LSTM Application for Automatic LHC Collimator Alignments

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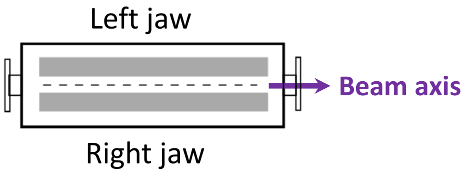
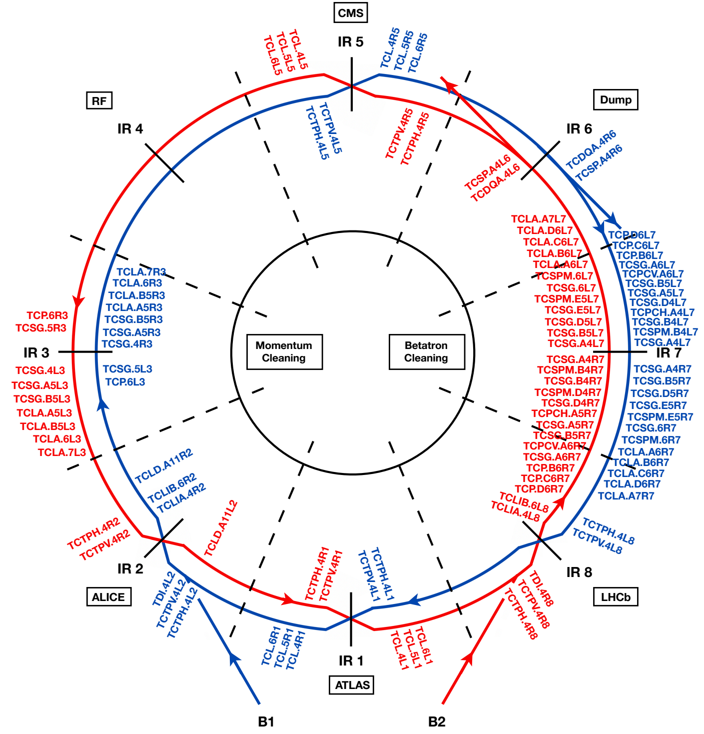
Introduction



- The LHC relies on a collimation system for passive protection
- Step precision of 5 µm
- Concentrate beam losses into warm location

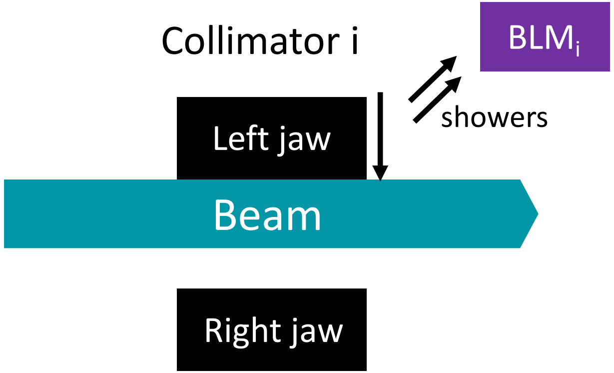
- Each year of operation begins with a commissioning phase to align all collimators
  - Ensure the correct settings for nominal operation
- Alignments performed at all machine states:
  - Injection, Flat top, Squeeze, Collisions



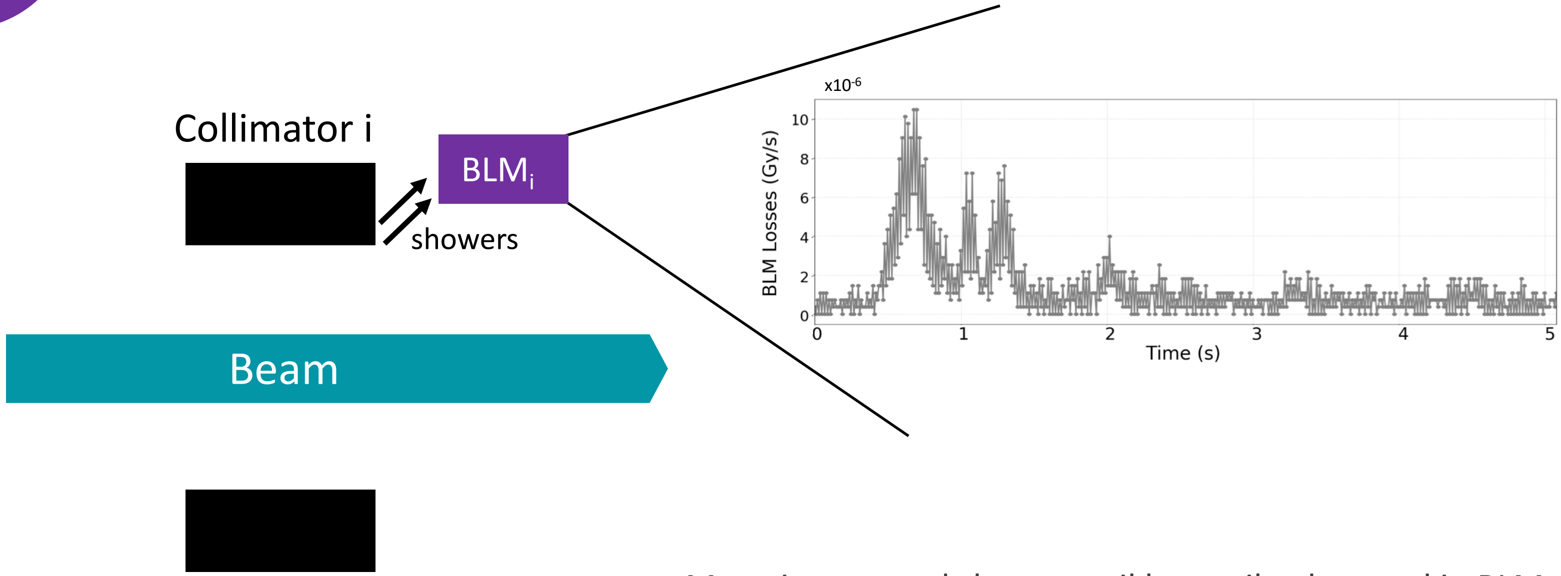
123 movable collimators at the start of Run 3

