Beam loss plane recognition for the LHC

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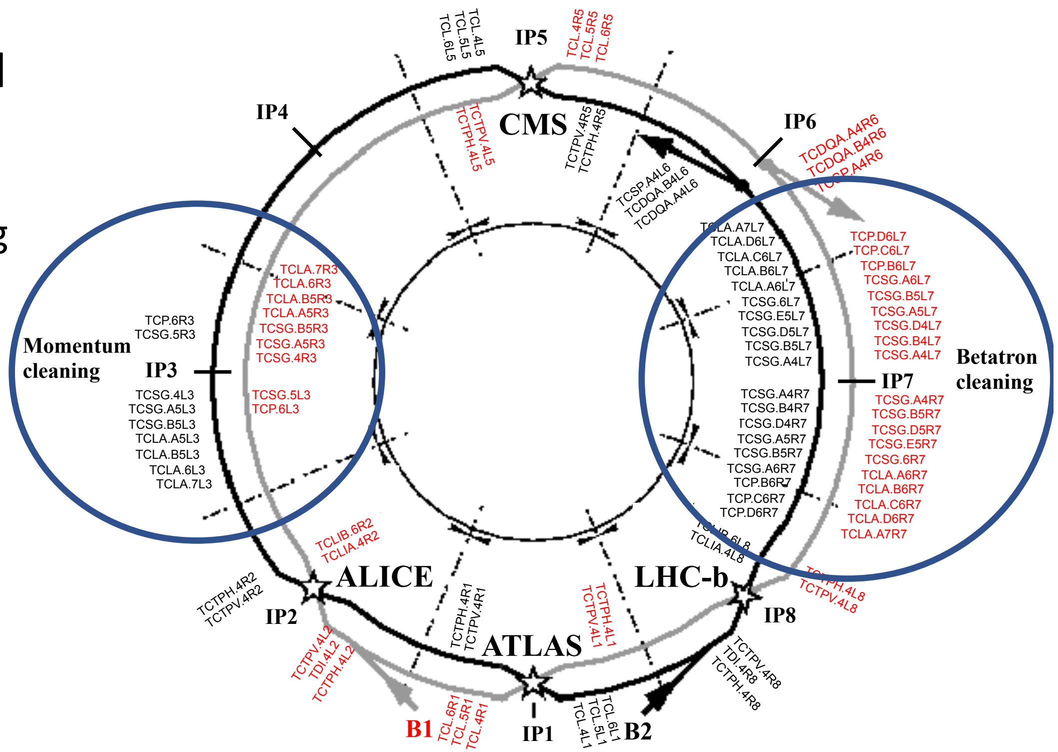
Outline

- Background and motivation: LHC collimation and loss maps
- Available datasets
- Feature selection
- Classification results using NN and GBC
- Conclusions

Background: LHC collimation

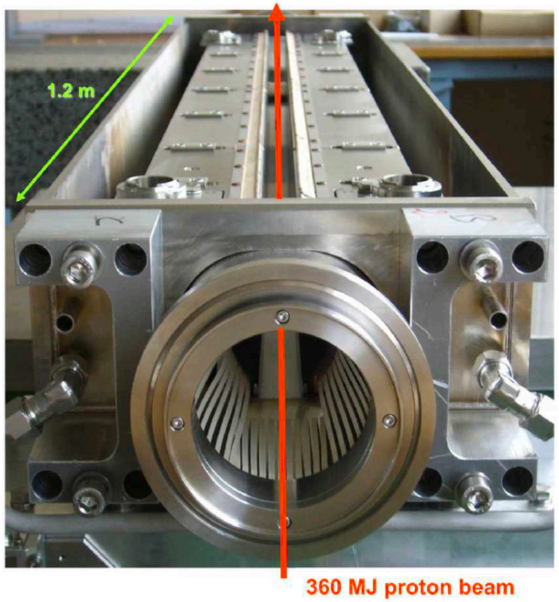
- The LHC is equipped with a multi-stage collimation system to protect it from normal and abnormal beam losses.
  - **Normal losses:** ensure that proton leakage to superconducting magnets is minimal, preventing quenches
  - **Abnormal losses:** protection against fast failure scenarios such as asynchronous beam dump

- The collimation system cleans particles with large betatron and off-momentum offsets

