Performance of different machine learning techniques for forecasting of particle accelerator interlocks

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May 19, 2020

Incentive

The Interlock system makes up $\sim 20\%$ of the total beam time loss

If interlocks can be predicted, we can prevent them

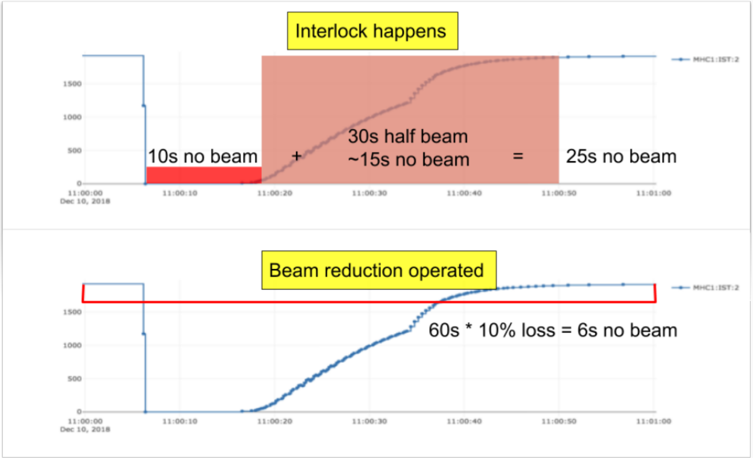
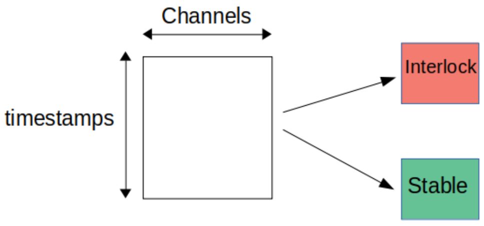


Figure by Sichen Li

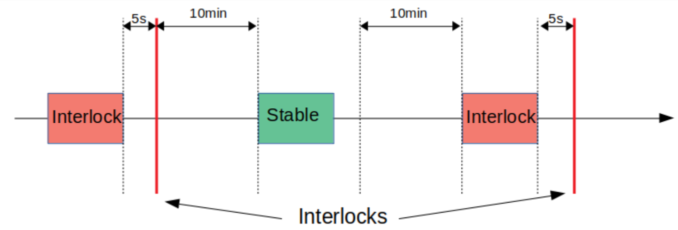
Formulating the problem

Classification approach: what gets classified?

"windows" of a multivariate timeseries

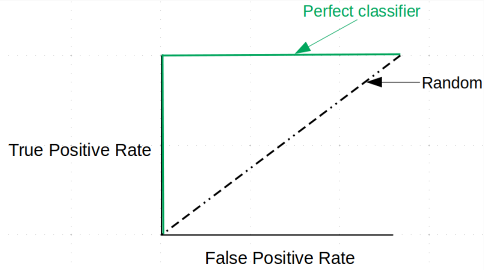


what are stable and interlock windows?



Receiver operating characteristic (ROC) plots

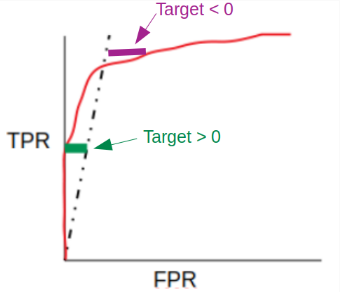
True positive rate (TPR) against the false positive rate (FPR) of the model predictions as a function of the discrimination threshold



Evaluation metrics

How many false positives can we tolerate?

Target $= \max(TPR - 10 * FPR)$



Evaluation metrics

How many false positives can we tolerate?