Beam Instrumentation

- Beam Loss Monitors (BLMs) used to align collimators.
- Record beam losses generated by collimators as they touch the beam.
- Beam-based alignment (BBA)

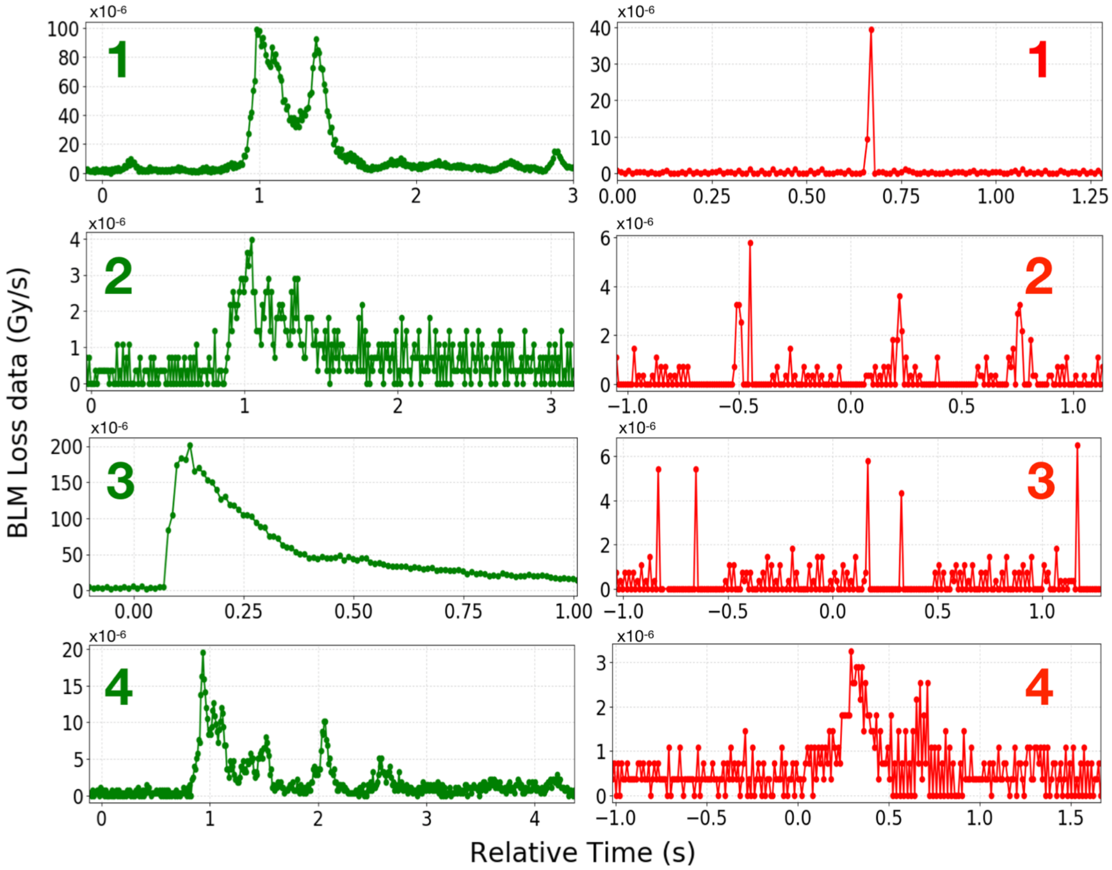


Beam-Based Alignment



- Move jaw towards beam until loss spike detected in BLM signal.
- Wait for loss spike to decay between alignments.
- A complete alignment campaign can produce more than 1000 observation spikes.

Beam-Based Alignment Observation Spikes



Recap. Collimator Alignments

Since 2011: Semi-Automatic Alignment

User	Select collimator
User	Select BLM threshold to stop jaw movement
AUTO	Collimator moves towards beam Movement stops when threshold is exceeded
User	Collimator aligned? No - repeat, Yes - save

BBA alignment of 40+ collimators require 4-5 collimation experts.

Recap. Collimator Alignments

Since 2018: **Fully**-Automatic Alignment

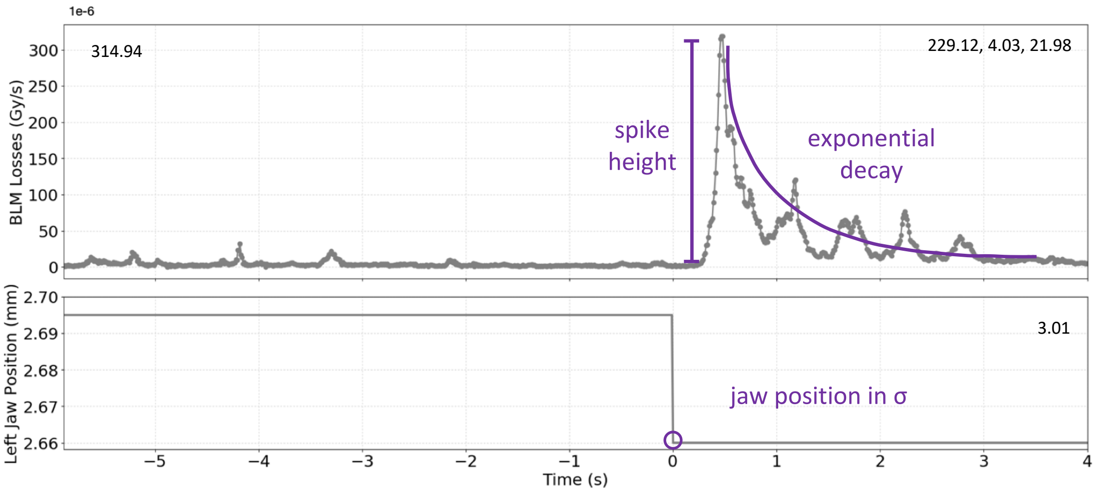
AUTO	Select collimator
AUTO	Select BLM threshold to stop jaw movement
AUTO	Collimator moves towards beam Movement stops when threshold is exceeded
AUTO	Collimator aligned? No - repeat, Yes - save

