FERMILAB-SLIDES-20-069-CMS-SCD-TD

Intelliquench – Real Time detection of magnet quenches in superconducting accelerator magnets.

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SIST/GEM Final Presentation.

8/5/2020

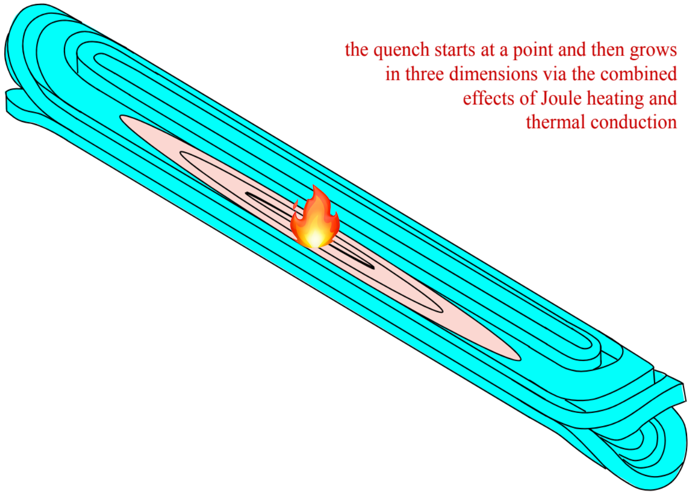
Outline

I. Overview of magnet quenches
II. Deep neural network for anomaly detection
III. Results
IV. Summary & Outlook

Magnet quenches

- Superconducting accelerator magnets must operate at **very low temperatures** to maintain superconductivity (**no resistance**).
- Due to several reasons (mechanical imperfections, conductor motion, …), a **specific spot** in the magnet **heats up.**
- This causes the magnet to become **resistive**, and with **huge amount of current** pumping through, it can be catastrophic.

Growth of the resistive zone

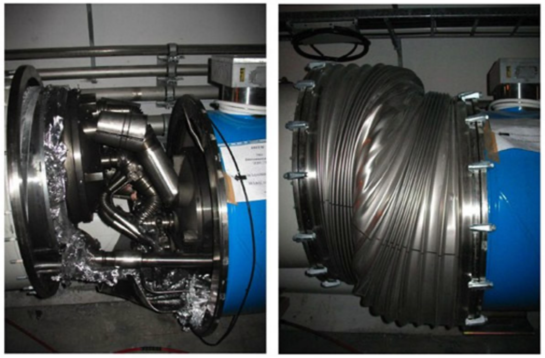


Wilson et al. Superconducting magnets for accelerators.

r/CatastrophicFailure

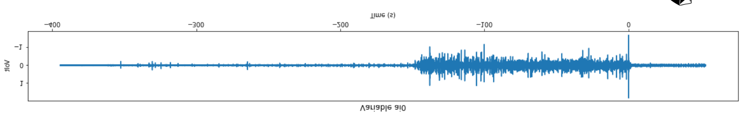
In **2008**, magnet quench occurred in **100 magnets at the LHC at CERN**, leading to a loss of approximately **six tonnes** of liquid helium.

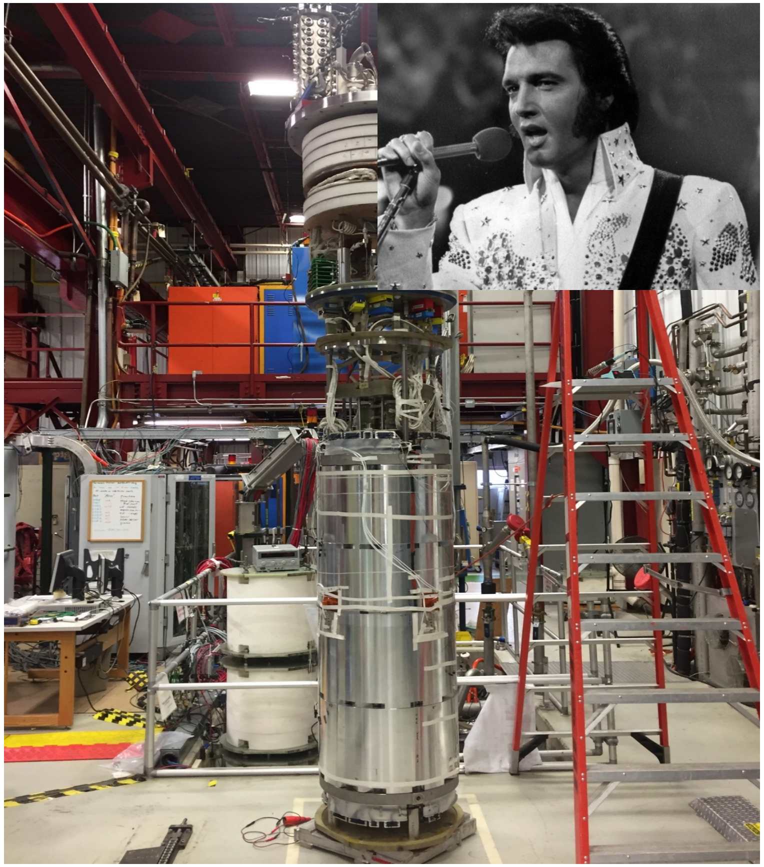
The escaping vapour expanded with **explosive force**, damaging a total of 53 superconducting magnets (each costs **several millions dollar**.)



