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

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

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New perspective 2020 - Fermilab

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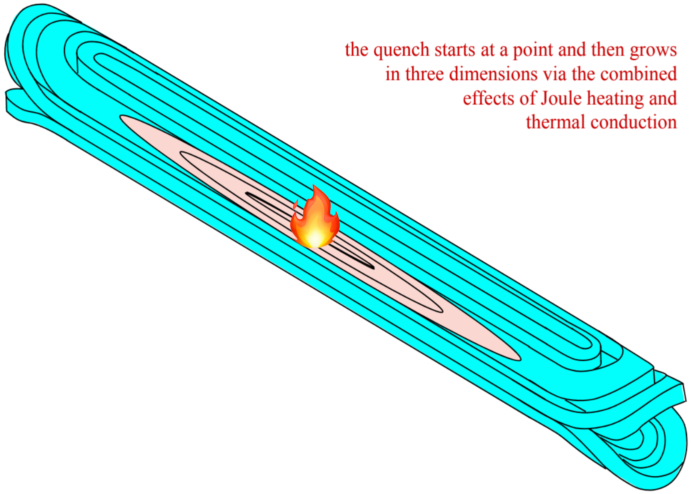
Outline

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

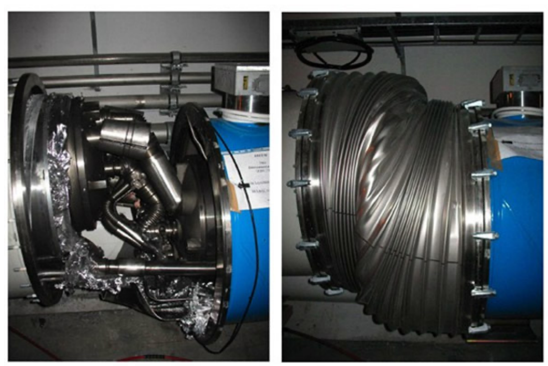


Wilson et al. Superconducting magnets for accelerators.

r/CatastrophicFailure

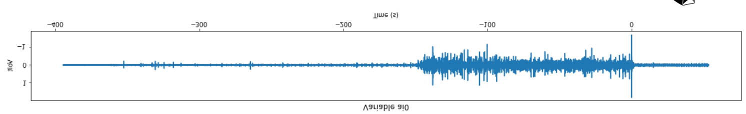
In **2008**, magnet quench occurred in **100 magnets at the LHC at CERN**, leading to a loss of approximately **six tonnes** of liquid helium.

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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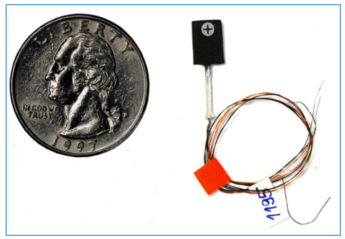
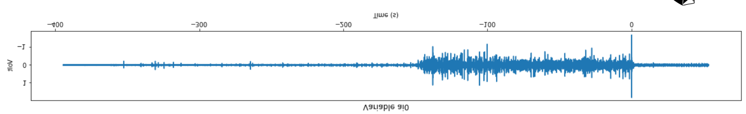
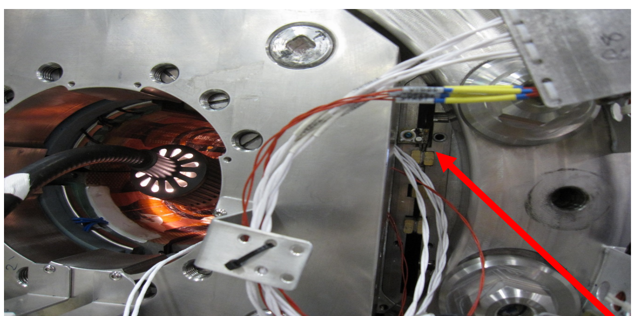
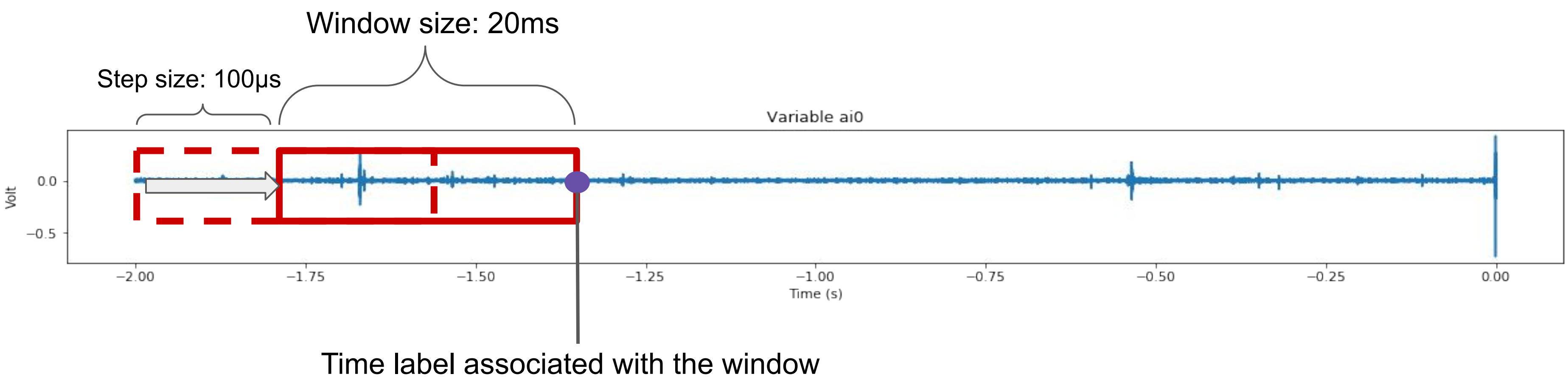