Supervised Machine Learning

Recap. Collimator Alignments ML

- Data sample taken when collimator stops moving
  - 100 Hz BLM data
  - 1 Hz Jaw Position (mm)
- Fixed waiting time:
  - 4 s @ injection
  - 6 s @ flat top

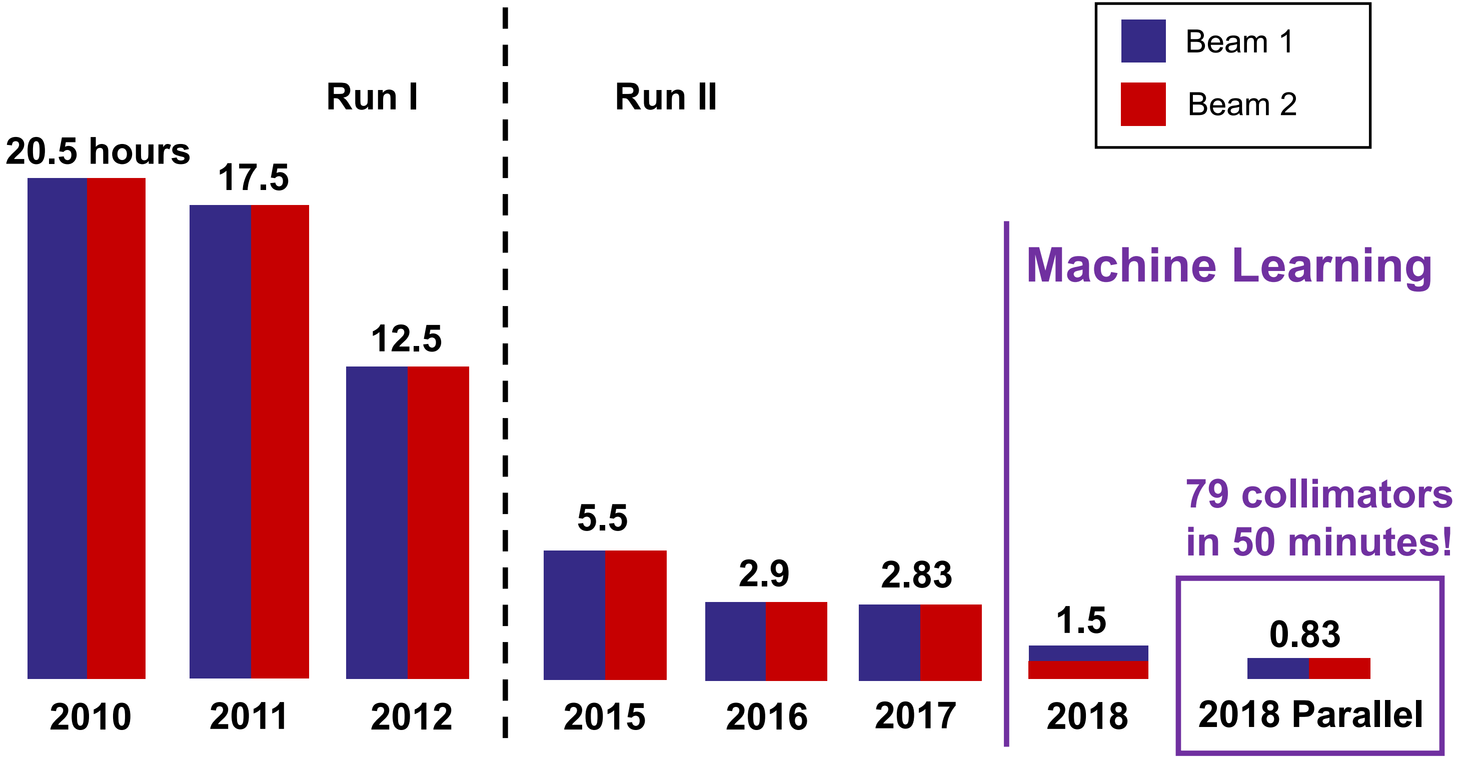
Precision > 95%



- 5 features extracted:
  - Spike Height (x1 feature)
  - Exponential Decay (x3 features)
  - Jaw Position in σ (x1 feature)

G. Azzopardi, et al., *Automatic Spike Detection in Beam Loss Signals for LHC Collimator Alignment*, NIM-A, 2019

Recap. Collimator Alignments Results



G. Azzopardi, et al., *Operational Results of LHC Collimator Alignment using Machine Learning*, IPAC'19

Semi- Vs Fully- Automatic Alignment

- Data collected using:
  - Semi-automation in 2016
  - Parallel fully-automation in 2018

- Can speed up the fully-automatic alignment by decreasing the time waiting for the signal to decay before extracting the features.

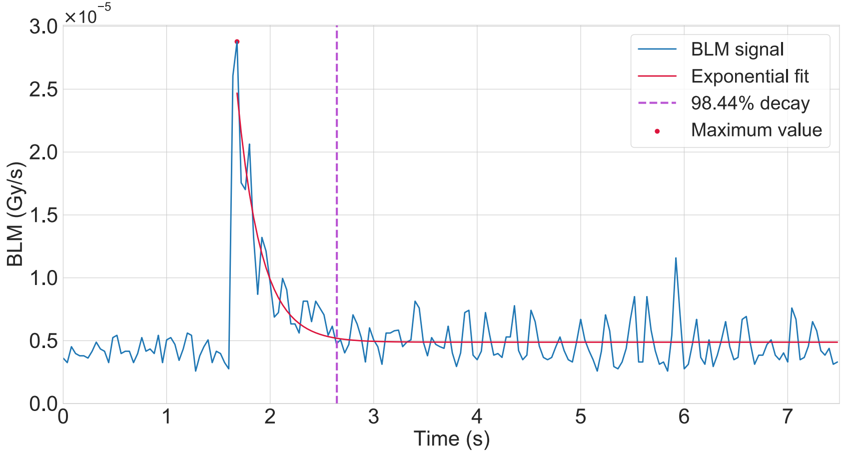
	Semi-Automatic	Fully-Automatic
Collimators	75	77
Total time	2h 31m 59s	49m 17s
Moving time	58m 13s	18m 14s
Total alignments	1903	637
Moving time	38.3 %	38.0 %
Alignments / Collimator	25.37	8.27