Acoustic sensors

- We placed **5 acoustic sensors** around the magnet to detect **abnormal sound signatures**.





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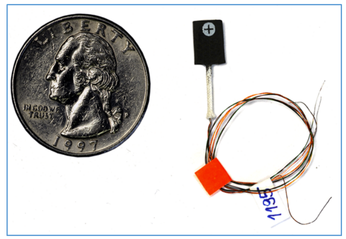
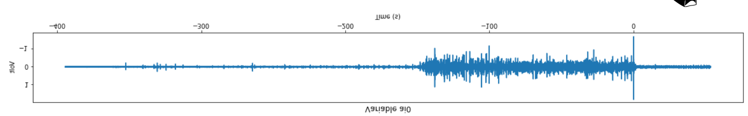
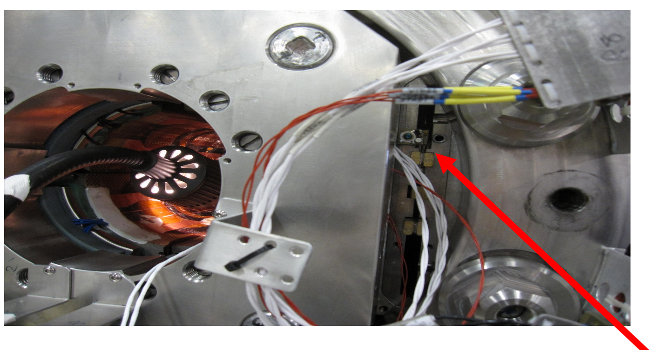
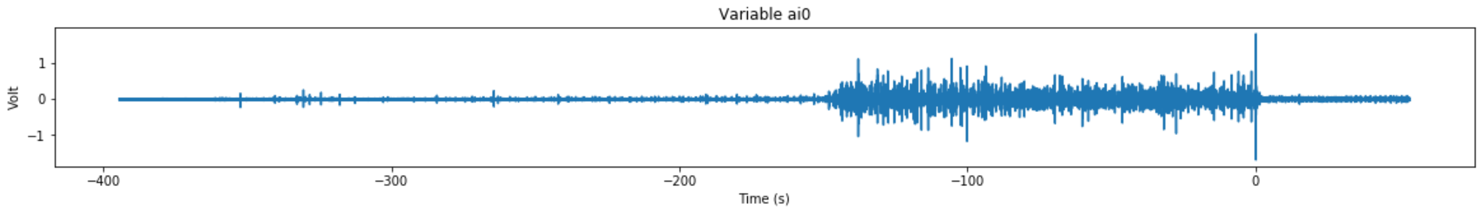


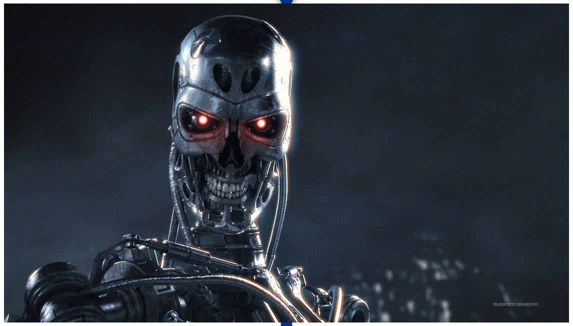




Sensor

Deep Neural Network to detect anomaly in the signal.