Signals' statistical features

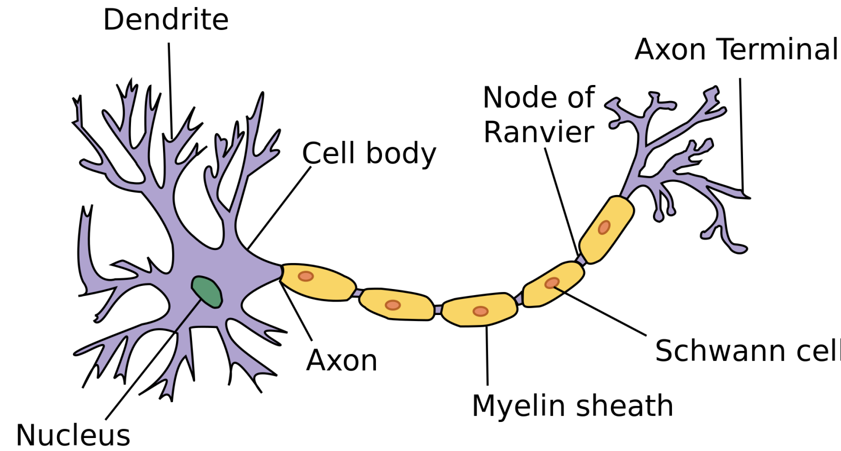
- From the main signals, we calculate two features, **standard deviation** and **mean of the amplitude**.

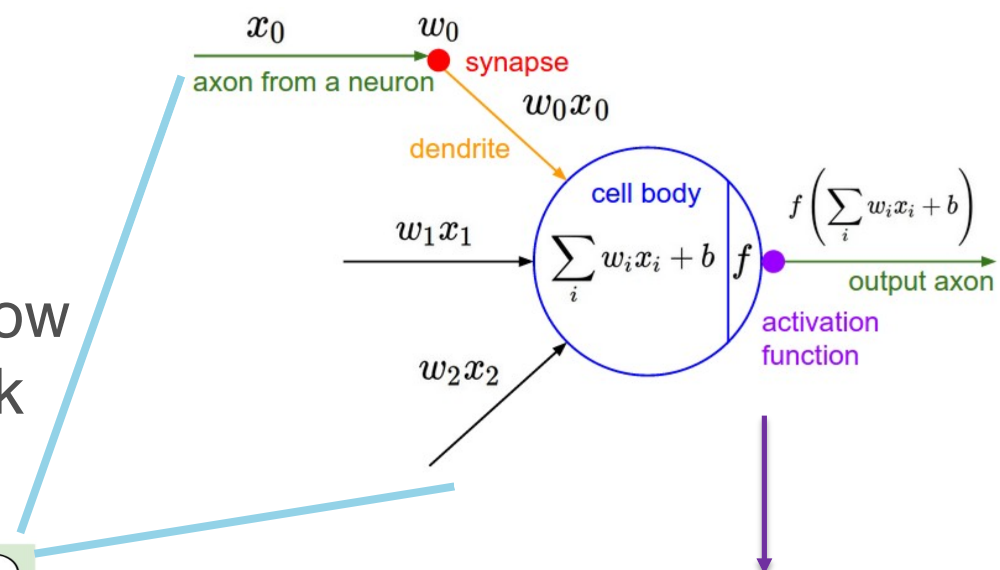
- These features are calculated using a **rolling window**.