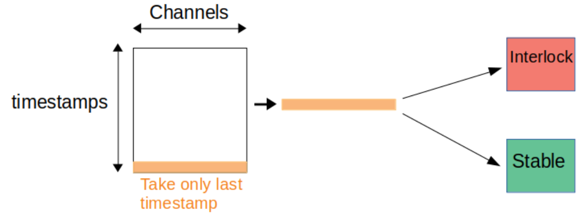
$$\text{Target} = \max(TPR - 10 * FPR)$$

Beam time lost w.r.t the non-intervention baseline of 25 seconds per interlock:

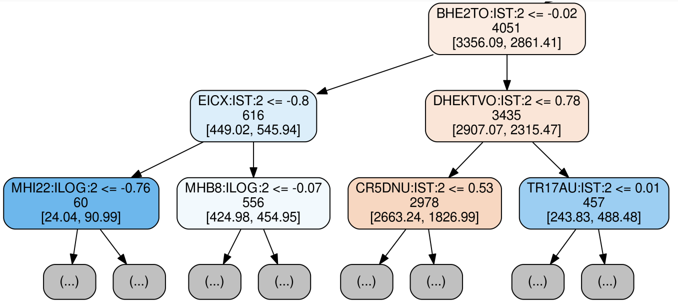
$$(1 - TPR) * 25 + TPR * 6 + FPR * 45 * 6$$