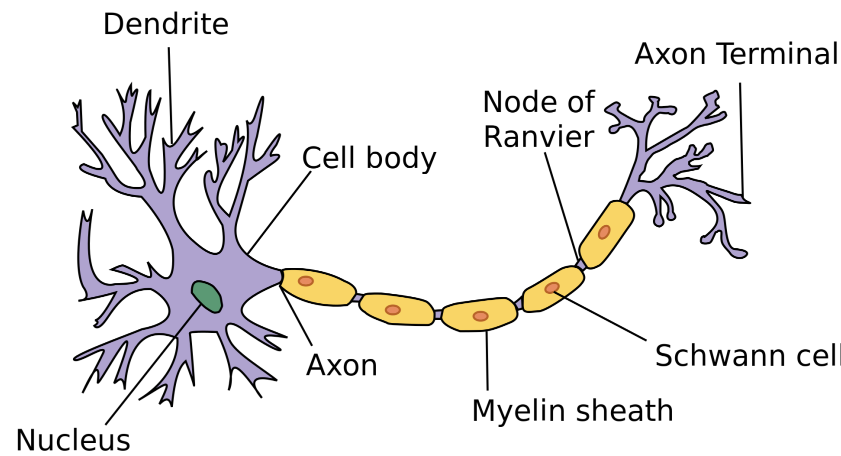


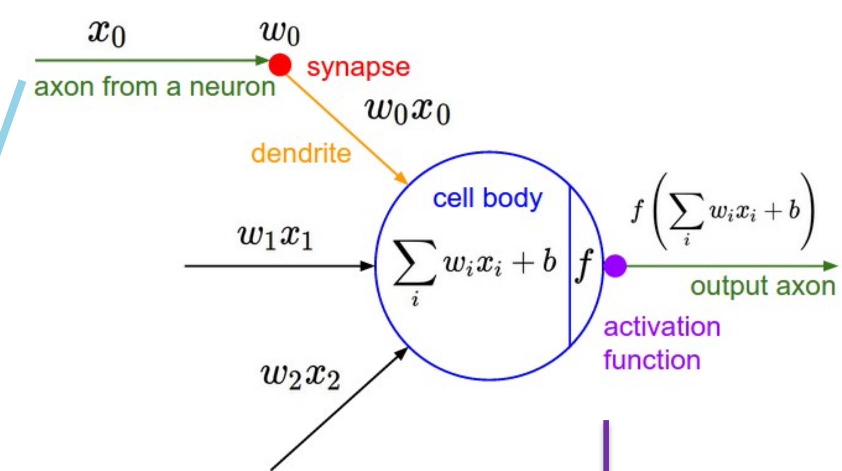
Deep Neural Network

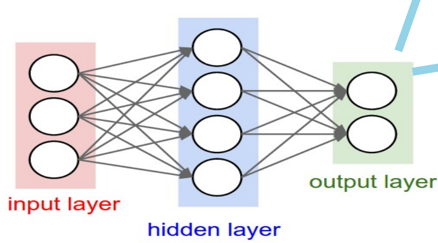
Abnormal sound signals?

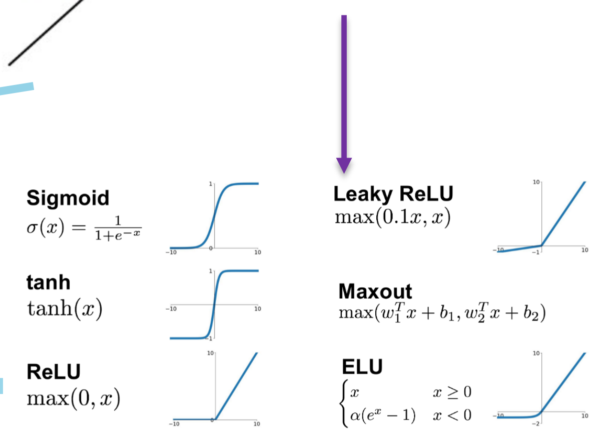
Deep Neural Networks

- Each **input** multiplied by a **weight**.
- **Weighted values** are summed, **Bias** is added.
- Non-linear **activation function** is applied
- Trained by varying the **parameters** to minimize a loss function (quantifies how many mistakes the network makes)







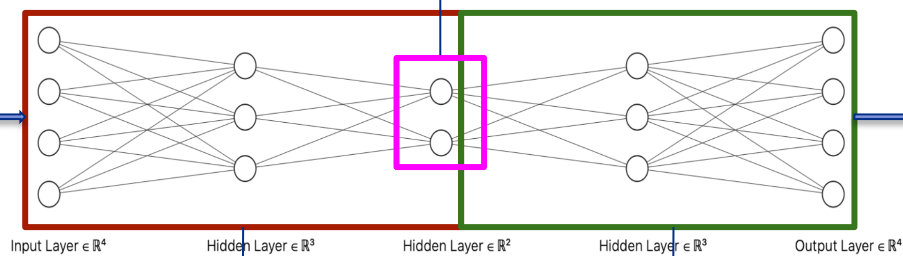


Deep Neural Network Auto-encoder

Compressed info

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y^{(i)} - \hat{y}^{(i)})^2}$$

Signals



Root mean square error (RMS)