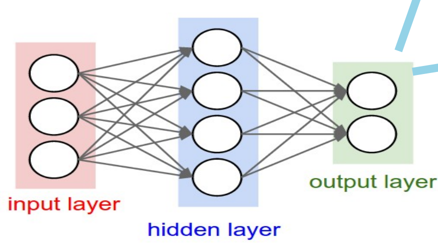


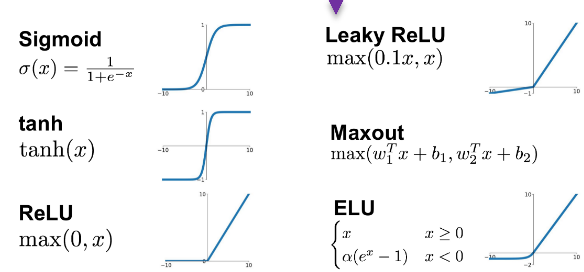
Deep Neural Networks

- 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)







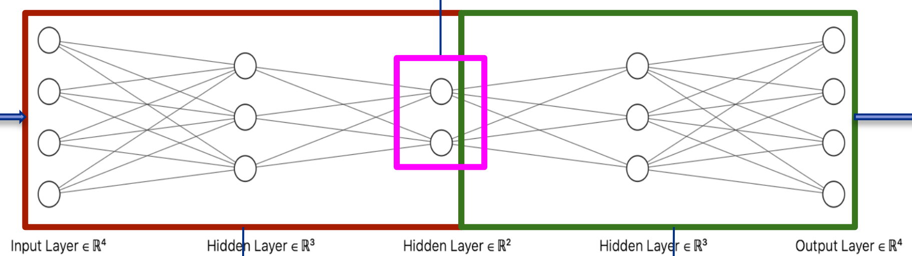


Deep Neural Network Auto-encoder

Compressed info

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

Statistical features



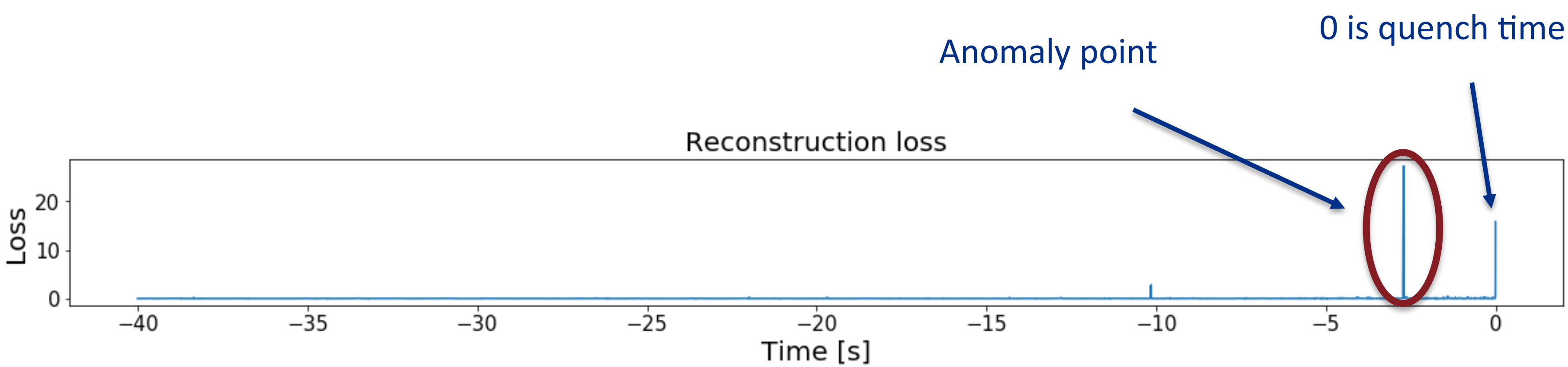
Root mean square error (RMS)

