

# Forecasting of Beam Interlocks in High Intensity (Hadron) Accelerators

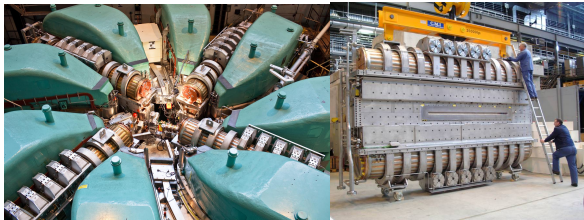
Andreas Adelman & Jochem Snuverink

March 1, 2018

# Modelling Challenges PSI

Consider a 0.59 GeV, 2.3 mA 1.4 MW (CW) Proton Cyclotron facility

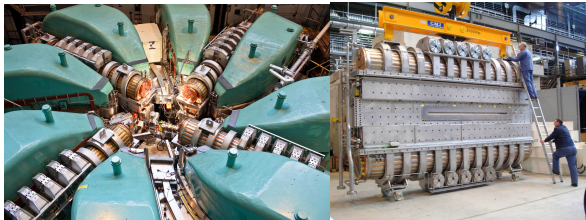
- uncontrolled & controlled beam loss  
 $\mathcal{O}(2\mu A = \text{const})$  in large and complex structures



# Modelling Challenges PSI

Consider a 0.59 GeV, 2.3 mA **1.4 MW** (CW) Proton Cyclotron facility

- uncontrolled & controlled beam loss  
 $\mathcal{O}(2\mu A = \text{const})$  in large and complex structures
- PSI Ring: **99.98% transmission**  
 $\rightarrow \mathcal{O}(10^{-4}) \rightarrow 4\sigma$



# Motivations for ML

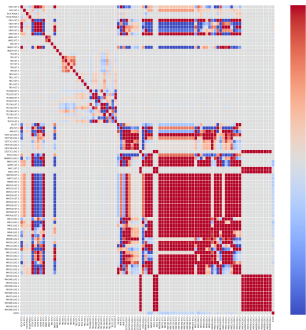
- **Predict and counteract interlocks**
  - aid/guide machine tuning
  - interlocks causes  $\mathcal{O}(2\%)$  beam time loss
- Reduce controlled and uncontrolled beam loss
  - less activation
  - better machine protection
- Cheap to Evaluate Surrogate Models
  - ab-initio models are impracticable for operation support
  - precise on-line models
  - check poster **Surrogate Models based on Supervised Learning and Polynomial Chaos for the Argonne Wakefield Accelerator**

# Challenges

<b>Beam-time statistics for HIPA</b> (Courtesy of A.Parfenova)		
	<b>2017</b>	<b>10 yr av.</b>
Scheduled user beam time	4838 hr	
<b>Current integral (Ah)</b>		
meson production targets	7.97	
SINQ	4.10	
UCN	0.064	
isotope production	0.013	
<b>Outages</b>	<b>228 hr</b>	
<b>Availability</b>	93.1%	90 %

# Challenges

- rare events
- large variability of the data
- high dimensionality of the data



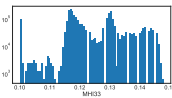
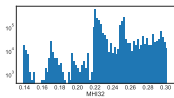
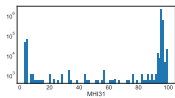
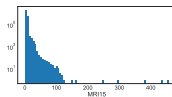
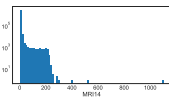
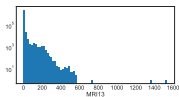
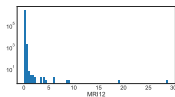
# Real Dataset from HIPA

more on data: see talk J. Snuverink on Friday

- $\approx 90$  values (magnet currents, non-intercepting diagnostics, etc.)
- cleaning and filtering: 57 significant parameters
- data from last two weeks of the 2017 run
  - 10 Hz (11 900 000 samples)
  - in total about 450 interlocks (very unbalanced!)