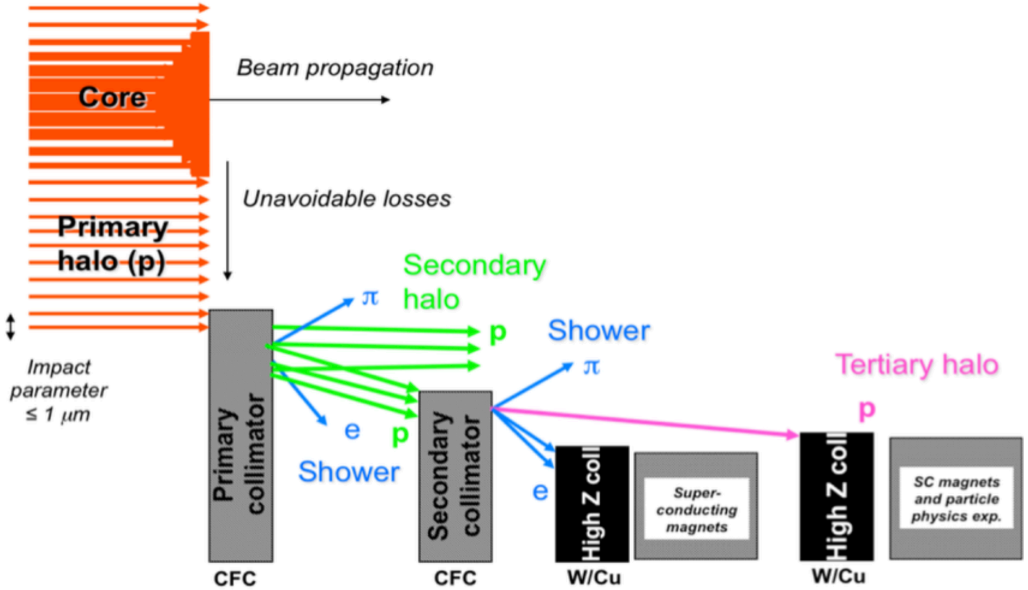


Background: LHC collimation

A double-sided LHC collimator (can be installed to clean in the horizontal, vertical or skew planes)



Multi-stage halo cleaning process



Primary collimator (TCP)

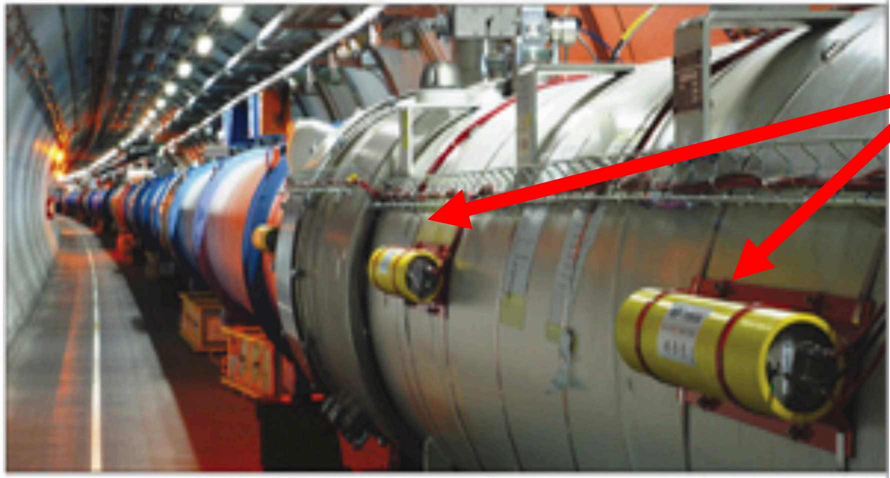
Secondary collimator (TCSG)

Absorber (TCLA)

Tertiary collimator (TCTP)

Background: beam losses

- In order to monitor beam losses, ~3600 Beam Loss Monitoring (BLM) ionization chambers are placed around the LHC.