Random Forest

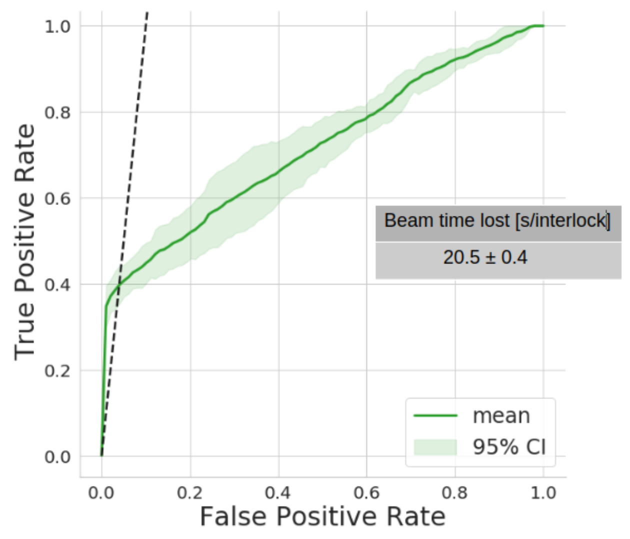
Input



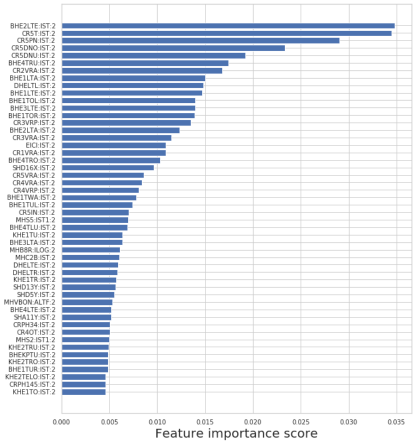
Model



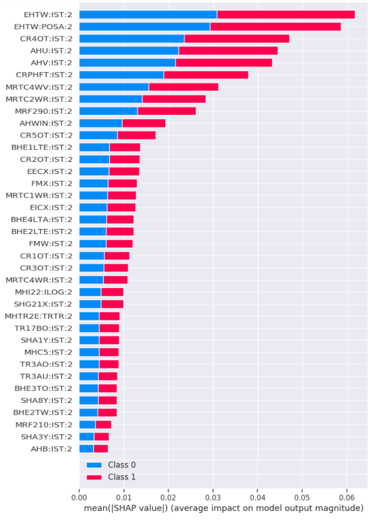
Random Forest



Feature importance



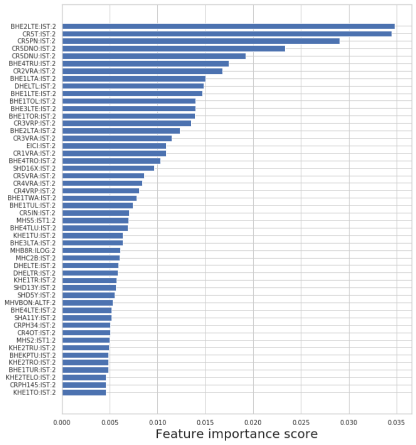
SHapley Additive Explanations



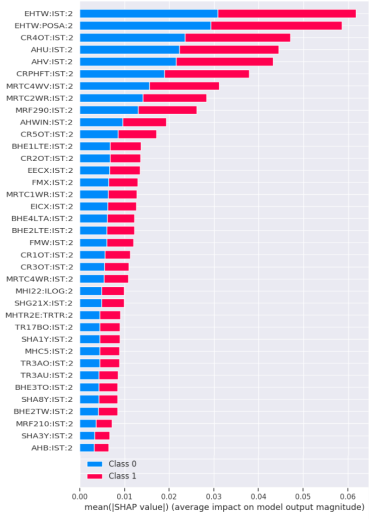
Random Forest

Feature Selection

Feature importance

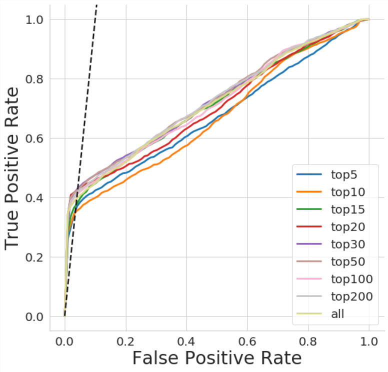


SHapley Additive Explanations

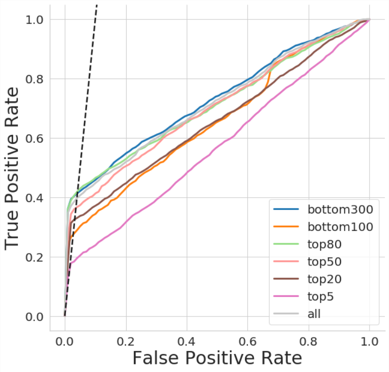


Only a few of the 311 channels seem to contain most of the information

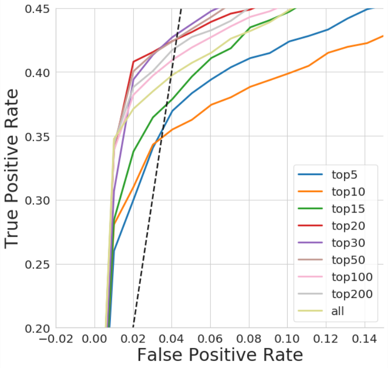
Feature importance



SHapley Additive Explanations

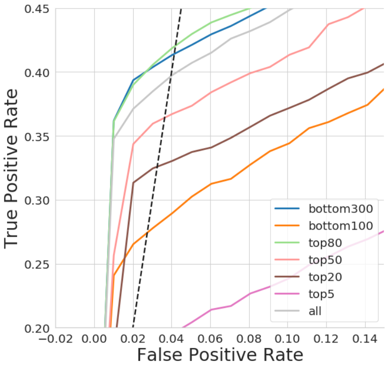