# Data is Key (ionisation monitors)

- raw data
- almost the same machine setup





# Interlock prediction: Binary Classifier I

- supervised learning
- Theano <http://deeplearning.net/software/theano/>

Logistic regression:

- $x$ : input variables  $\dim x = 57$
- $y$ : 0,1 (0: no interlock, 1: interlock)
- Logistic function:

$$P(y = \textit{interlock} | x, w, b) = \frac{1}{1 + e^{-b - w * x}}$$

# Interlock prediction: Binary Classifier II

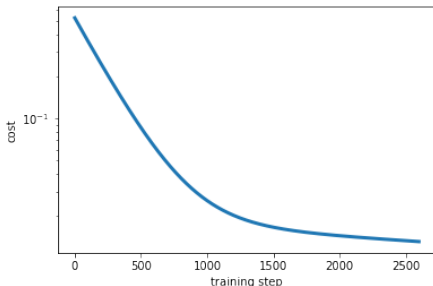
- Cost function  $c$  to be minimised (cross entropy loss +  $L_2$ -regularisation):

$$c = - \frac{1}{N} \sum (y \log(P(y)) + (1 - y) \log(1 - P(y))) + \lambda * \Sigma w^2$$

- Optimisation method: stochastic gradient descent
- Hyper parameters: regularisation factor  $\lambda$  (0.01), learning rate  $\alpha = 0.1 \dots 0.01$

# Training

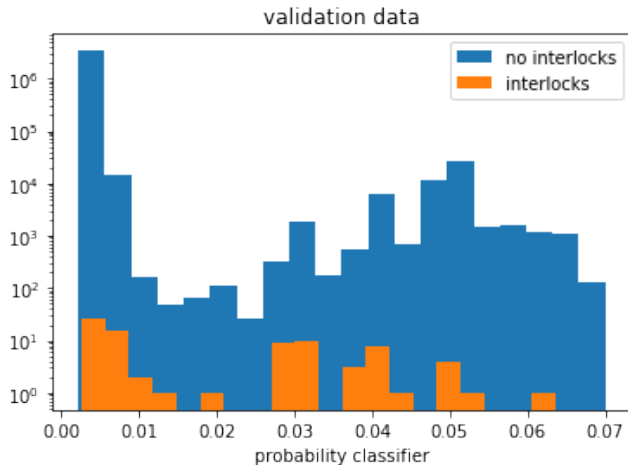
- 4 days of training data
- training until model error is acceptable (empirical tuning of  $\alpha$ )
- 4 days of validation data



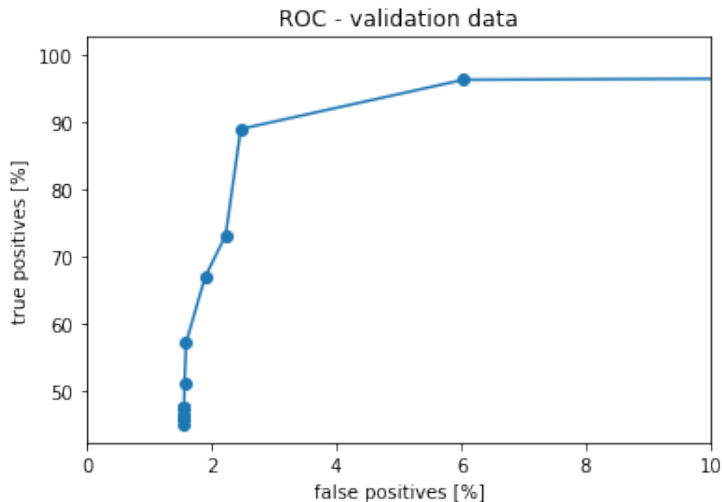
# Training Results (super prelim.)



# Validation (super prelim.)



# Selecting what you want ...



# An Example from Fusion I

Most critical problem for Magnetic Fusion Energy (MFE)

avoid/mitigate large-scale major disruptions

- Current Status: 8 years of R&D results using Support Vector Machine ML
  - reported success rates in mid-80% range for JET 30 ms before disruptions , BUT  $> 95\%$  with false alarm rate  $< 3\%$  actually needed for ITER (P. DeVries, et al. (2015))

# Deep Recurrent Neural Networks (RNNs) I

- Deep
  - Hierarchical representation of complex data, building up salient features
  - Obviating the need for hand tuning, feature engineering, and feature selection
- Recurrent
  - Natural notion of time and memory: at every time-step, the output depends on  $s(t-1)$  and  $x(t)$
  - The internal state can act as memory and accumulate information of what has happened in the past



# Summary and Outlook

- We used a very simplistic model for static prediction of interlocks (many thanks to Auralee for guidance)
- Reasonable results are encouraging

## Most critical for high intensity accelerators

- Predict a rare event (interlock)  
 $T_p = \mathcal{O}(x \times 10)$ ,  $x$  small [ms]
- Develop a surrogate model for measured losses

# Summary and Outlook

- Use the simplistic regression model to properly select/normalise data
- Learn / understand quality requirements of the data  $x$
- Follow the ITER route by using Deep Recurrent Neural Networks (RNNs)
- your input is very welcome ...