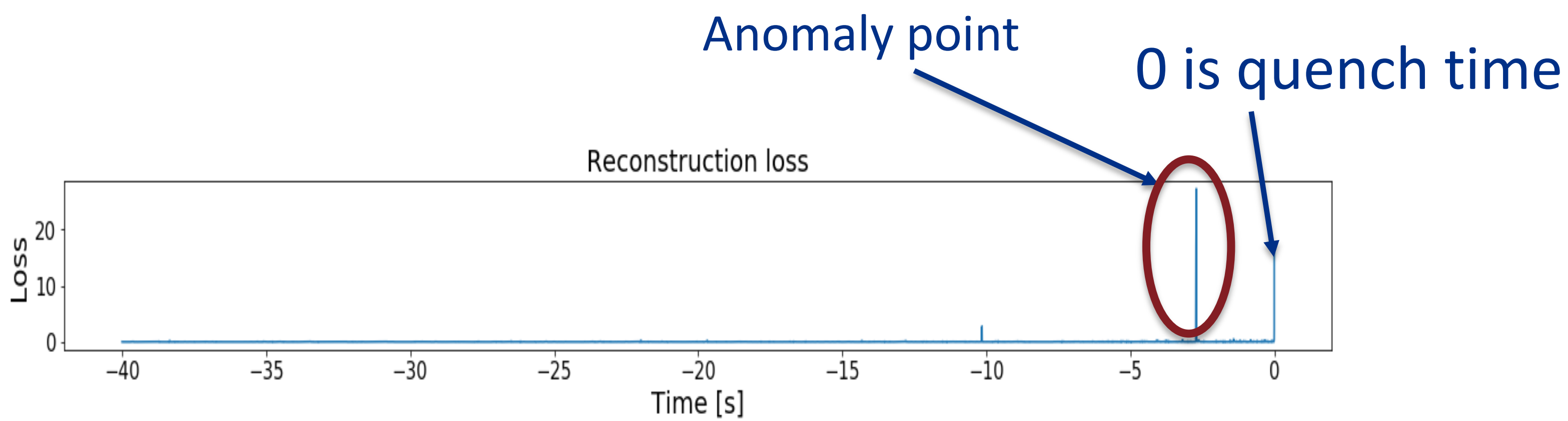
Encoder

Decoder

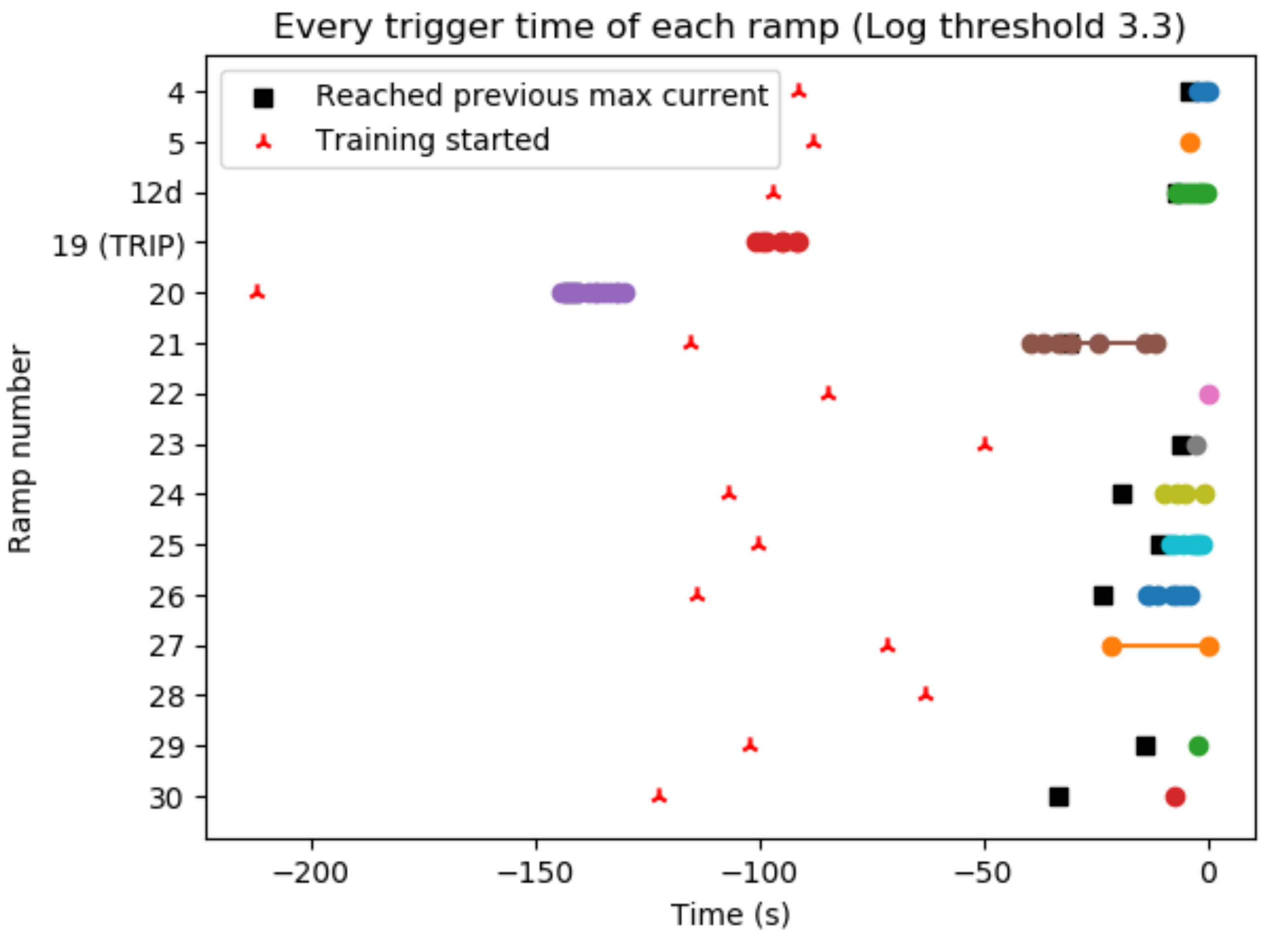
Large error? Anomaly

Fermilab

Reconstruction loss visualization

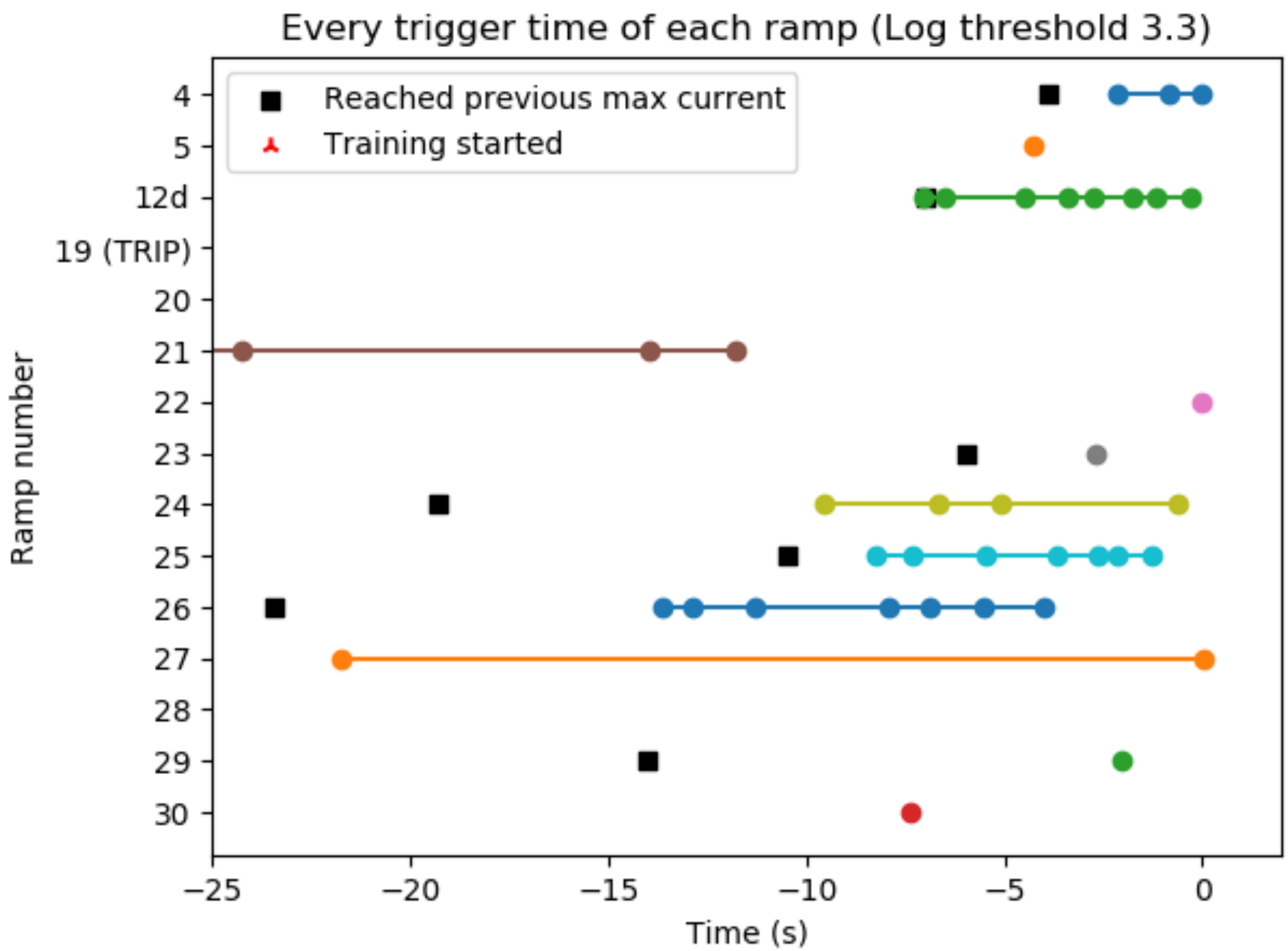


Results

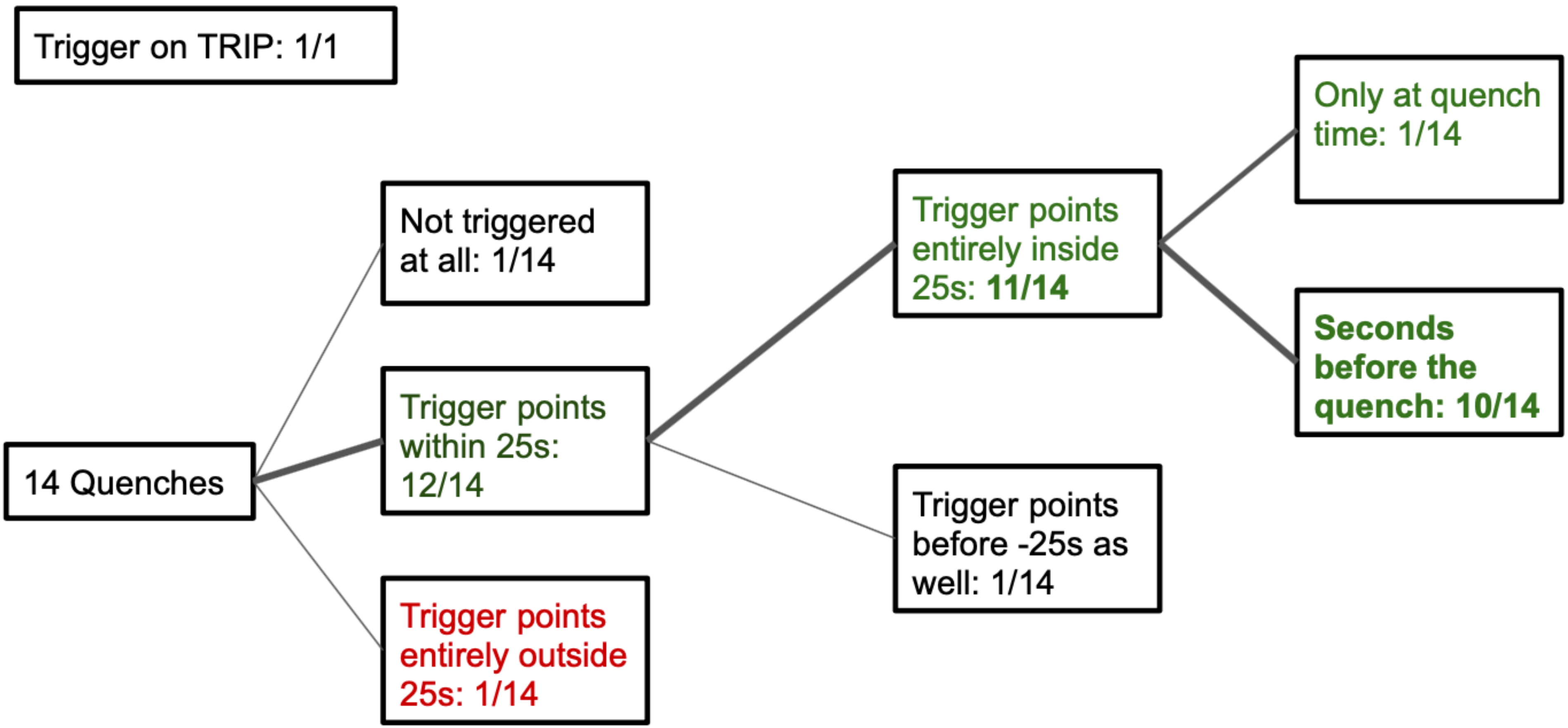


Every trigger time of each ramp (Log threshold 3.3)
Reached previous max current
Training started
4
5
12d
19 (TRIP)
20
21
22
23
24
25
26
27
28
29
30
Ramp number
−200
−150
−100
−50
0
Time (s)

Zoomed in -25s near the quench



Results – summary



Summary & Outlook

- Magnet quenches **are expensive**.