Feature importance

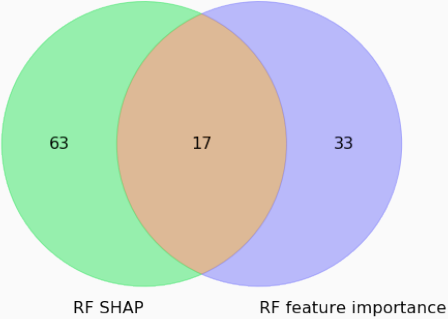


need top 50 features

SHapley Additive Explanations



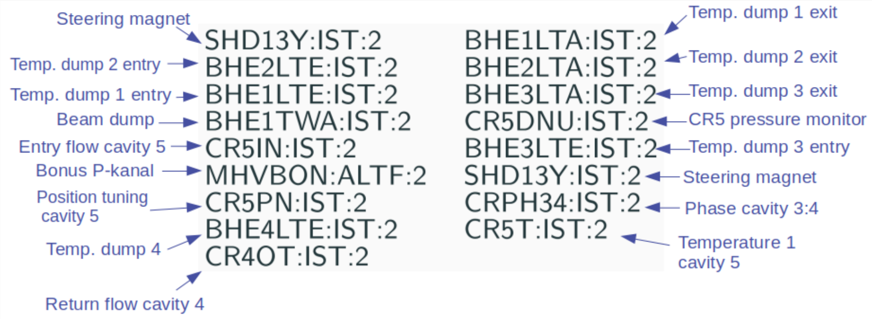
need top 80 features



SHD13Y:IST:2
BHE2LTE:IST:2
BHE1LTE:IST:2
BHE1TWA:IST:2
CR5IN:IST:2
MHVBON:ALTF:2
CR5PN:IST:2
BHE4LTE:IST:2
CR4OT:IST:2

BHE1LTA:IST:2
BHE2LTA:IST:2
BHE3LTA:IST:2
CR5DNU:IST:2
BHE3LTE:IST:2
SHD13Y:IST:2
CRPH34:IST:2
CR5T:IST:2

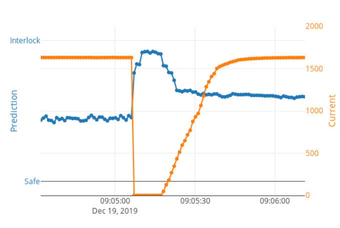
→ redundancy in the data

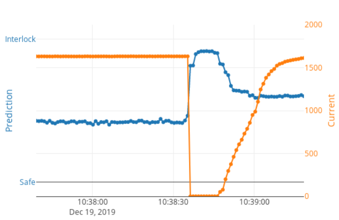

Steering magnet
SHD13Y:IST:2
Temp. dump 2 entry
BHE2LTE:IST:2
Temp. dump 1 entry
BHE1LTE:IST:2
Beam dump
BHE1TWA:IST:2
Entry flow cavity 5
CR5IN:IST:2
Bonus P-kanal
MHVBON:ALTF:2