Ionization chambers

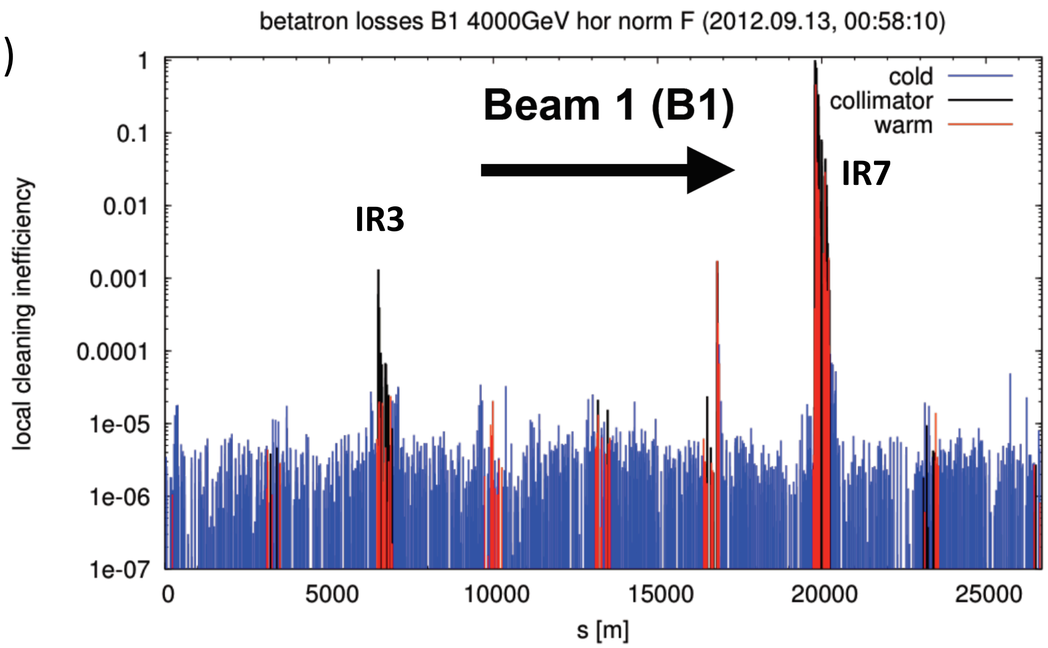
Background: beam loss maps

- The betatron cleaning system is qualified by intentionally creating high losses in the horizontal (H) or vertical (V) planes using the transverse damper.

- Cold = losses in superconducting magnets (arcs)
- Warm = losses in normal magnets / IRs
- Collimator = losses at BLM at collimator

- Loss maps are generated during test fills with low intensity (few bunches).

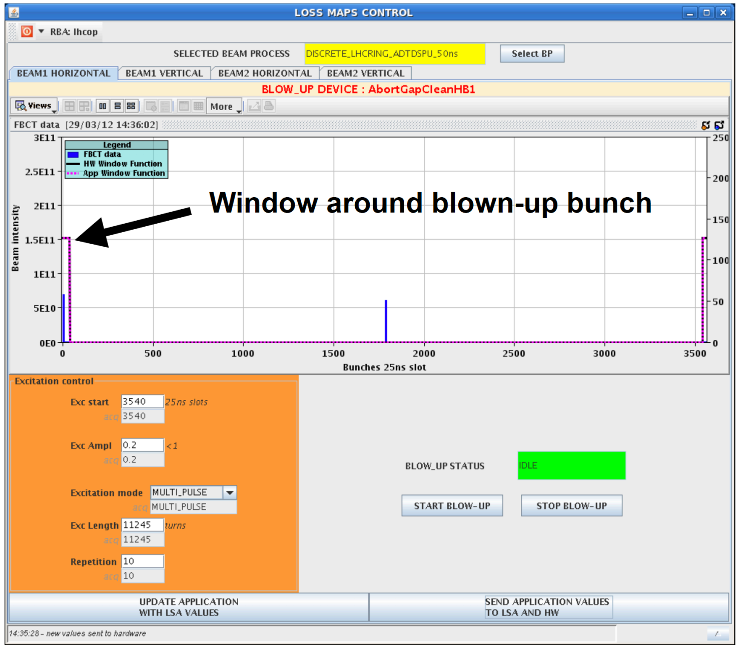
- With the collimation system properly set up, we expect highest losses at the bottleneck in IR7.