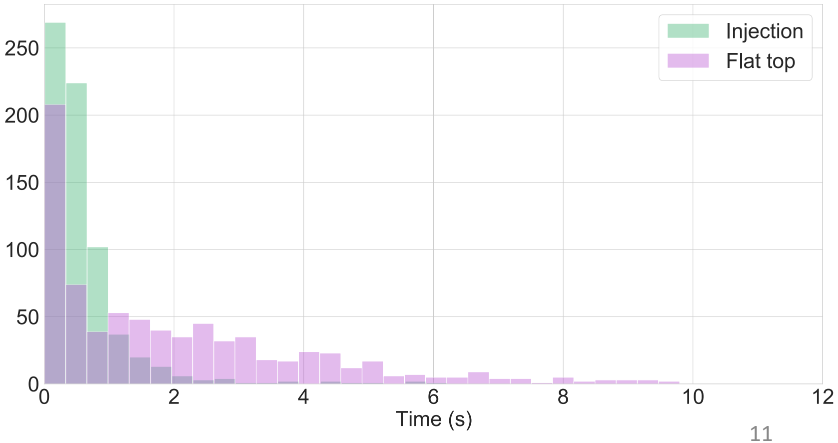
Decay Time Analysis

- **Analysis:** Actual time required for BLM signal to decay.
- Modelled the decay rate as an exponentially falling distribution, with optimal losses achieved after 6 half-lives.

Mean decay time:

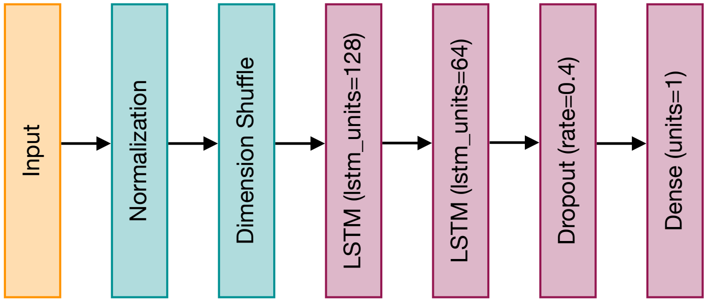
- 0.61 s at injection
- 2 s at flat top





LSTM-RNN for Spike Classification

- **Proposed Solution:** Long Short-Term Memory (LSTM) - Recurrent Neural Network (RNN):
  - Continuously classify spikes in real-time.
  - Automatically adjust to spike decay length.
- Dataset collected from alignments during 2016-2018:
  - 1550 alignment spikes
  - 1423 spurious spikes
- Input:
  - BLM signal scaled with the collimator position in sigma.
  - Z-Score used as the normalization technique to re-scale the features.

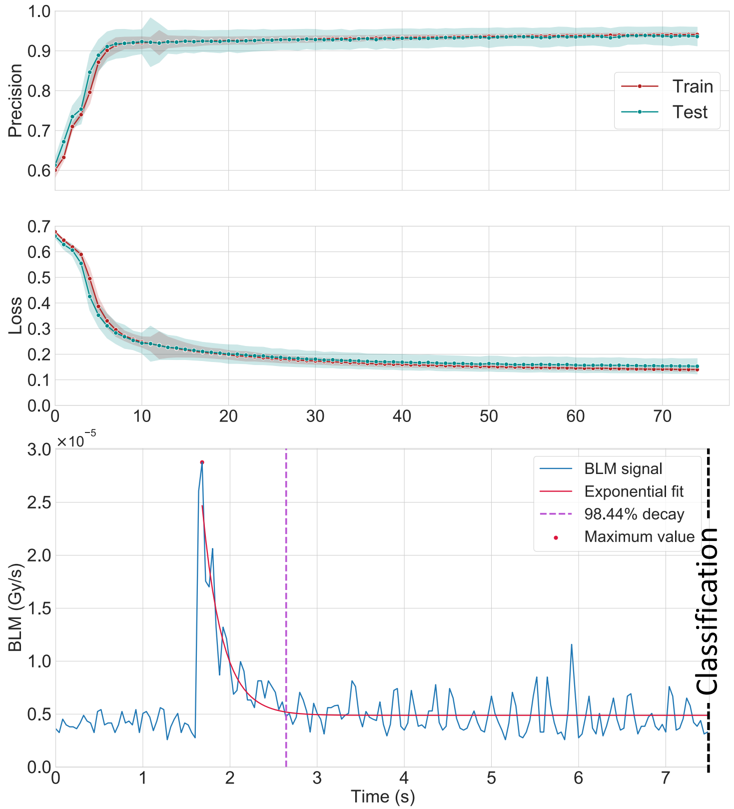



```
tf.keras.layers.LSTM(num_units)
```