Encoder

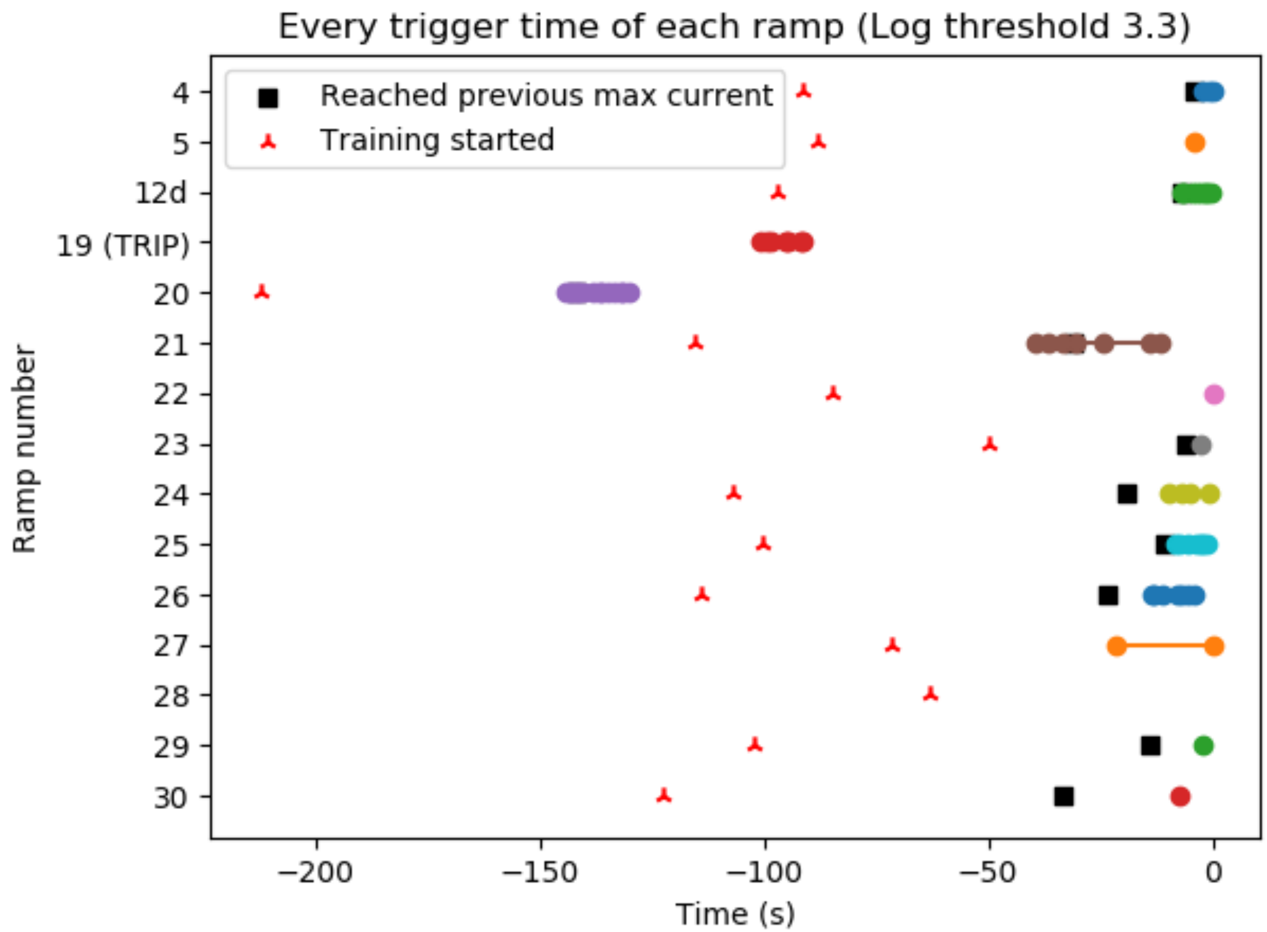
Decoder

Large error? Anomaly

Reconstruction loss visualization



Results



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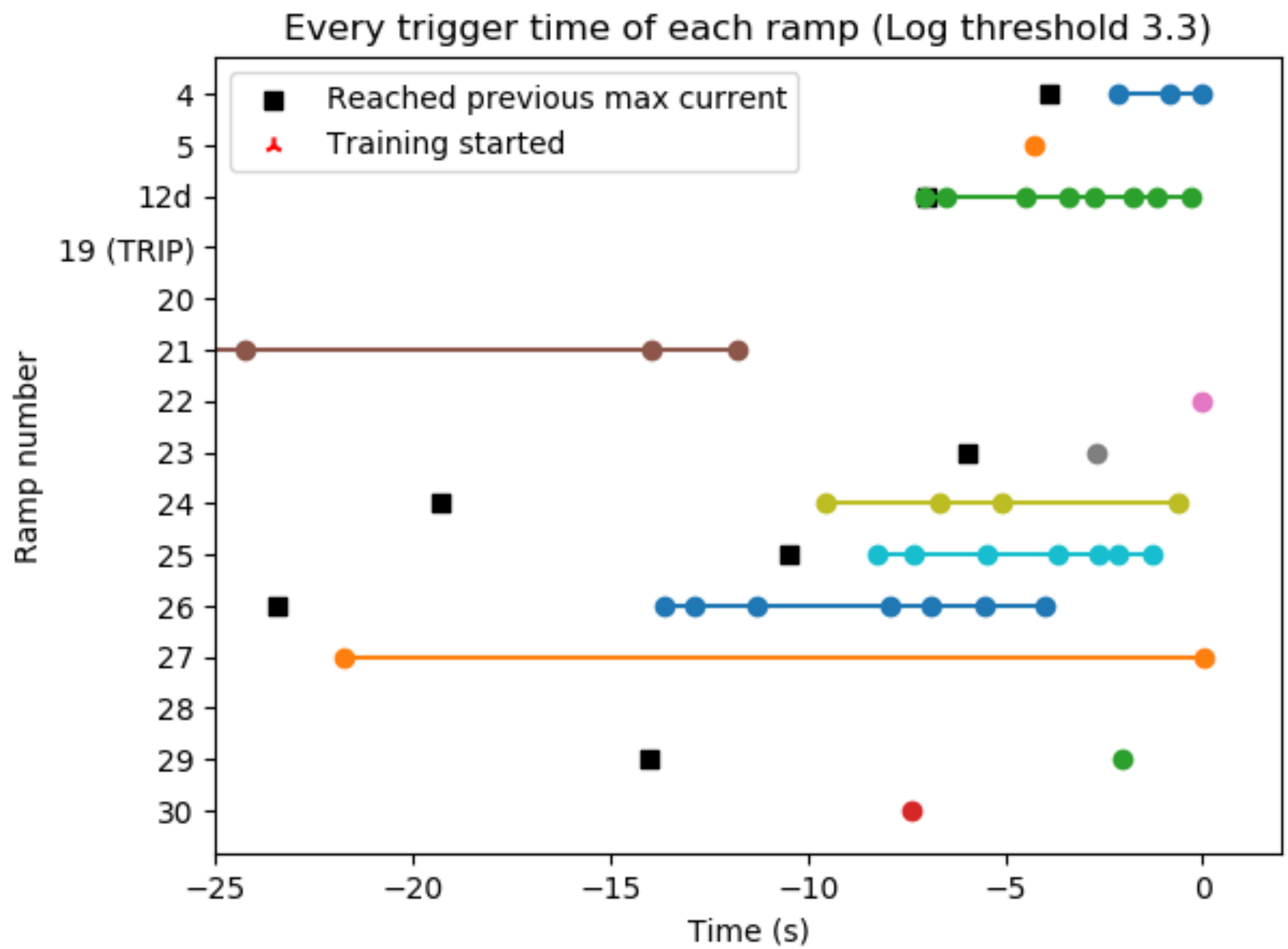
Zoomed in -25s near the quench