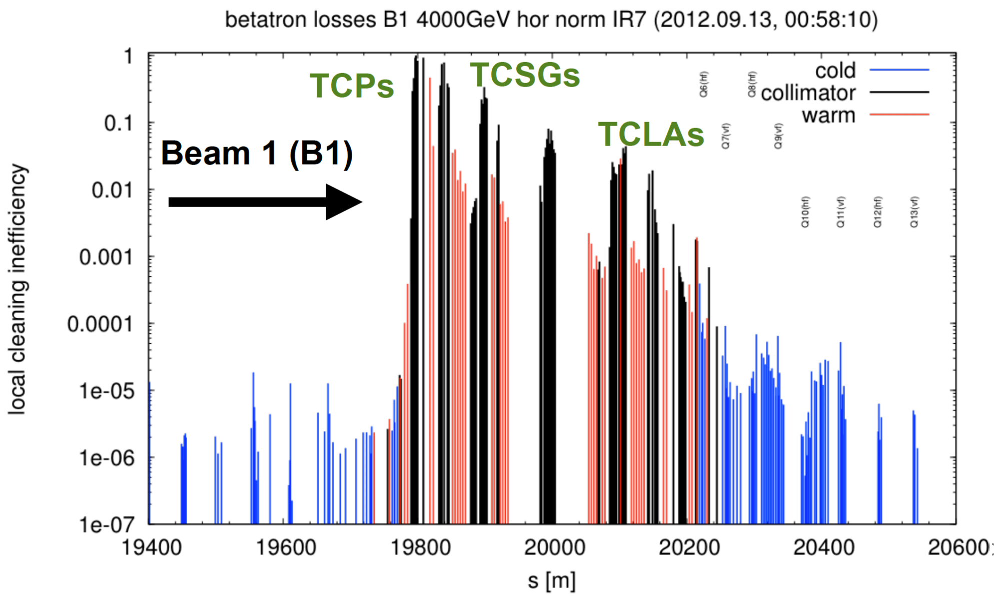
~3600 BLM readings around the ring

Background: beam loss maps

- We can blow-up individual bunches in a given beam & plane:



- A **zoom into IR7** gives a better view of the hierarchy:



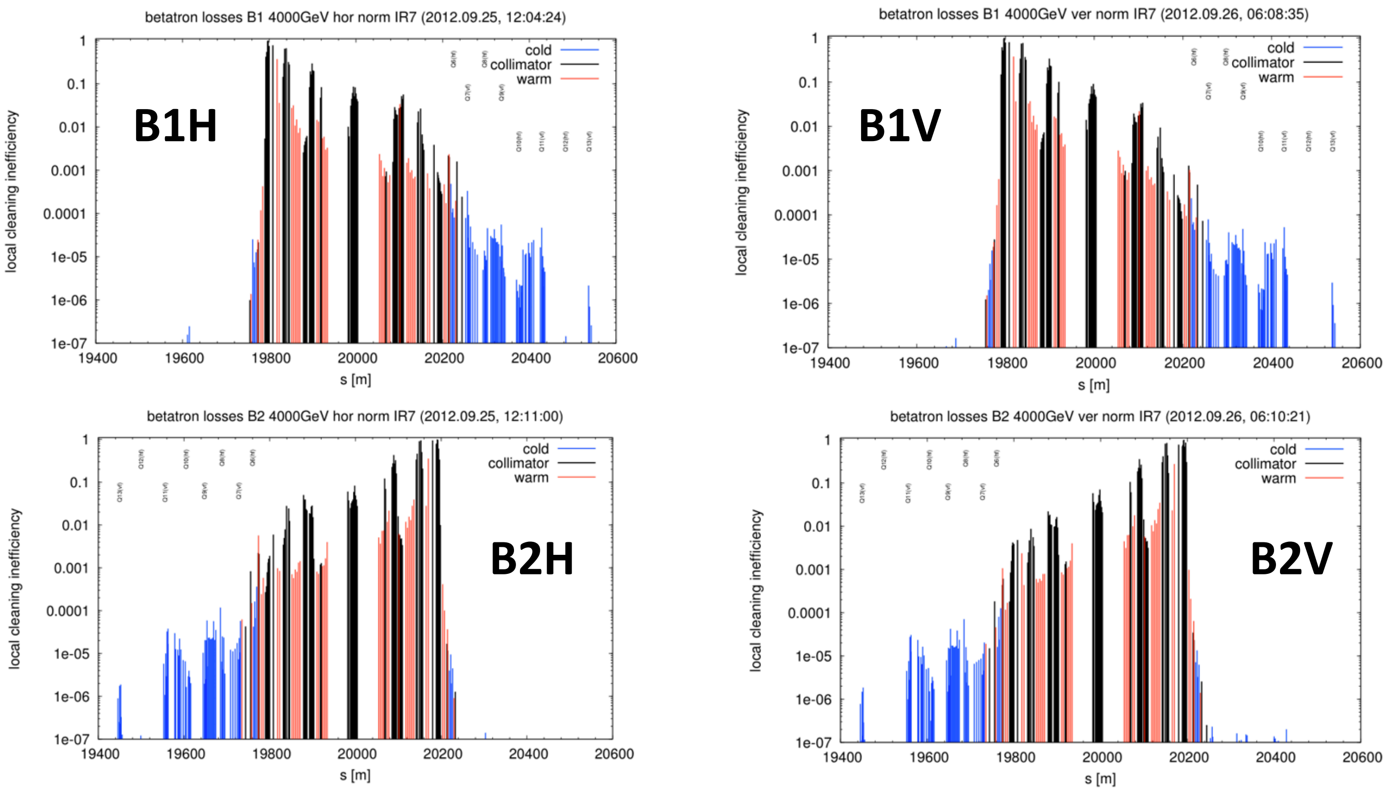
Problem definition & motivation

- The objective is to be able to automatically classify between the four types of loss planes:
  - Beam 1 Horizontal (B1H)
  - Beam 1 Vertical (B1V)
  - Beam 2 Horizontal (B2H)
  - Beam 2 Vertical (B2V)

- Therefore our problem has 4 output classes.

- Understanding the beam loss characteristics and dynamics during normal operation is crucial to correct them and understand their long-term impacts e.g. R2E effects

Problem definition & motivation



Available datasets

- The data from the ~3600 LHC BLMs were extracted each time the transverse damper blow-up was running during 2017.

- This resulted in 5893 loss maps, which were then narrowed down based on:
  - **Beam intensity loss:** the intensity loss in each loss map should be > 1E8 protons to have sufficient resolution;
  - **Collimator settings:** the collimator positions have to be identical in each loss map;
  - **Visual checks:** to ensure a correct hierarchy was in place.

Available datasets

- As the beam parameters, collimator settings etc are different between injection and flat top, separate models were trained for both cases:

Beam & Plane	Injection	Top Energy
B1H	84	496
B1V	132	599
B2H	127	383
B2V	123	129

Feature selection

- Two feature sets were considered:

  1. All the BLMs in the IR7 longitudinal position range (19400 – 20600 m): 261 BLMs.
  2. Only the BLMs located at collimators in the same longitudinal position range: 41 BLMs.

- The BLM readings in each loss map were normalized to the same BLM (TCP.A6L7.B1 @ 19796 m), which generally gives the highest readings for B1 loss maps.

Training Procedure

- Two separate models were trained for the loss maps:
  - at injection energy (450 GeV)
  - at top energy (6.5 TeV)

- Loss maps in each of the four datasets (B1H, B1V, B2H, B2V) were split using a 50:50 ratio between training and testing datasets.

- The allocation of a particular loss map to the training or testing datasets was done randomly.

- The models were then use to predict labels for the as yet unseen testing dataset, which were compared to the original ground truth.

- The final classification success rate was calculated by averaging the prediction performance on the testing dataset over 5 tries (test + train) to avoid a lucky split.

Results with a Neural Network

4 hidden layers: (300, 130, 75, 30)

Using only the collimator BLMs

Beam & Plane	Injection	Top Energy
B1H	98.1%	99.8%
B1V	99.7%	99.9%
B2H	96.9%	98.5%
B2V	97.7%	96.9%

Using all IR7 BLMs

Beam & Plane	Injection	Top Energy
B1H	76.6%	99.4%
B1V	91.8%	98.5%
B2H	96.8%	99.5%
B2V	96.5%	96.6%

Results with Gradient Boosting Classifier

n_estimators = 1000, max_depth = 20

Using only the collimator BLMs

Beam & Plane	Injection	Top Energy
B1H	97.6%	99.0%
B1V	98.2%	99.5%
B2H	95.3%	99.5%
B2V	97.1%	96.3%

Using all IR7 BLMs

Beam & Plane	Injection	Top Energy
B1H	97.6%	100%
B1V	99.1%	99.2%
B2H	95.9%	99.1%
B2V	96.5%	96.2%

Classification of losses during LHC operation

- Loss maps are performed in controlled conditions (beam and plane is known), and ML models were trained on these data.
- Next step: applying the models trained on loss map data to actual losses in operation.
- Two scenarios considered:
  - Long-Range Beam-Beam (LRBB) beam test
  - Losses during the standard LHC machine cycle

