Recurrence Plot - Convolutional Neural Network [1]



1. Take the two classes of samples, of size (376, sample length)
2. Transform each 1D time series into 2D *Recurrence Plot*
3. Train with *CNN* and get probability output $\in [0, 1]$

More on Recurrence Plots

- 1D series $\rightarrow$ 2D image for developed CNN to exploit
- Detect hidden dynamical patterns
- Global recurrence plot [2]: a distance matrix within a cutoff limit ϵ (trainable)



RPCNN result

RPCNN: Complex model, yet high FP rate!

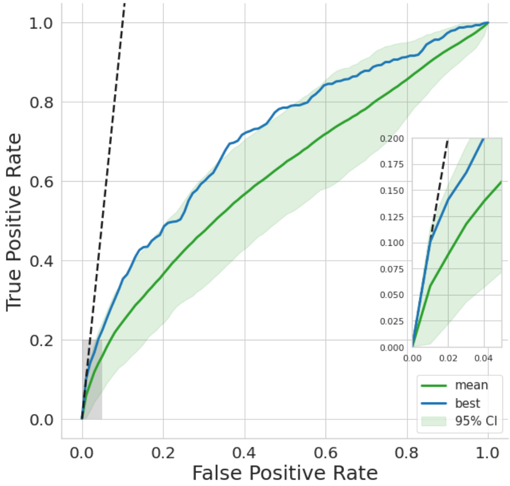
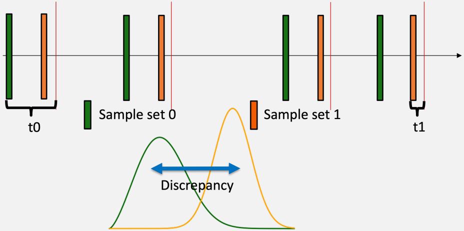
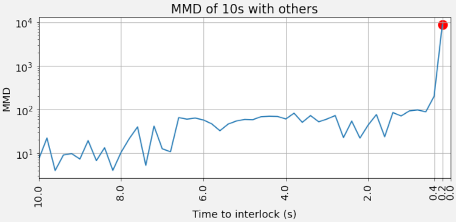


Figure: The Receiver Operating Characteristic (ROC) curve of best and mean RPCNN results.

Problem - Interlocks are abrupt events

- **Two sample test** [3]: Statistically compare *Maximum Mean Discrepancy (MMD)* of samples taken at t_0 and t_1 before all interlocks
- 0.2 s is abruptly different, essentially no gradual change
- Positive class of RPCNN is taken before 1 s $\rightarrow$ fail to capture the difference





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Model 2 - Logistic LASSO regression

Penalized regression with the Least Absolute Shrinkage and Selection Operator

1. **Class Positive (1)**: interlock samples, taken $t_1 = 0.2\text{s}$ before interlock

   Class Negative (0): stable samples, taken $t_0 = 10\text{s}$ before interlock

2. Input $\{\mathbf{x}_i \in \mathbb{R}^d\}_{i=1}^n$, label $\{y_i\}_{i=1}^n \in \{\pm 1\}$, fit weight $\omega \in \mathbb{R}^d$

   Minimize Loss

$$\min_\omega L = \min_\omega \underbrace{\frac{1}{n}\sum_{i=1}^{n} \log\left[1 + \exp\left(-y_i \cdot \omega^T \mathbf{x}_i\right)\right]}_{\text{logistic loss for binary classification}} + \underbrace{\lambda\|\omega\|}_{\text{regularization}}$$

   Simple linear sparse $\rightarrow$ interpretablity

3. Also a probability output $\in [0, 1]$

Model comparison – classification metric

LASSO:
better classification;
stable performance

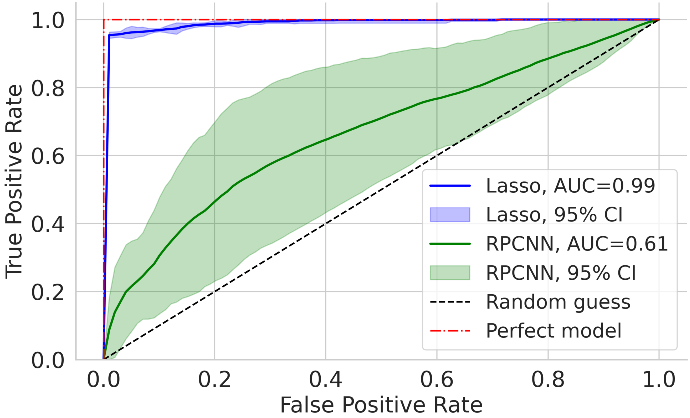


Figure: The Receiver Operating Characteristic (ROC) curves of both models.