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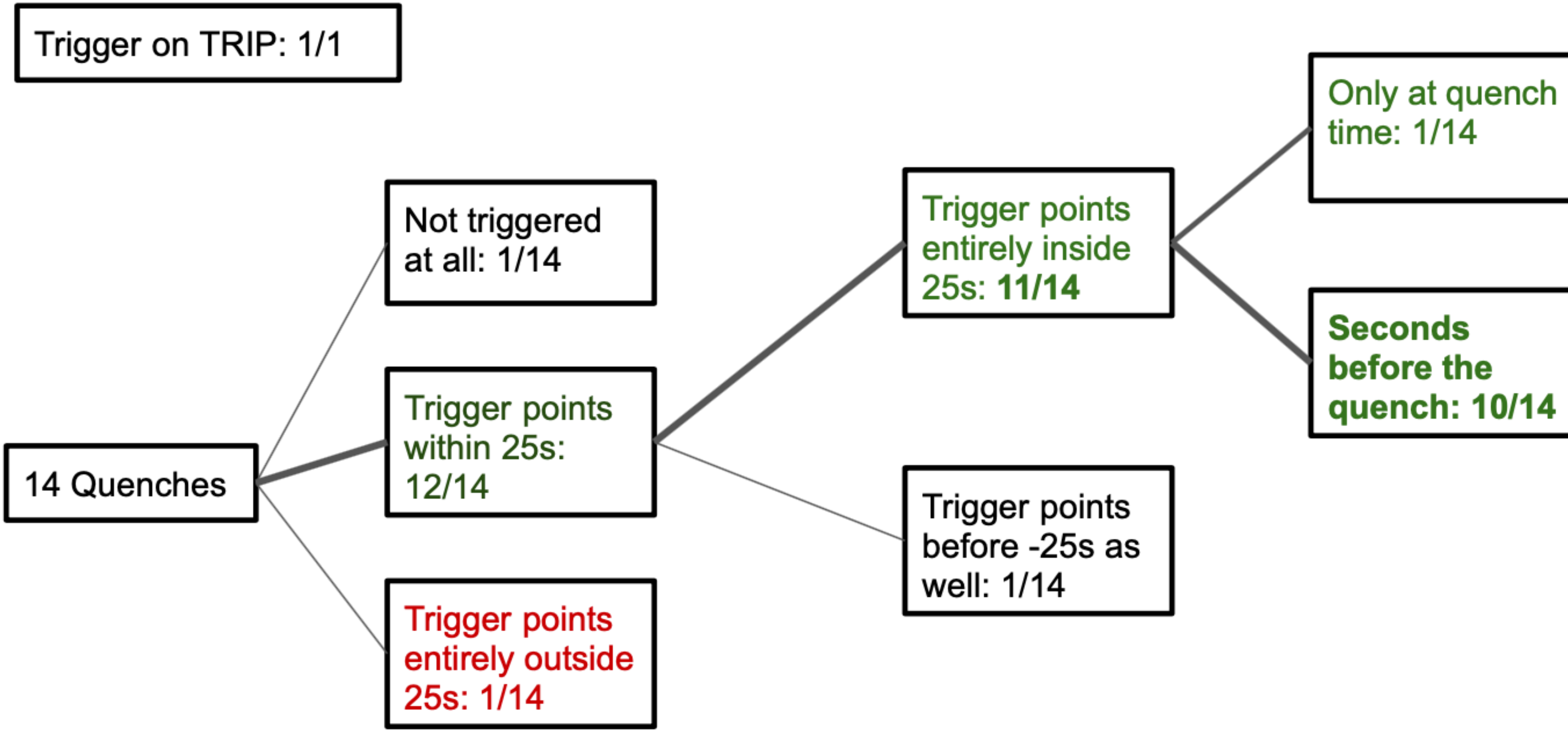
Results – summary