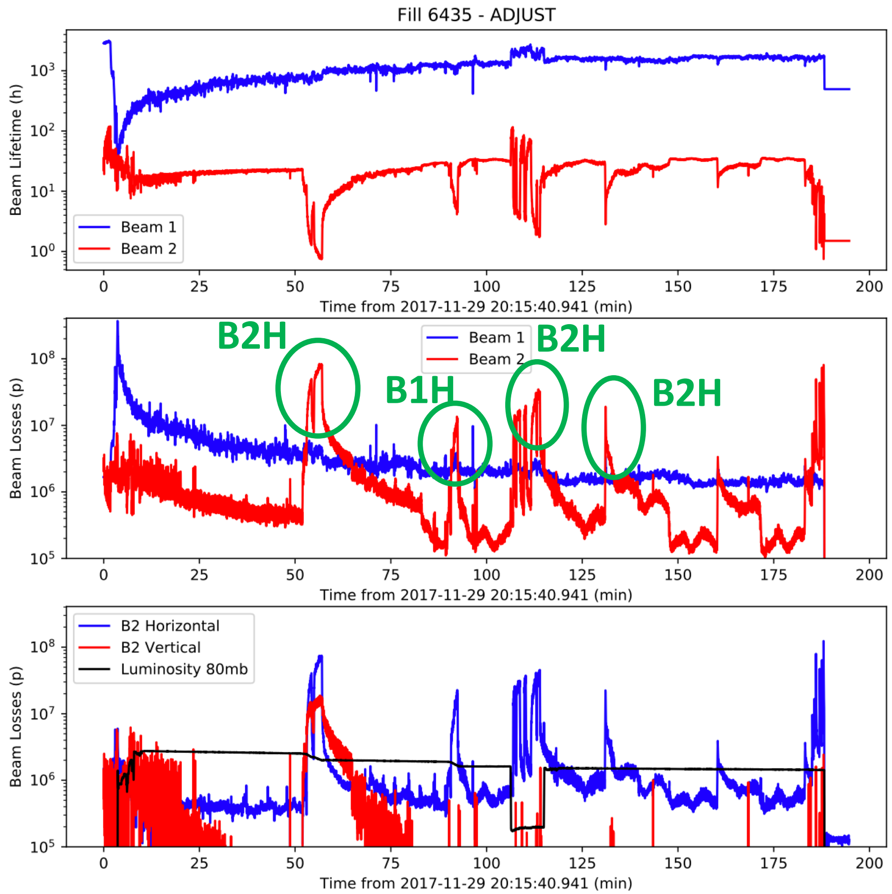
Existing beam loss decomposition method

- Based on SVD (see M. Wyszynski, CERN summer student project & B. Salvachua et al., "Decomposition of beam losses at LHC", IPAC'17).
- Works for both off-momentum and betatron losses.
- Uses a calibration factor (obtained through dedicated collimator scraping measurements) to convert BLM readings in Gy/s to proton/s.
- A subset of only 6 BLMs per beam, at H and V collimators, is used. This vector is then decomposed as a linear combination of the individual B1H/B1V/B2H/B2V contributions.
- It is static and not easily adaptable to new machine configurations (requires manual selection of BLMs).