Courtesy of G. Ricci, Sapienza Università di Roma

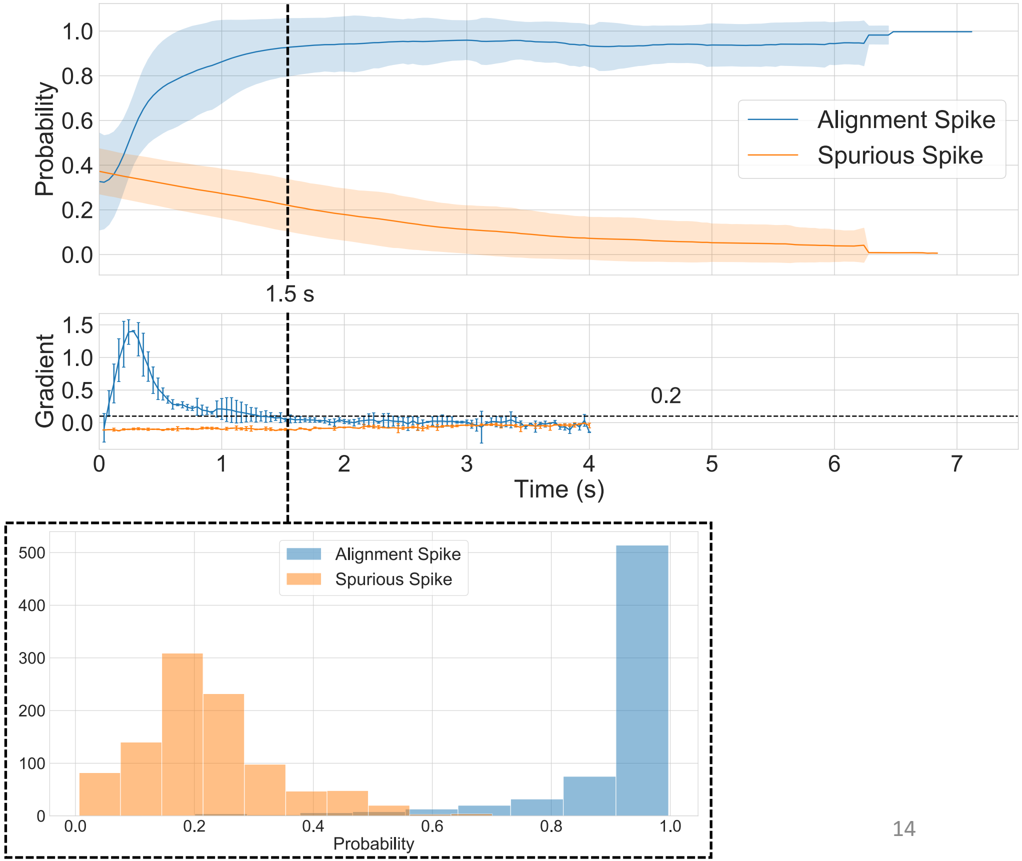
LSTM-RNN for Spike Classification

- Results collected over a 10-fold cross-validation randomly stratified 30 times.
- **Average of 94% precision on testing sets.**
- Precision is used to avoid false positives:
  - False detection of an alignment spike is more grievous than not detecting an alignment spike.
- Precision calculated by evaluating the classification probability at the end of the available sample:
  - A classification score >50 % is classified as an alignment spike.
- Further analysis to determine the best moment to predict the spike class and the ideal probability threshold, to possibly improve the model's precision.



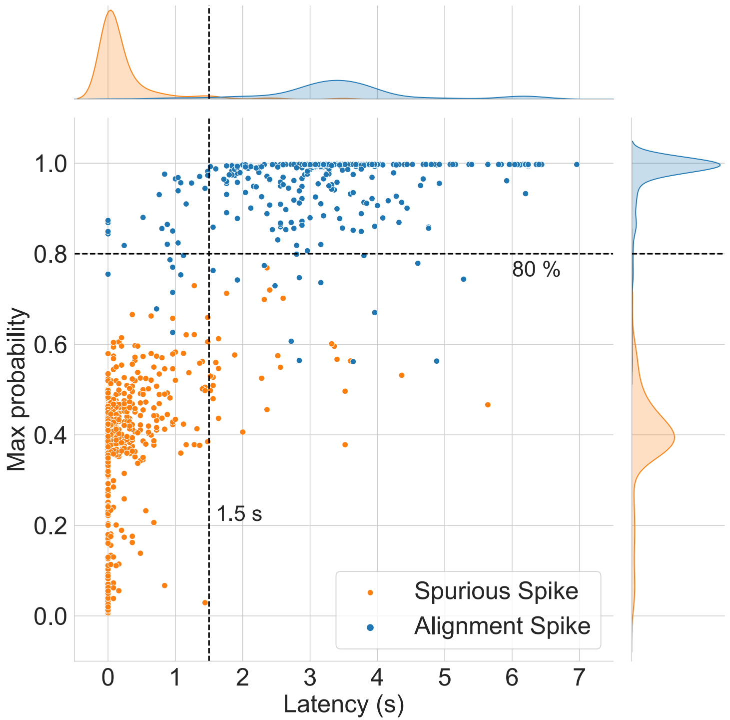
Spike Classification Analysis

- **Analysis:** LSTM continuous classification of each sample at each time step.
  - Clear distinction between spike classes at 1.5 s.
  - Rate of change of classification probabilities for alignment spikes falls below 0.2.
  - No overlap at 80 % probability at a latency of 1.5 s.



Spike Classification Analysis

- **Analysis:** Latency required to obtain max. probability per spike class:
  - ~98% of spurious spikes obtain a max probability within 1.5 s.
  - 100% of spurious spikes constantly < 80 % classification probability.
- **Conclusion:** The LSTM can be used classify:
  - When the probability gradient < 0.2 (requires ~1-1.5 s @ Inj).
  - Classify spurious spike when probability <80 %, then the next alignment can begin.
  - Otherwise alignment spike, then fit an exponential function to determine when ~98.5 % of the BLM signal decays
    - On average already decayed (mean 0.61 s).



Classification Results

- Classifying the BLM signals as proposed by the presented analysis increases the classification precision on the dataset to 98 %.
- **Analysis:** The time taken to classify the BLM signals at the two machine states.

	Injection	Flat top
Start time	1 s	1.5 s
Mean	1.07 s	1.54 s
Stand. dev.	0.1 s	0.06 s
Maximum	1.72 s	2.04 s

- Factor 4 speed-up compared to the present implementation with supervised ML .

Theoretical Improvement of Alignment Time

The time required for automatic alignments using supervised machine learning.