Custom real-time metric

- True positive (TP), False positive (FP) according to 1min inspection window
- Beam time saved T_s in any given time: $T_s := 19 \cdot N_{TP} - 6 \cdot N_{FP}$

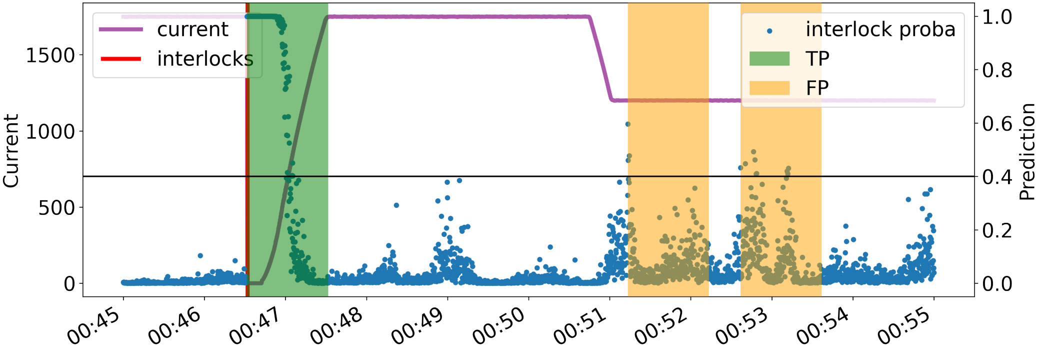
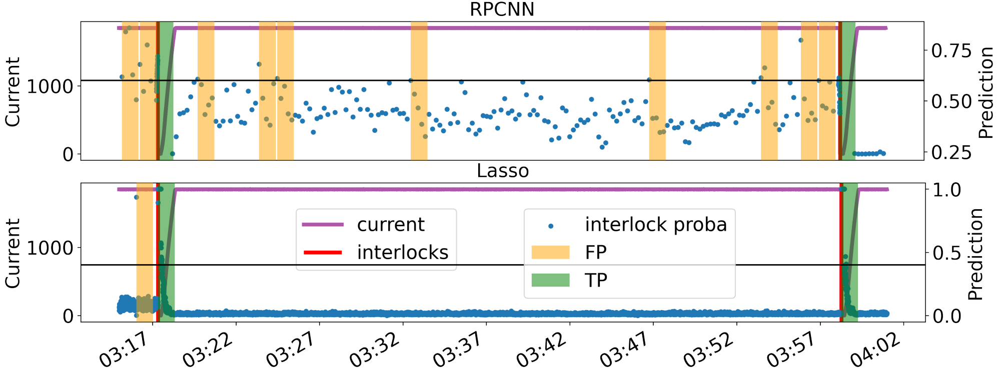


Figure: Examples of real-time TP and FP of the LASSO model.

Model comparison - Beam time saved

Model	N_{TP}	$N_{TP}/N_{int}(\%)$	N_{FP}	T_s (Min/day)
RPCNN	277	23.2	5408	-10.53
LASSO	1134	95.1	1214	5.63

Table: Real-time metrics of both models in 2 months with $N_{int} = 1192$.



Conclusion and outlook

- Formulate forecasting problem into binary classification
- RPCNN model transforms 1D time series into 2D images $\rightarrow$ complex, high false positive, improper input
- Two sample MMD test shows beam interruptions are more abrupt than gradual
- LASSO model outperforms RPCNN in both classification and real-time metrics
- Further experiments on real-time implementation, specific types of interlocks and recover operations are ongoing

Thanks to

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- Dr. Andreas Adelmann

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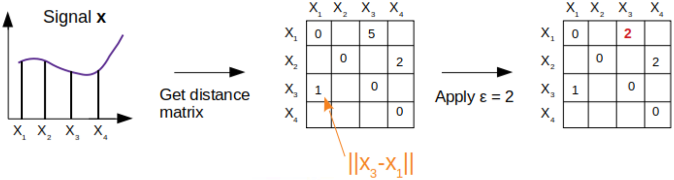
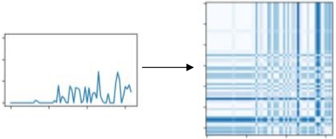
Backup: Recurrence Plot (RP) of time series

- Global recurrence plot / Distance plot [2]: a distance matrix within a cutoff limit ε

$$D_{ij} = \begin{cases} \|x_i - x_j\|, & \|x_i - x_j\| \leq \varepsilon \\ \varepsilon, & \|x_i - x_j\| > \varepsilon \end{cases}$$