- We are using Deep Neural Network to **detect anomaly sound signals**, which hopefully enable us **trigger before the quench happens.**
- We've achieved some promising results and will be moving on to **verification step on unseen data.**
- Eventually, we want to have a **real-time system** deployed on **FPGAs** to process streaming acoustic data.

Acknowledgements

- My supervisor: Dr. Nhan Tran & other collaborators in the superconducting technology division: Sujay, Cristian, Steve, Vittorio, Stoyan.
- The SIST committee & my mentor group.
- Other awesome interns:

2019

2020

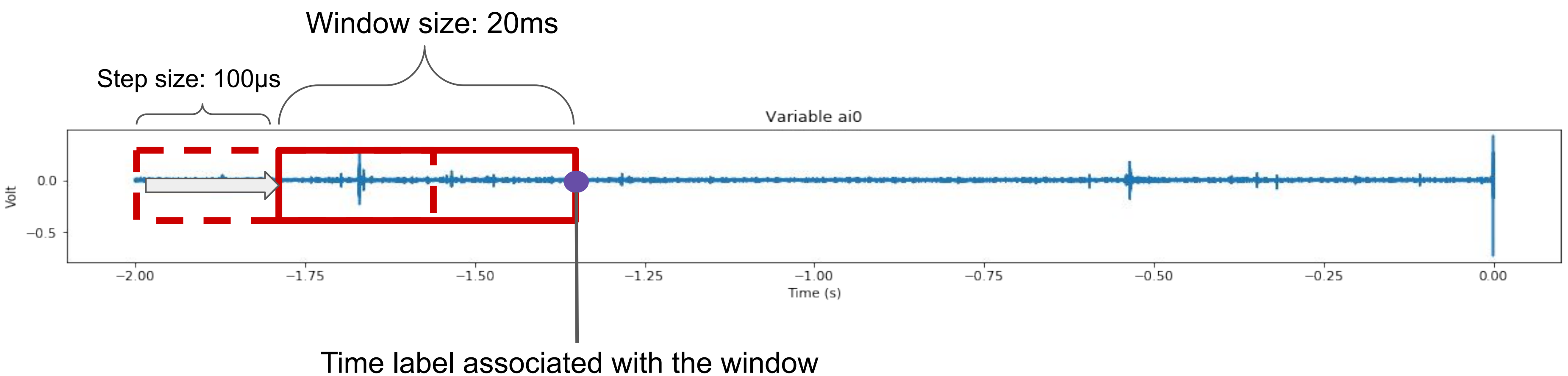
1	Last Name	First Name
2	Chavez	Elise
3	Collins	Eboni
4	Griggs	James
5	Guy	Khalil
6	Hoang	Duc
7	Logsdon	Morgan
8	Lopez Gutierrez	Diego
9	Marquez	Jose Manuel
10	Matos	Alejandro
11	Miranda	Lovizna
12	Neely-Brown	LaRayah
13	O'Neil	Judah
14	Paton	Elizabeth
15	Petit-Bois	Elisabeth
16	Pham	Linh
17	Price	Tiffany
18	Stanton	Sevio
19	Tuttle	Ethan
20	Yancey	Mirica
21	Youssef	Rahaf

Back-ups

Signals' statistical features

- From the main signals, we calculate two features, **standard deviation** and **mean of the amplitude**. s

- These features are calculated using a **rolling window**.