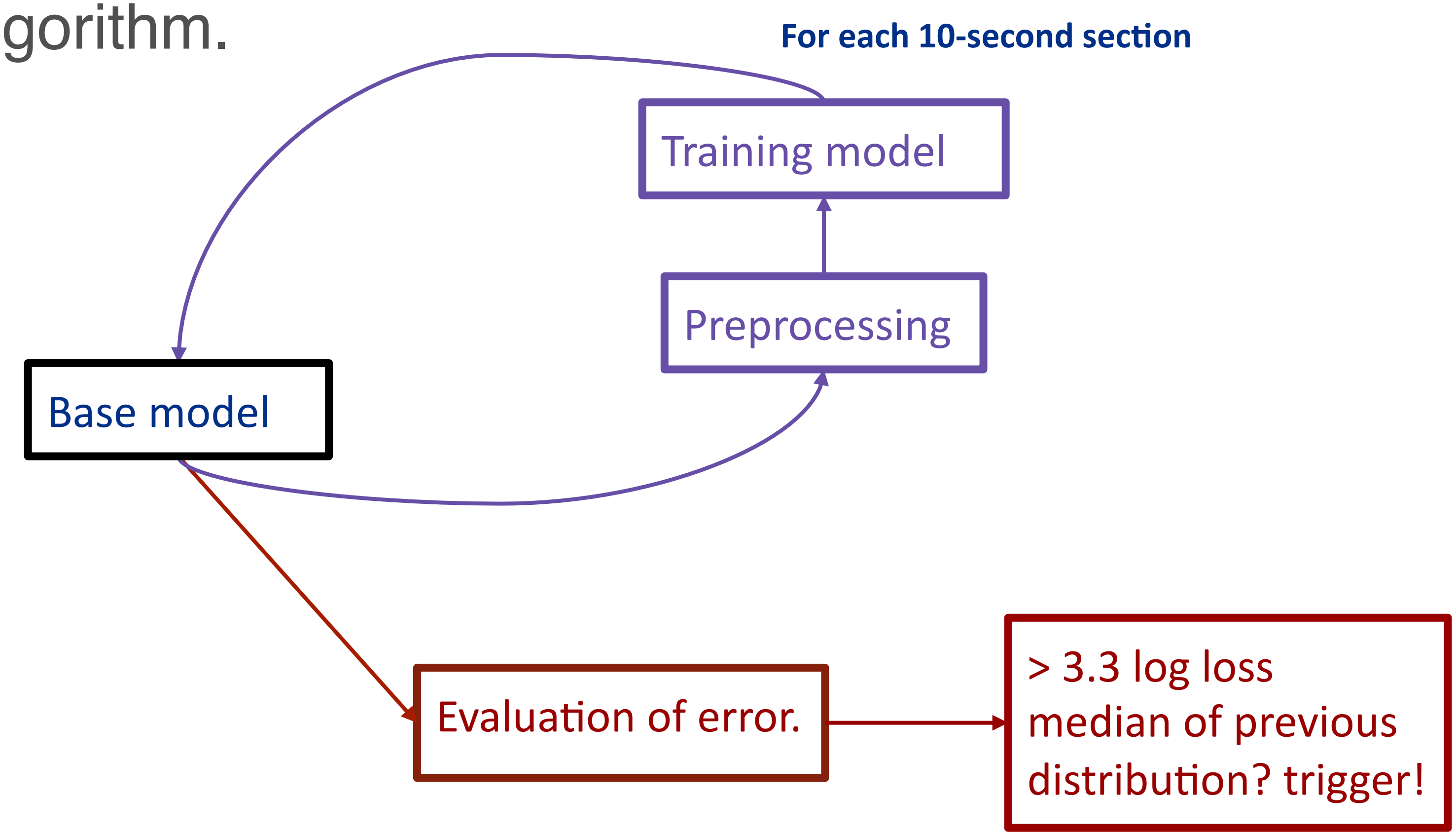
Summary & Outlook

- 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.

Back-ups

Dynamic learning

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