Position tuning cavity 5
CR5PN:IST:2
Temp. dump 4
BHE4LTE:IST:2
CR4OT:IST:2
Return flow cavity 4
Temp. dump 1 exit
BHE1LTA:IST:2
Temp. dump 2 exit
BHE2LTA:IST:2
Temp. dump 3 exit
BHE3LTA:IST:2
CR5 pressure monitor
CR5DNU:IST:2
Temp. dump 3 entry
BHE3LTE:IST:2
Steering magnet
SHD13Y:IST:2
Phase cavity 3:4
CRPH34:IST:2
Temperature 1 cavity 5
CR5T:IST:2

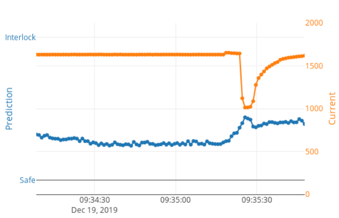
Random Forest

Online predictions:

Tool developed by Coello de Portugal Martinez Vazquez Jaime Maria







Random Forest

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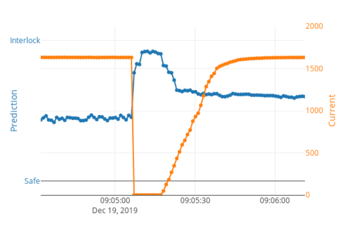
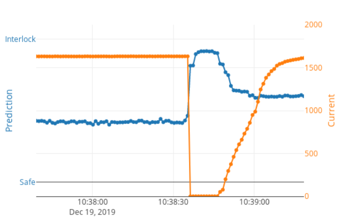
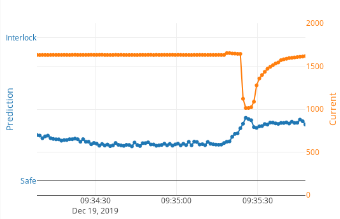