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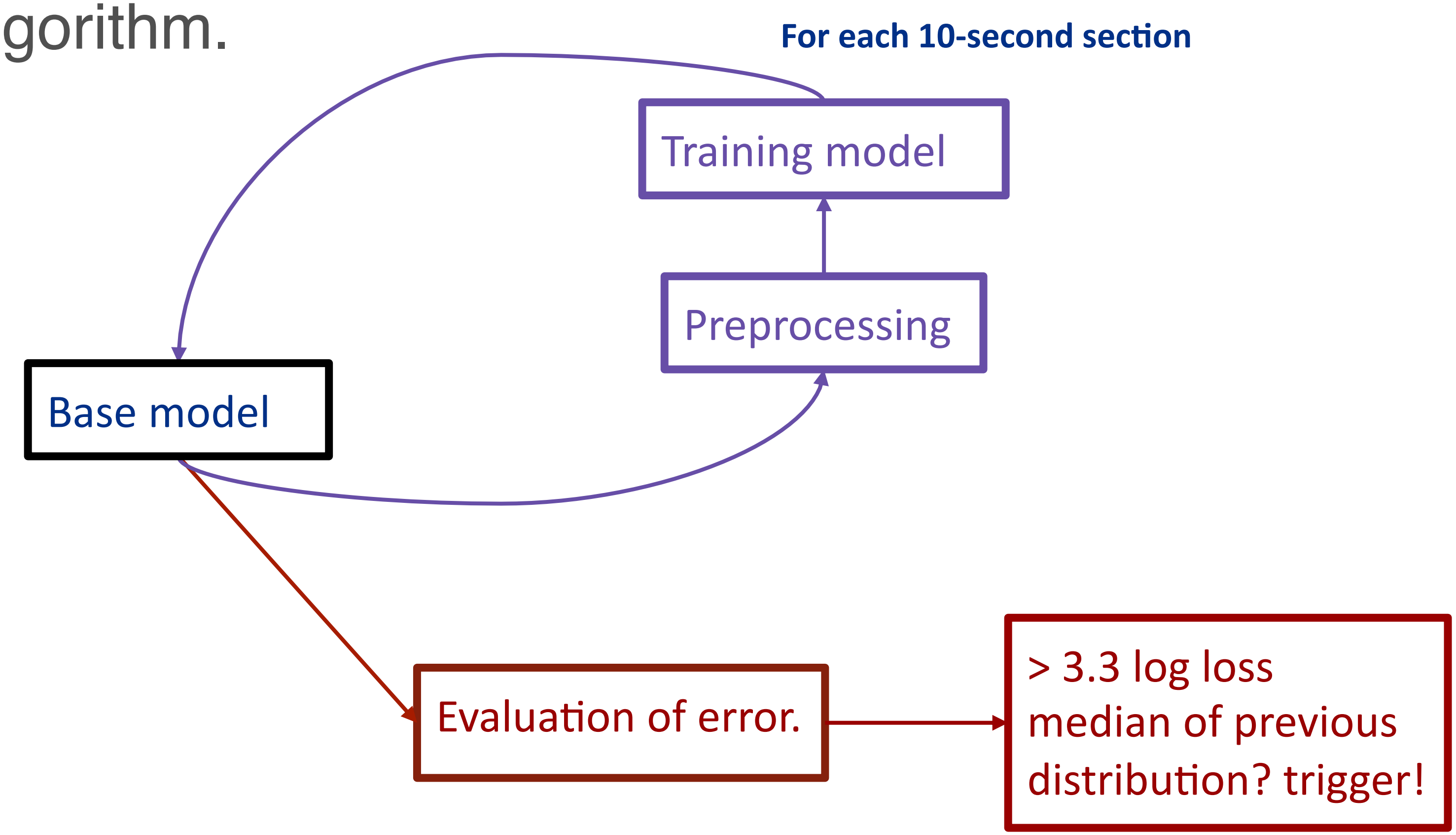
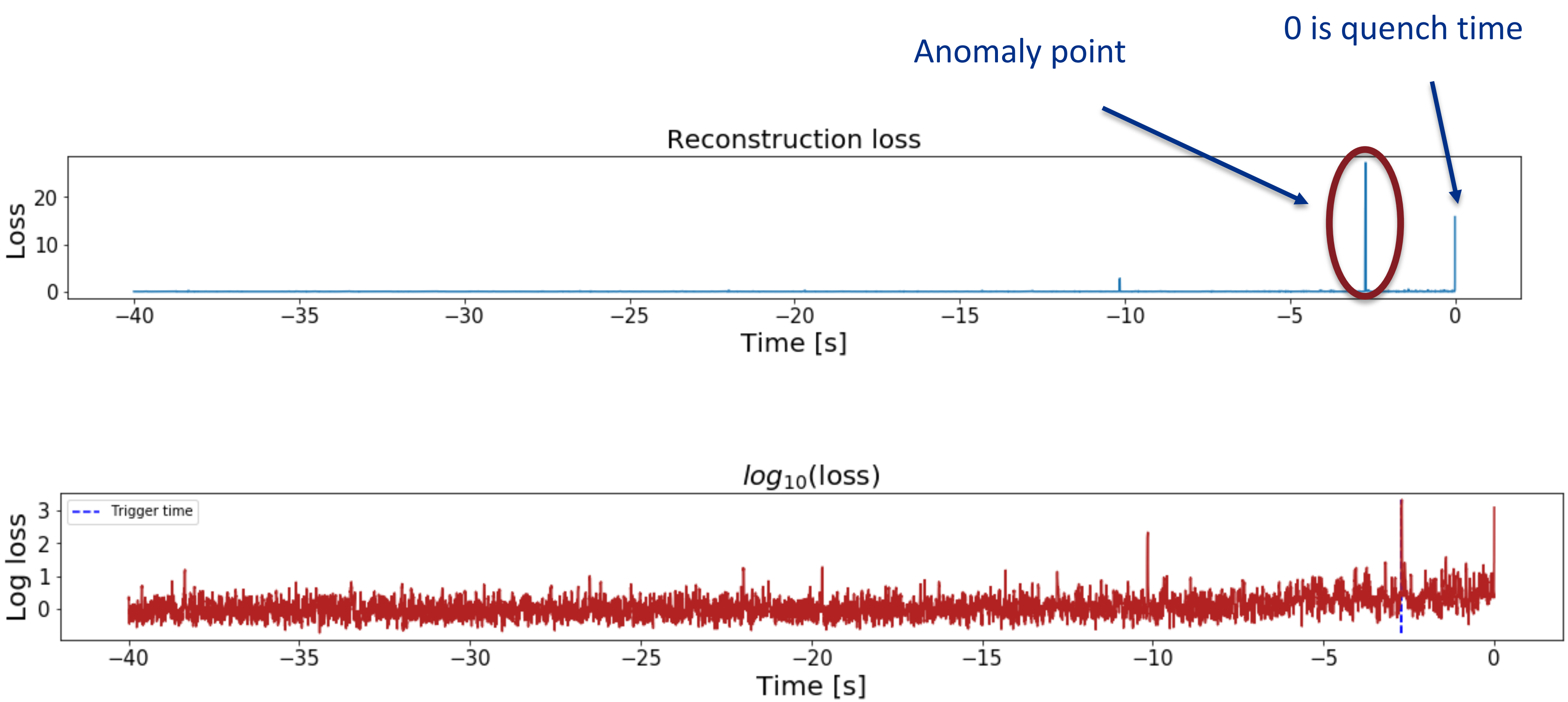
Dynamic learning