Step	Action	Time (s)
1	Move both jaws to 4 mm	~8
2	Wait for losses to decay	**x**
3	Classification delay	1
4a	Align Left Jaw	2*(0.1 + **x** + 1)
4b	Align Right Jaw	2*(0.1 + **x** + 1)
5a	TCP before (Left Jaw)	0.1 + **x** + 1
5b	TCP before (Right Jaw)	0.1 + **x** + 1
6	TCP after (Left + Right)	2 * (0.1 + **x** + 1)
Total	**17.8 + 9x**	**@Inj x >= 4** **@FT x >= 6**

- The proposed LSTM model is capable of dynamically classifying spikes of varying lengths in real-time.
- This will decrease the mean time waiting for the losses to decay:
    - x_1 = 1.07 s @ Inj, 2 s @ FT
    - x_0 = 1.07 s @ Inj, 1.54 s @ FT

(from slides 11, 16)

Theoretical Improvement of Alignment Time

Case	Supervised ML	~50% speed-up LSTM-RNN
1 coll @ Inj	53.8 s	27.43 s
+ 1 spurious spike/align	69.1 s	33.94 s
79 colls @ Inj	70.84 mins	36.12 mins
+1 spurious spike/align	90.98 mins	44.69 mins
1 coll @ FT	71.8 s	35.8 s
+1 spurious spike/align	93.1 s	43.72 s
79 colls @ FT	94.53 mins	47.14 mins
+1 spurious spike/align	122.58 mins	57.56 mins

*1 spurious spike/align = 3 * (0.1 + x_0 + 1)*

- The average theoretical minimum time to **sequentially** align LHC collimators.
- Aligning the two beams in **parallel**, resulted in 79 collimators aligned in 50 minutes at injection.
  - The LSTM could theoretically align 79 collimators at injection in ~24.56 minutes.

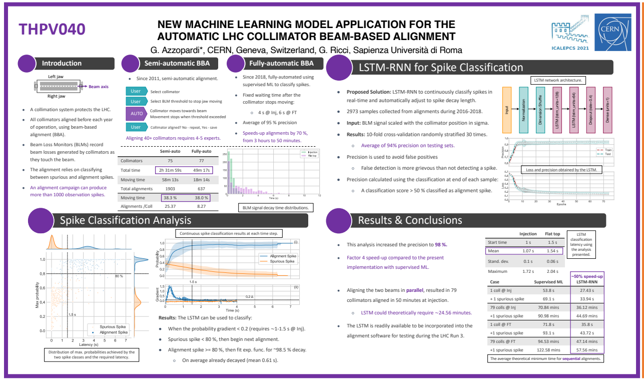
Summary

- 123 LHC collimators automatically aligned using supervised ML, using the software introduced in 2018.
- First-use performance analysis identified a bottleneck caused by the fixed observation window used by the ML model to classify the BLM loss signal.
- Trained an LSTM model to continuously classify BLM signals.
- Able to classify spikes within 1-2 s of a collimator stopping its movement, once the rate of change in classification probabilities is below 0.2.
  - Following each alignment spike classification, the suggestion is to fit an exponential function to the losses to determine whether the next alignment can begin.
- This work allows for classifying BLM signals independent of whether the losses decayed or not, decreasing the alignment time by ~50 %.
- The LSTM is readily available to be incorporated into the alignment software for testing during the LHC Run 3.

Thank you for your attention!

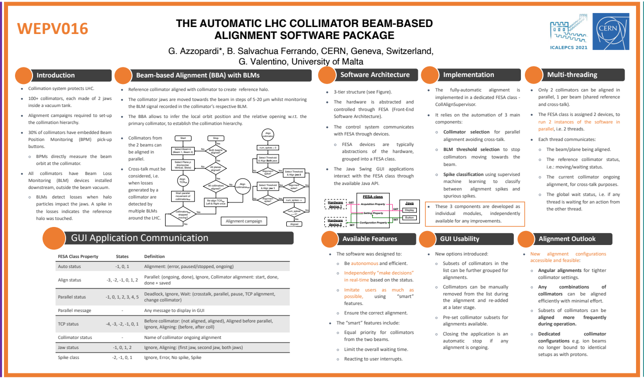
Questions?