Reacts well to interlocks but cannot predict them

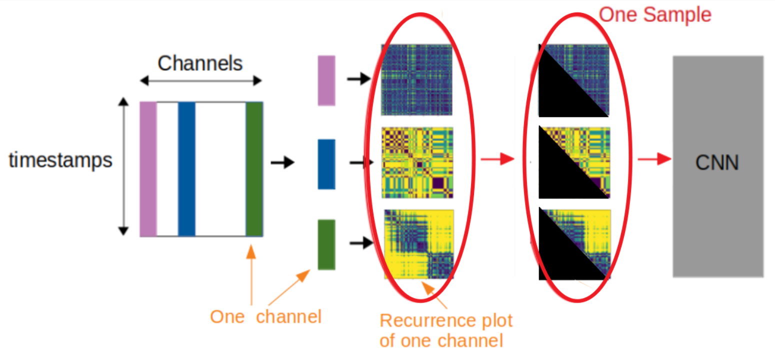
Random Forest

- Performance of the Random Forest model is not sufficient
- The model is interesting for the feature selection

Conclusion: do feature selection for all future models

Input

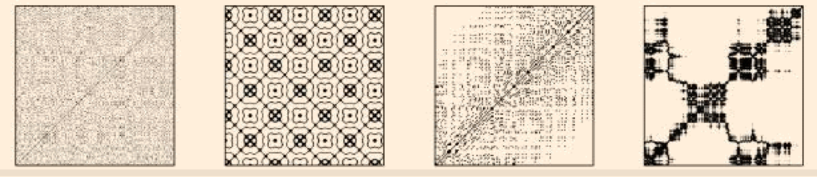
Recurrence Plots of the data windows



Time series classification → Image classification

What is a recurrence plot(RP)?

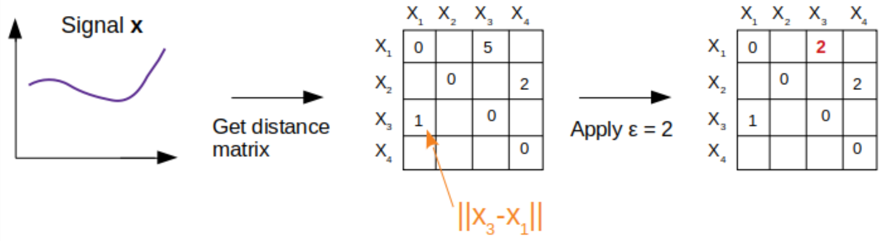
Tool to analyze dynamical systems and detect hidden dynamical patterns and nonlinearities

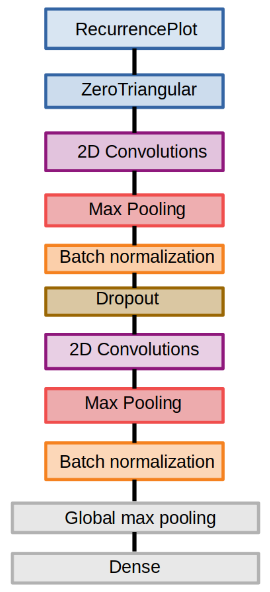


Source: http://www.recurrence-plot.tk/glance.php

Global Recurrence Plots with fixed epsilon

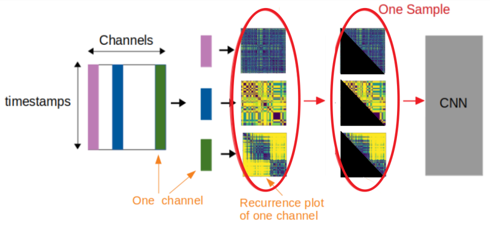
$$D_{i,j} = \begin{cases} ||x_i - x_j||, & ||x_i - x_j|| \leq \epsilon \\ \epsilon, & ||x_i - x_j|| > \epsilon \end{cases}$$