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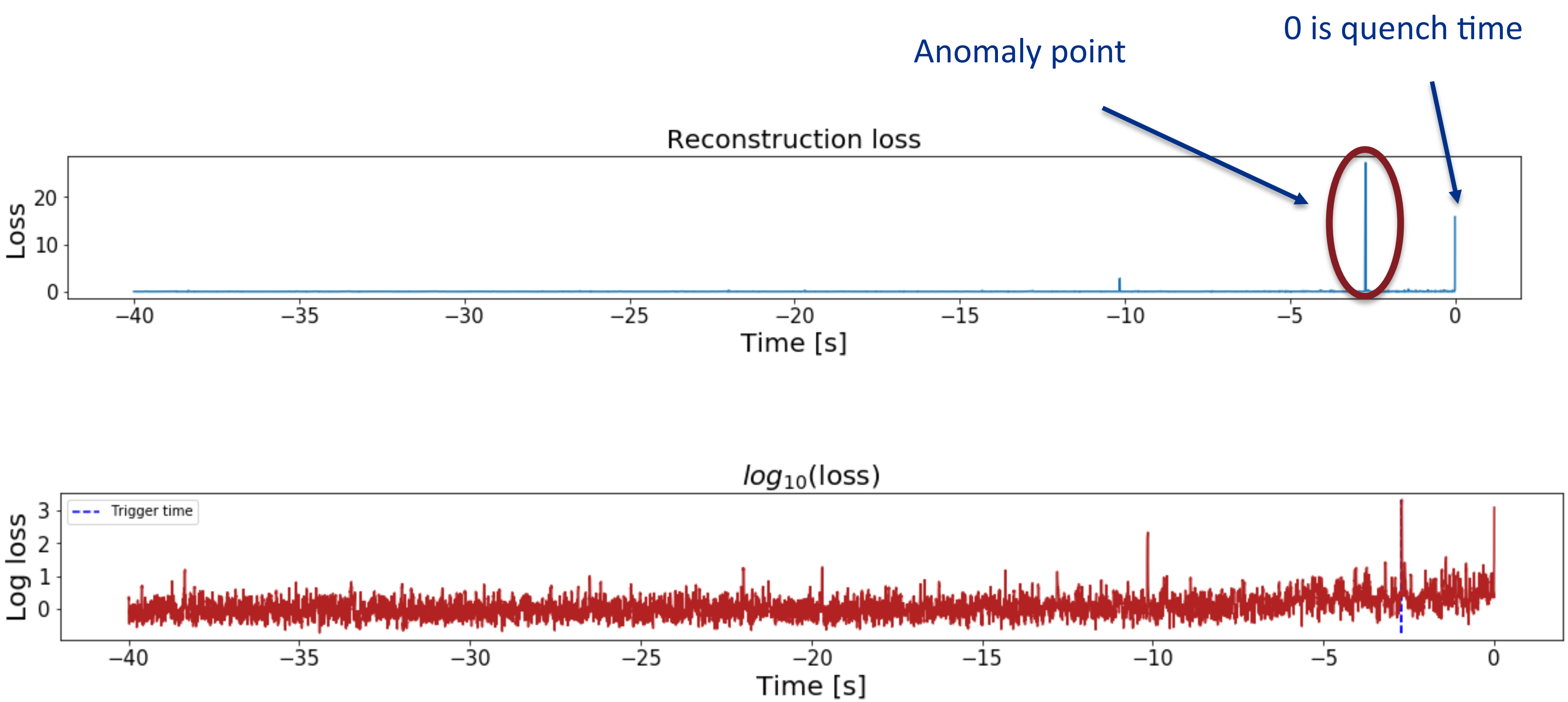
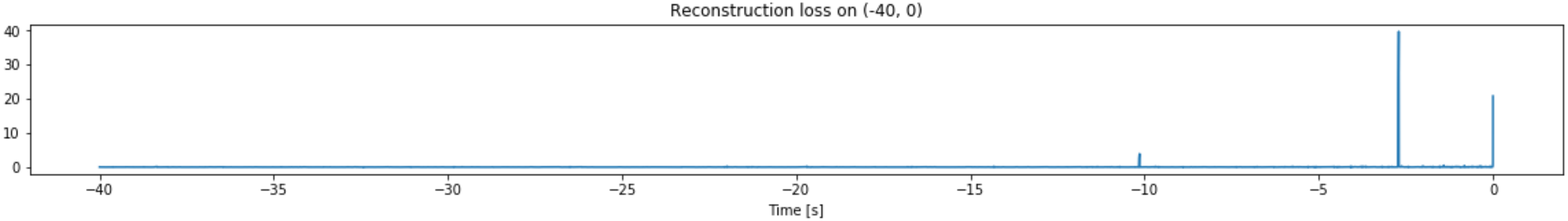
Reconstruction loss visualization