LSTM for Automatic Alignment



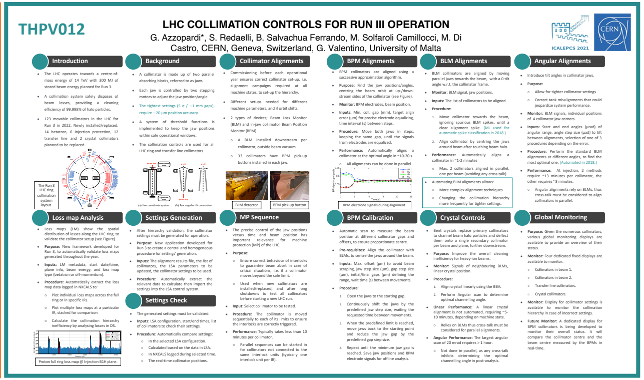
THPV040

Automatic Alignment Software



WEPV016

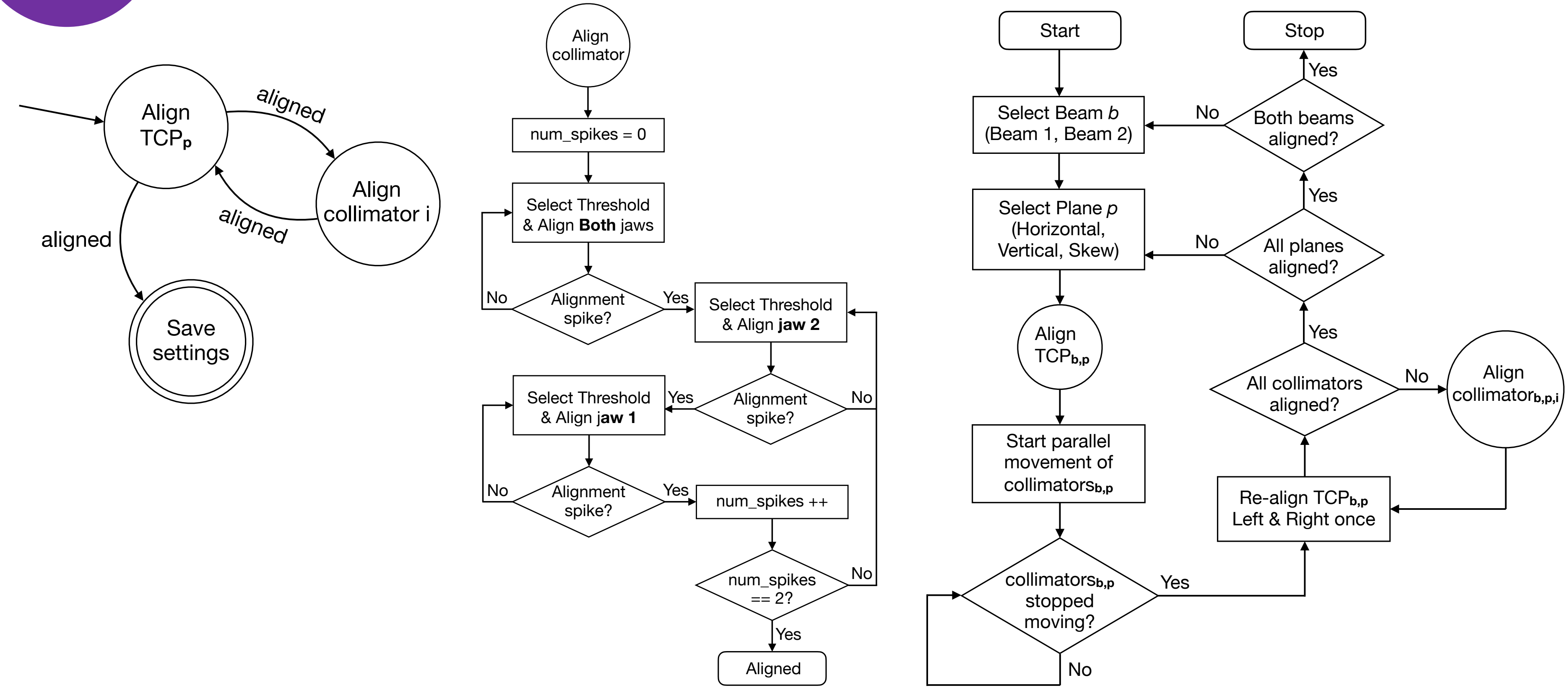
Collimation Controls for Run 3



THPV012

Backup slides

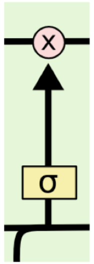
Collimator Alignment Procedure



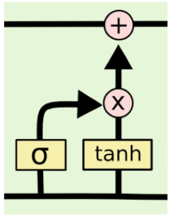
G. Azzopardi, et al., *The Automatic LHC Collimator Beam-based Alignment Software Package*, ICALEPCS'21

Long Short-Term Memory model

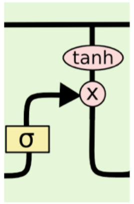
- LSTMs are a type of RNN that can learn long-term dependencies.
- 3 activations inside:
  - Forget gate layer: What information to keep from the cell state.

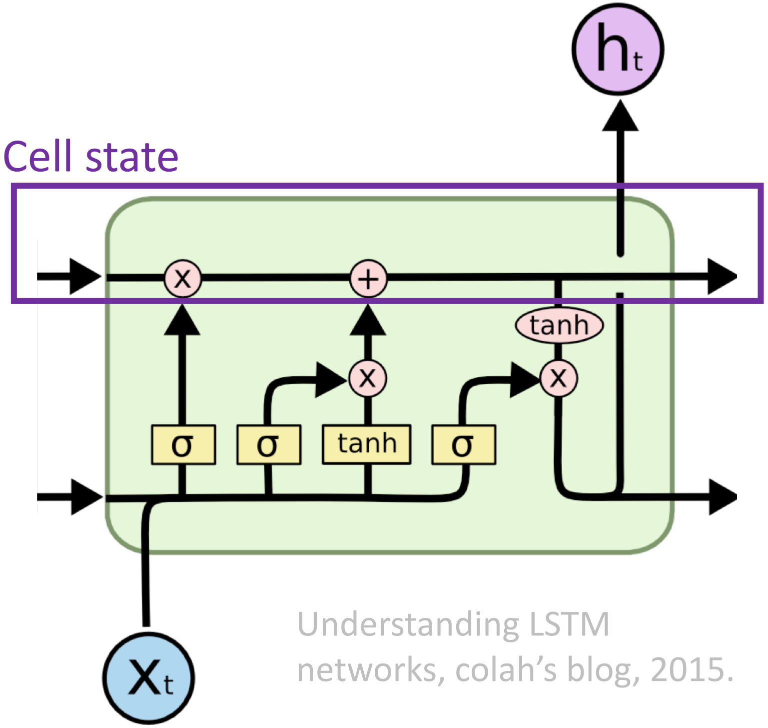


  - Input gate layer: Which values to be updated.



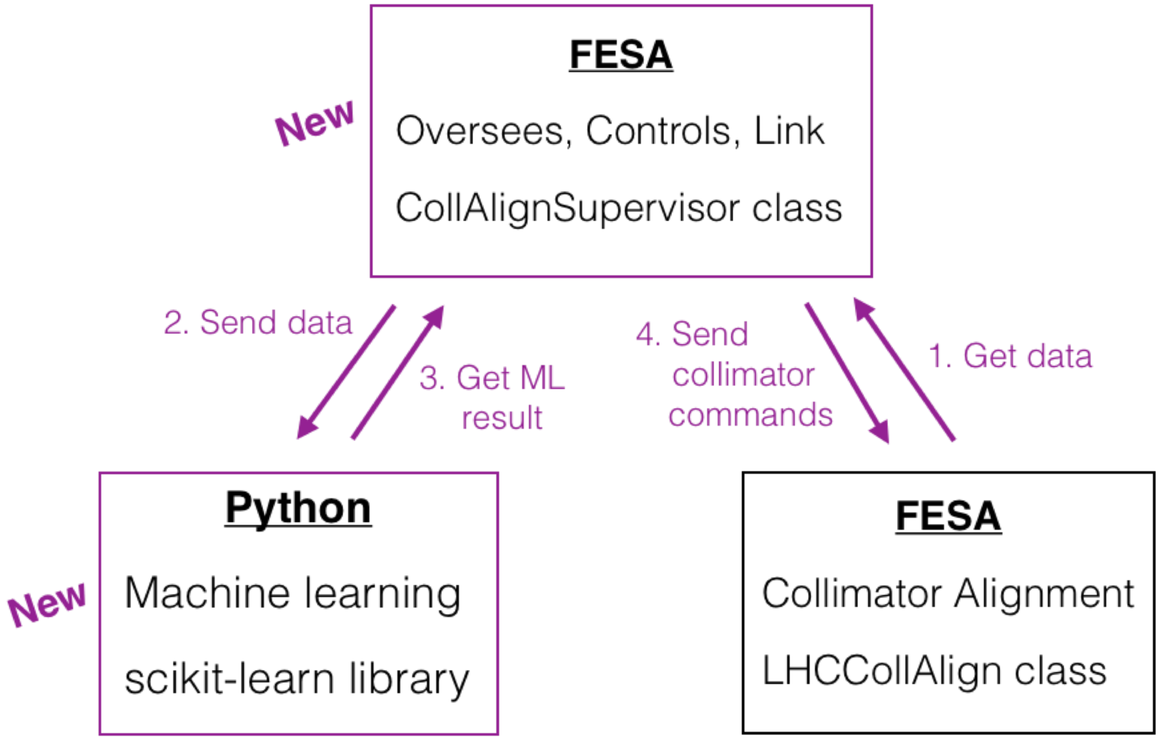
  - Output layer: Decide what to output.