- To adapt to increasing higher level of noise as we get to higher current, we also implement a dynamic learning algorithm.

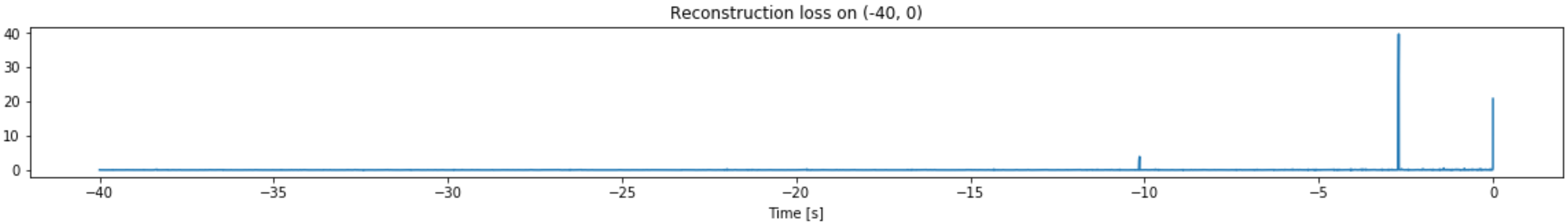


Reconstruction loss visualization

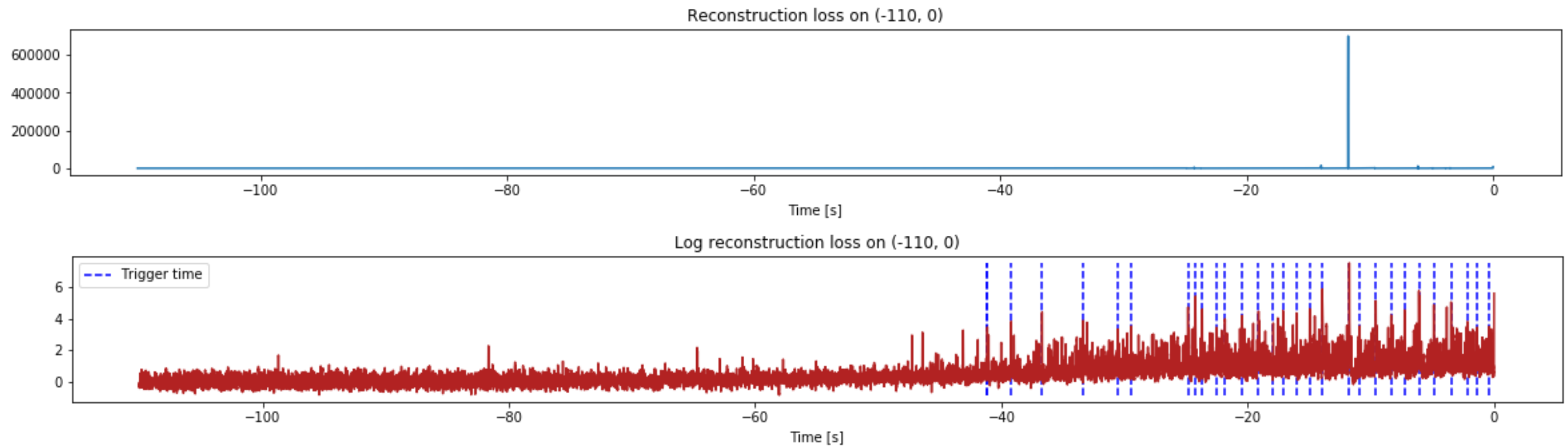


Problems with static learning

You generally see very clean signal when doing static learning (just learn on the firs few seconds)



However, the loss scale is different in each ramp and it’s hard to set a consistent threshold.



Dynamic threshold