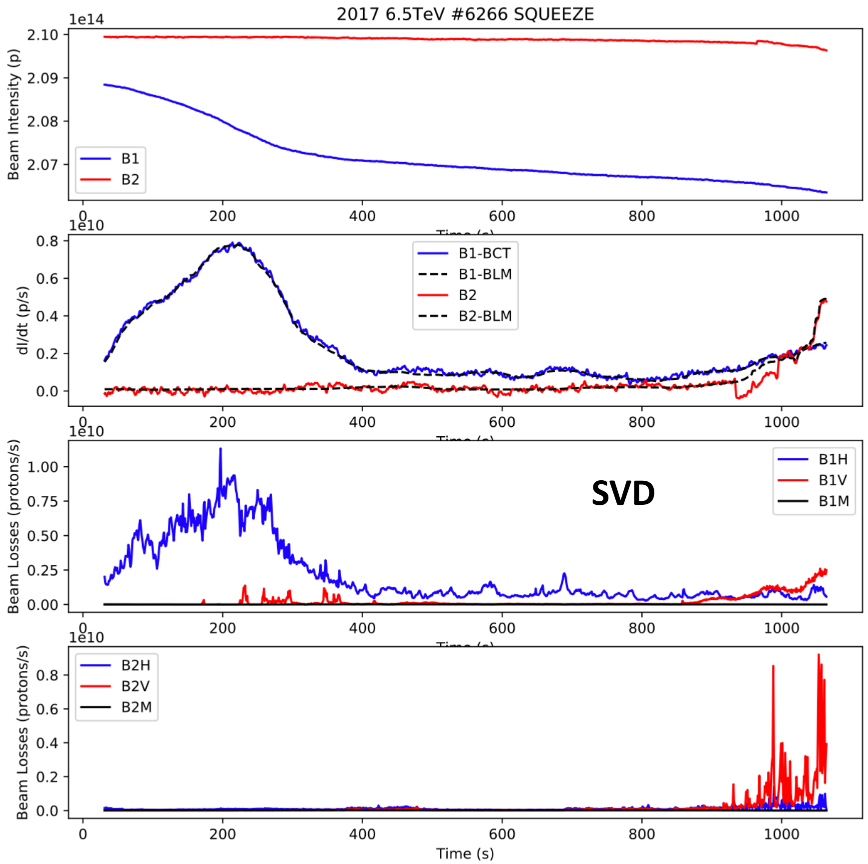
Long-Range Beam-Beam test

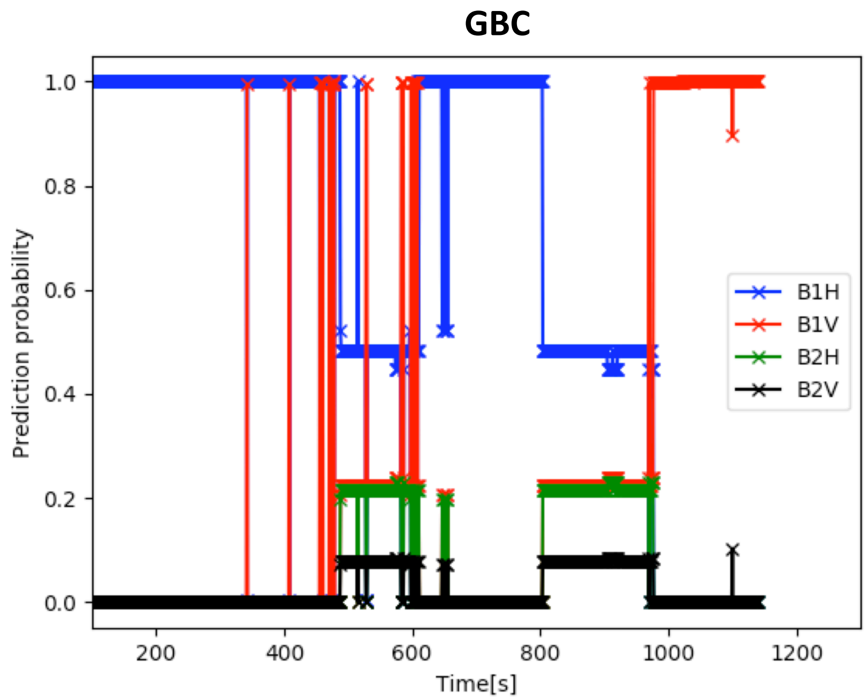
- Beam test using wires installed in collimators to compensate the octupolar term of the beam-beam in IR5.
- There was an initial B2H blow-up, followed by additional losses in B2H as the wires were switched on and off.
- The ML algorithm correctly classified the 3 spikes in losses which were ~1e8 p. There was one misclassification (though here the losses in B1 and B2 are ~equal & ~1e7 p).

***classification result**



Losses during the squeeze in standard operation





Future work: change to more "hierarchical" classification (i.e. consider that we can have losses simultaneously in B1 and B2)

Conclusions

- Machine learning techniques were used to train models to classify between different types of loss planes in the LHC.
- The Gradient Boosting Classifier gave the best performance.
- Using only the collimator BLMs gave similar or better results than using all BLMs.
- Future work:
  - Explore cross-validation of parameters once more data is available
  - Investigate different feature selection & scaling techniques
  - more systematic tests to classify losses during the standard machine cycle + comparison with SVD technique.