RecurrencePlot
ZeroTriangular
2D Convolutions
Max Pooling
Batch normalization
Dropout
2D Convolutions
Max Pooling
Batch normalization
Global max pooling
Dense

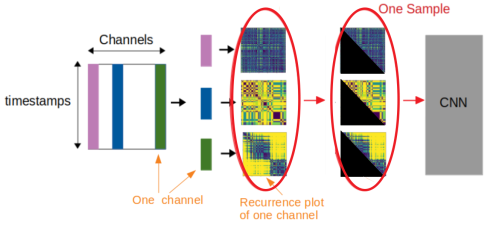
CNN

One plot per feature variation

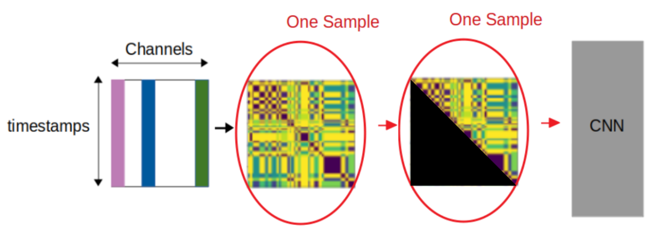


CNN

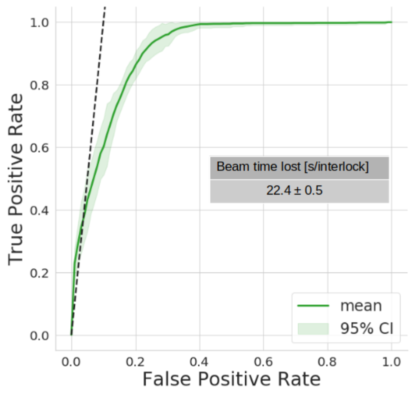
One plot per feature variation



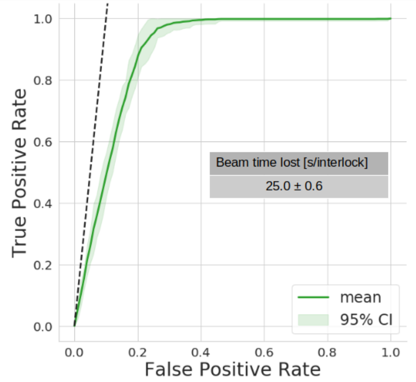
One plot variation



Windows of length 25 time stamps

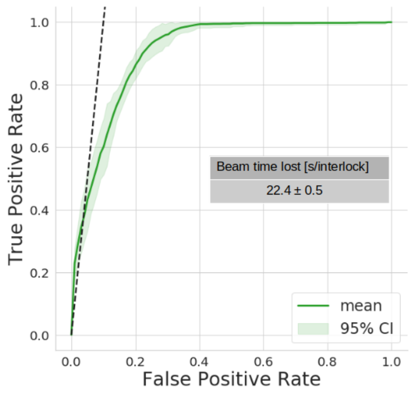


One plot per feature

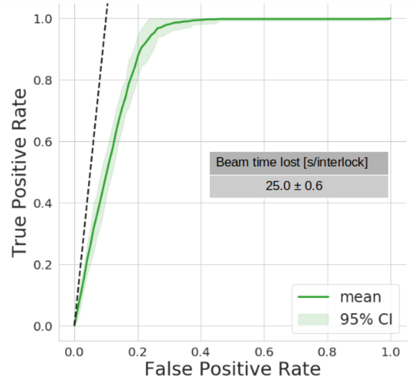


One plot

Windows of length 25 time stamps



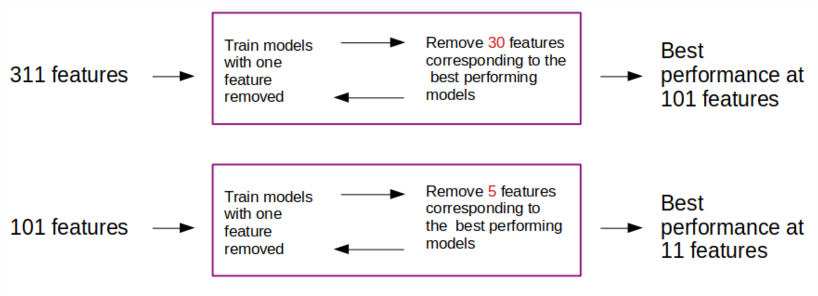
One plot per feature



One plot

→ one plot per feature variation seems better suited for this task

Recursive Feature Elimination



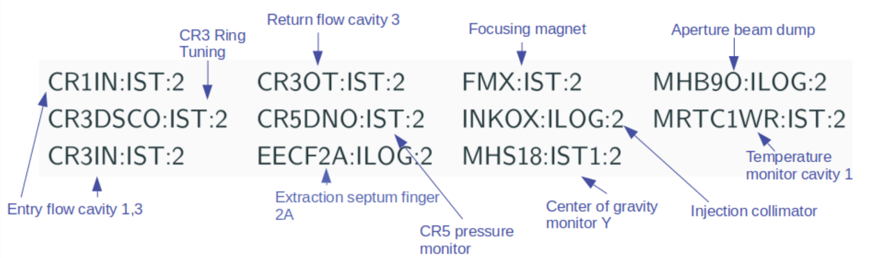
Reduced dataset for performance reasons:

- Trained on only the first and last stable windows
- Validated on 16% of the stable windows

11 selected features

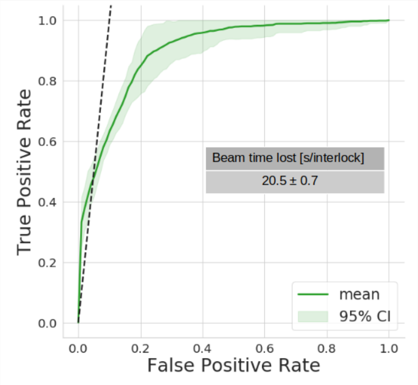
CR1IN:IST:2	CR3OT:IST:2	FMX:IST:2	MHB9O:ILOG:2
CR3DSCO:IST:2	CR5DNO:IST:2	INKOX:ILOG:2	MRTC1WR:IST:2
CR3IN:IST:2	EECF2A:ILOG:2	MHS18:IST1:2	