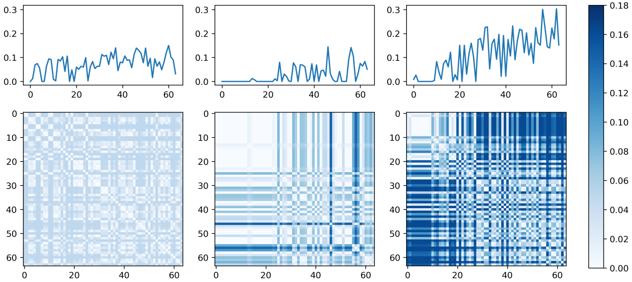




The Recurrence Plot - Convolutional Neural Network (RPCNN) model

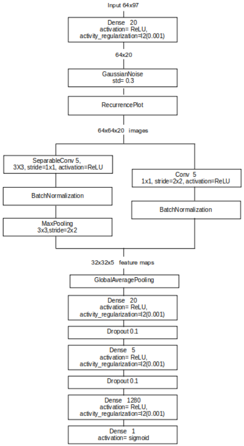
- Recurrence plot: detect hidden dynamical patterns
- 1D time series -> 2D image for developed CNN to exploit
- Global recurrence plot[2]: a distance matrix within a cutoff limit ε (trainable)

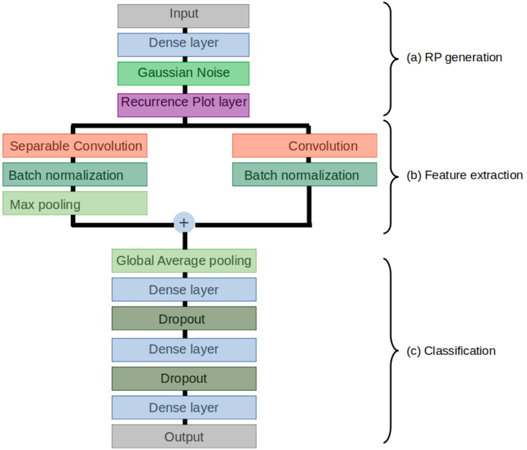
$$D_{ij} = \begin{cases} \|x_i - x_j\|, & \|x_i - x_j\| \le \varepsilon, \\ \varepsilon, & \|x_i - x_j\| > \varepsilon \end{cases} \qquad i,j \text{ are indices}$$



(a) uncorrelated stochastic (b) starting to grow (c) stochastic with a linear trend

Backup: model structure[5]



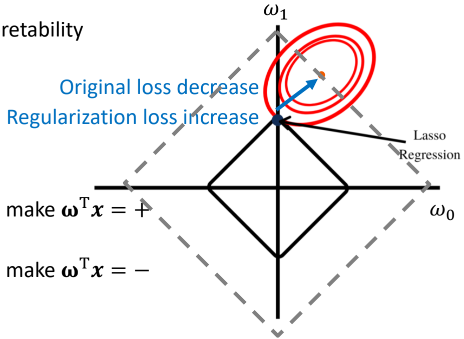


LASSO model

- Input $X \coloneqq \{\boldsymbol{x}_i\}_{i=1}^{n}, \boldsymbol{x}_i \in \mathbb{R}^d$, Output $Y \coloneqq \{y_i\}_{i=1}^{n} \in \{\pm 1\}$, weight $\boldsymbol{\omega} \in \mathbb{R}^d$
- **L**east **A**bsolute **S**hrinkage and **S**election **O**perator
- Loss function L

$$\min_{\omega} \mathrm{L} = \min_{\omega} \underbrace{\frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \log[1 + \exp(-y_i \cdot \boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{x}_{\mathrm{i}})]}_{\text{logistic loss}} + \underbrace{\lambda \|\boldsymbol{\omega}\|_{\mathrm{L1}}}_{\text{regularization}}$$

- Simple, sparse model -> interpretability
- λ: regularization parameter



- Output for : $y_i = +1$, try to make $\boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{x} = +$
- Output for : $y_i = -1$, try to make $\boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{x} = -$

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Two-sample test – preliminary results

- Currently use a fast test called the Mean embeddings (ME) test
- $\alpha = 0.01$
- 0.2s is significantly different, while 0.4s is slightly different from others

	0.2	0.4	0.6	0.8
0.2	Same $\widehat{\lambda_n}$=1.2	Different $\widehat{\lambda_n}$=4935.6	Different $\widehat{\lambda_n}$=8102.1	Different $\widehat{\lambda_n}$=7999.4
0.4		Same $\widehat{\lambda_n}$=5.6	Different $\widehat{\lambda_n}$=177.0	Different $\widehat{\lambda_n}$=165.3
0.6			Same $\widehat{\lambda_n}$=2.6	Same $\widehat{\lambda_n}$=3.7
0.8				Same $\widehat{\lambda_n}$=3.6