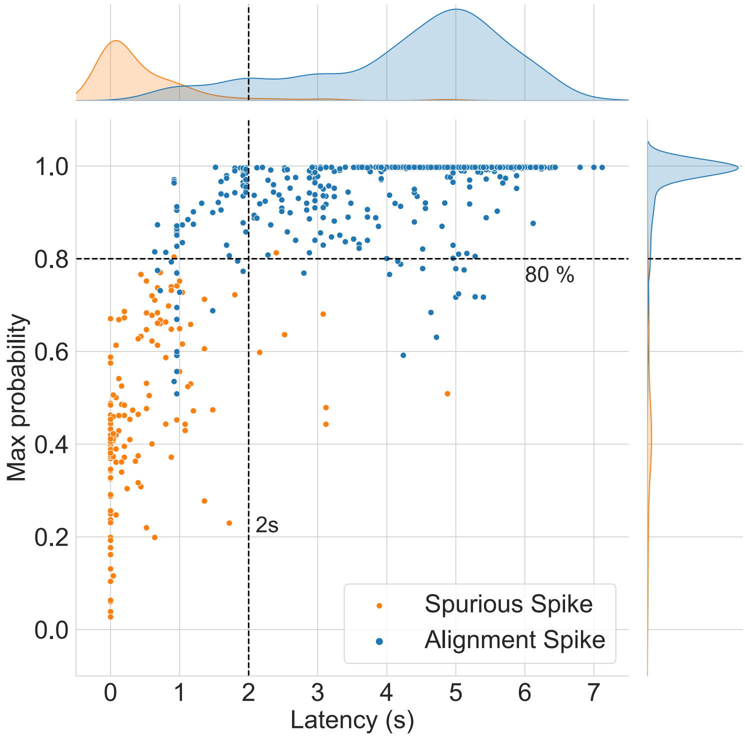
Understanding LSTM networks, colah's blog, 2015.

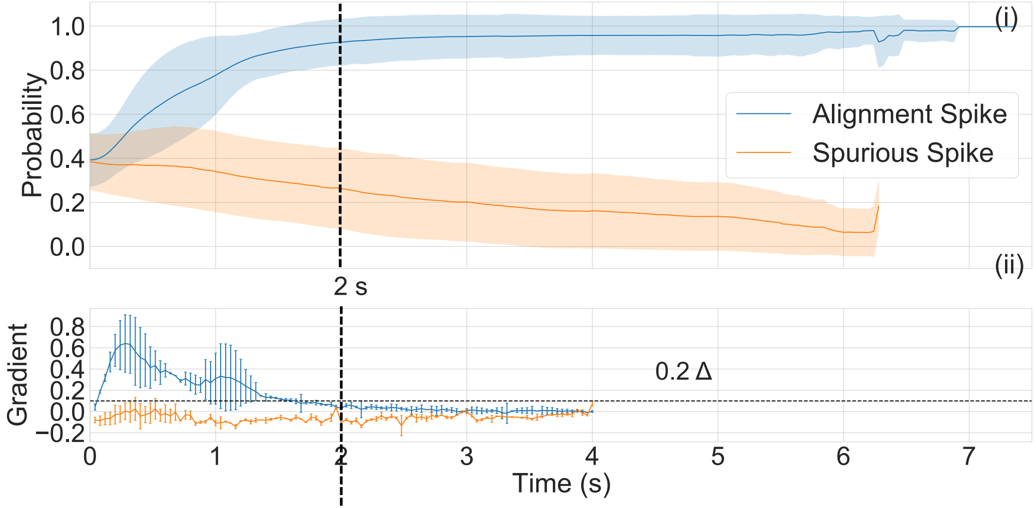
Fully-Automatic Alignment Implementation

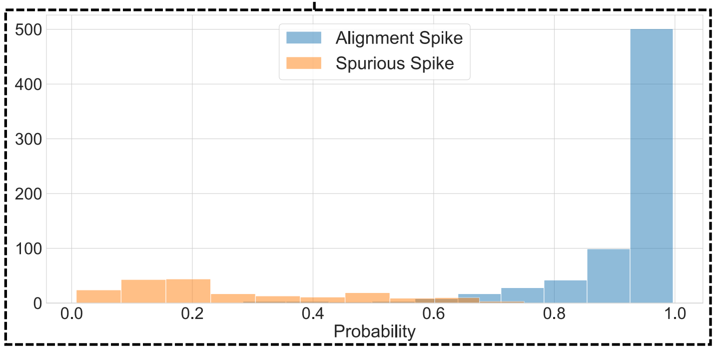


(FESA - Real-time control framework to develop LHC ring front-end equipment software)

Spike Classification Analysis @ FT







Spike Classification Analysis Results Overview

	Proton beams		Ion beams
	Injection	**Flat top**	**Collisions**
Decay time	~0.61 s	~2 s	~1.08 s
Classification probability threshold	80 %	80 %	80 %
Classification probability gradient	0.2	0.2	0.2
Classification latency	~1.07 s	~1.54 s	~2.08 s
Classification precision	**98 %**		**97 %**