11 selected features

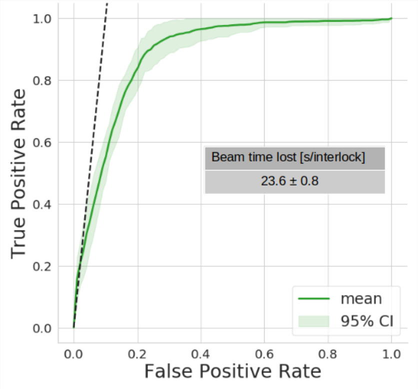


CNN

windows of length 500 time stamps subsampled at every second timestamp

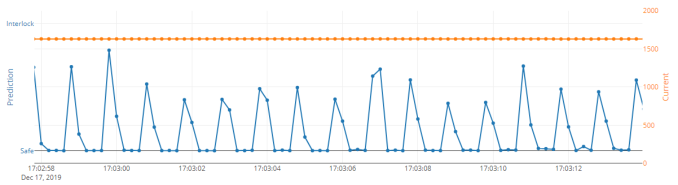


One plot per feature

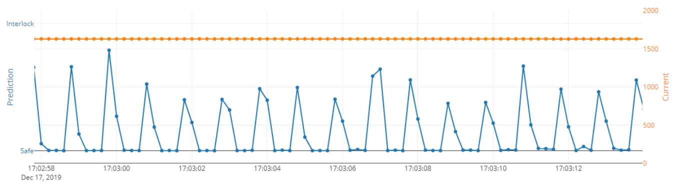


One plot

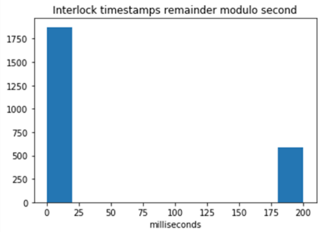
Online testing showed periodic interlock predictions



Online testing showed periodic interlock predictions



This periodicity matched the labeling pattern of the interlock timestamps: x.0 seconds or x.2 seconds



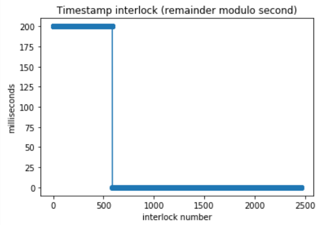
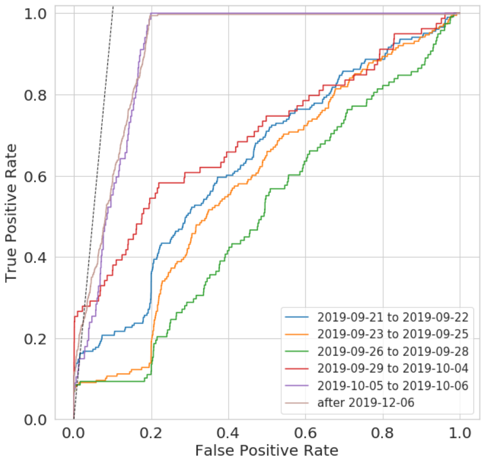


Figure by Jochem Snuverink

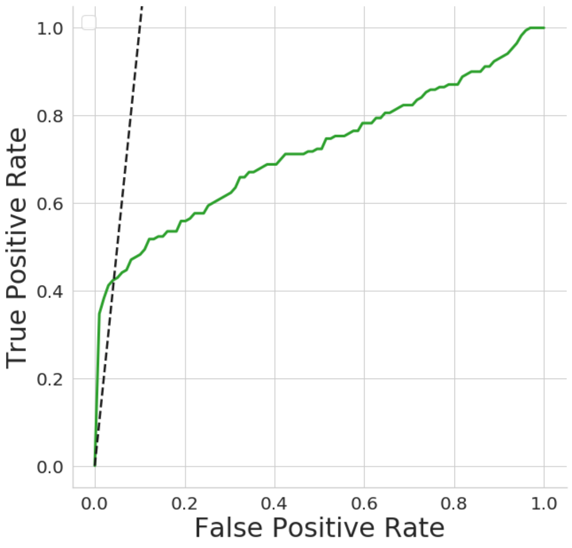
Cross-validation shows a relevant drop in performance of the model coincides with the change in time step labeling, namely the 4th of october



Uncertainty in the interlock time stamp allocation

Solution to the leakage problem:

- Random allocation of the interlock time stamp in the uncertainty range $\rightarrow$ has been done for Random Forest results presented here
- Better: allocate interlock to time stamp at which the beam current drops to 0 $\rightarrow$ CNN currently being tuned to this dataset


True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0

Summary

- do feature selection for all future models
- **Random Forest**: need to do online testing to verify model performance
- **CNN**: very promising model, needs tuning to the new dataset

Thank you to

Dr. A. Adelmann (ETH)
Sichen Li (ETH)
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Jaime Coello (PSI)
Dr. Perez Cruz Fernando (SDSC)