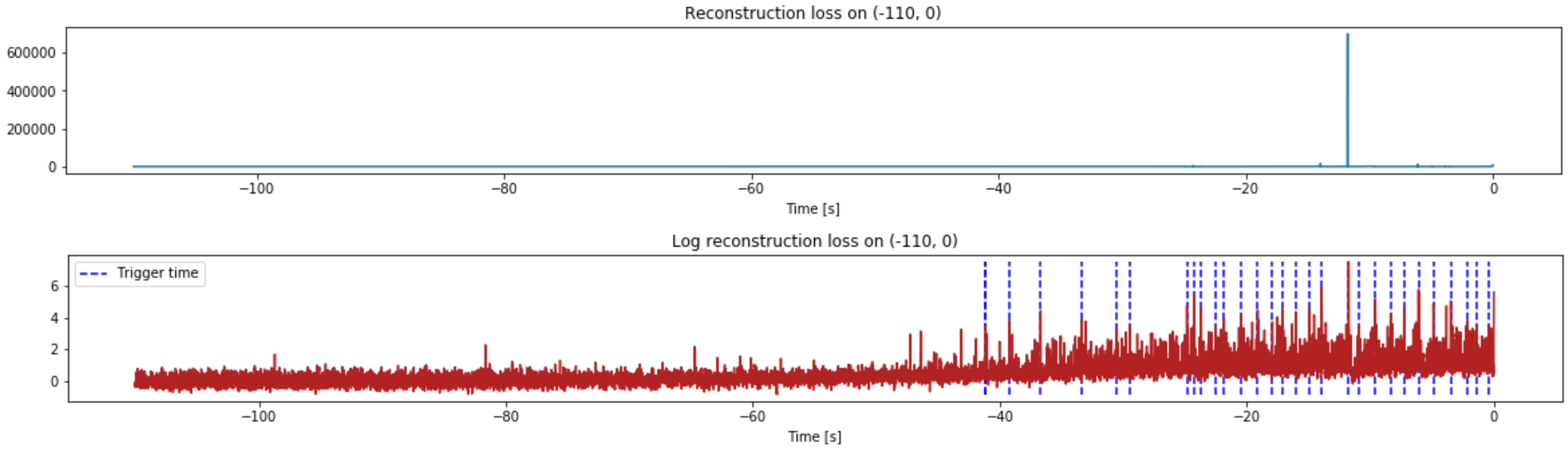


Problems with static learning

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