Identification of Superconducting Magnet Quenches with Machine Learning

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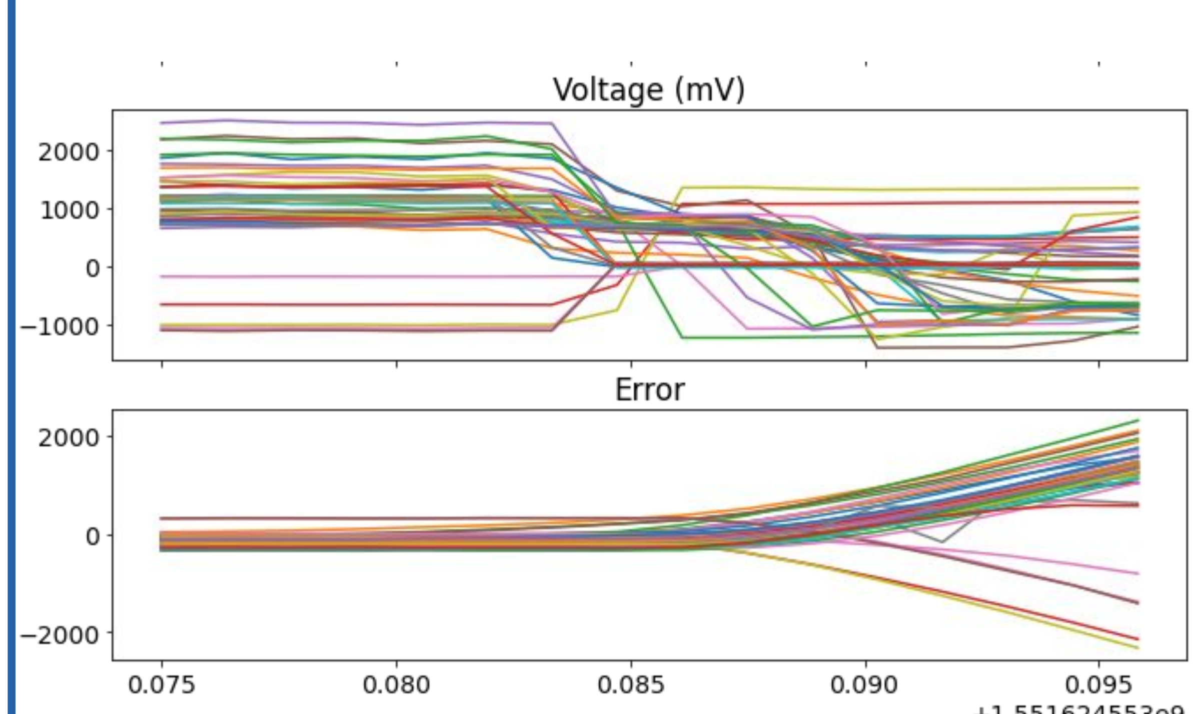
Abstract

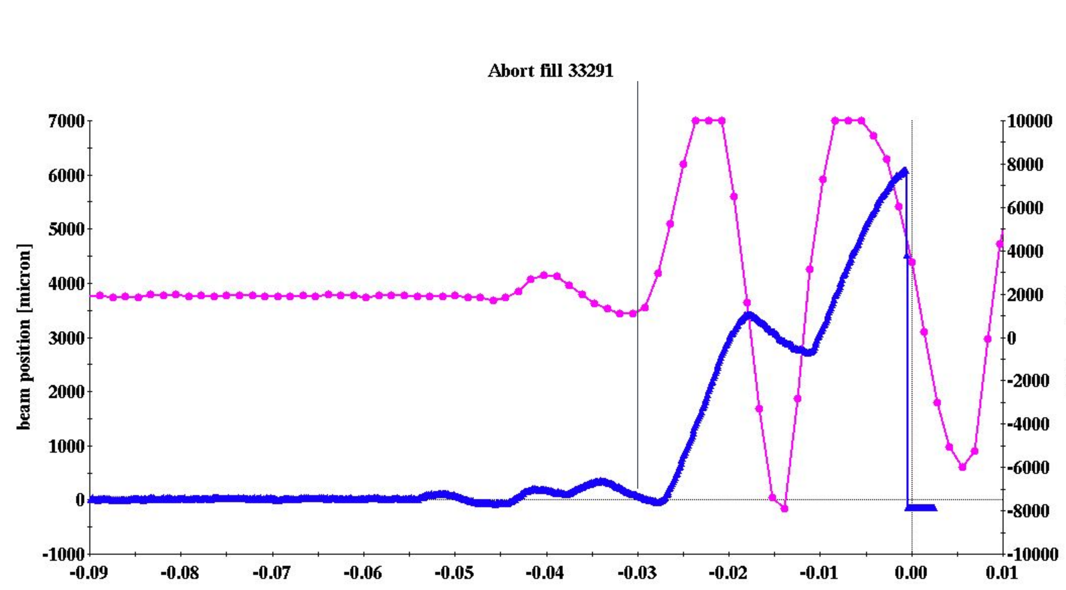
Superconducting magnet technology is one of the cornerstones of large particle accelerator facilities. A challenge with operating these systems is the possibility for the magnets to quench. The ability to predict quenches and take preventative action in advance, would no doubt decrease the likelihood of a catastrophic failure and increase the lifetime operability of particle accelerators. We are in development of a machine learning workflow for the deployment of quench detection and prediction systems that can be integrated with real time systems and accelerator operations. In collaboration with Brookhaven National Laboratory, our methods for algorithm development will utilize magnet data from singular test stands and those that are in operation at the Relativistic Heavy Ion Collider to allow for a robust identification of magnet quenches. We aim to reduce the false positive identification of magnet quenches and identify precursors to prospective quench events in magnet data.

Data Parsing

We have acquired three years of quench data from collaborators at BNL. Each of these years has numerous triggered events which could be a real quench event or a possible fake event. From each of these readouts, we have PS and beam position monitoring (BPM) data from the magnets in the yellow and blue rings of the accelerator. There are 75 magnets in each direction of the ring, but these are not always readout in the quench protection system. Once a quench event is triggered, the beam position, difference in position, and coherence are readout from the BPM at a rate of 10 kHz. At the same time, the reference currents, measured currents, voltages, and error of the voltage are readout from the PS at a rate of 720 Hz. It should be noted that the PS of the rings are connected to varying magnets along the ring of the accelerator. This means we must mesh the data together to get an accurate time reading of the various data channels.

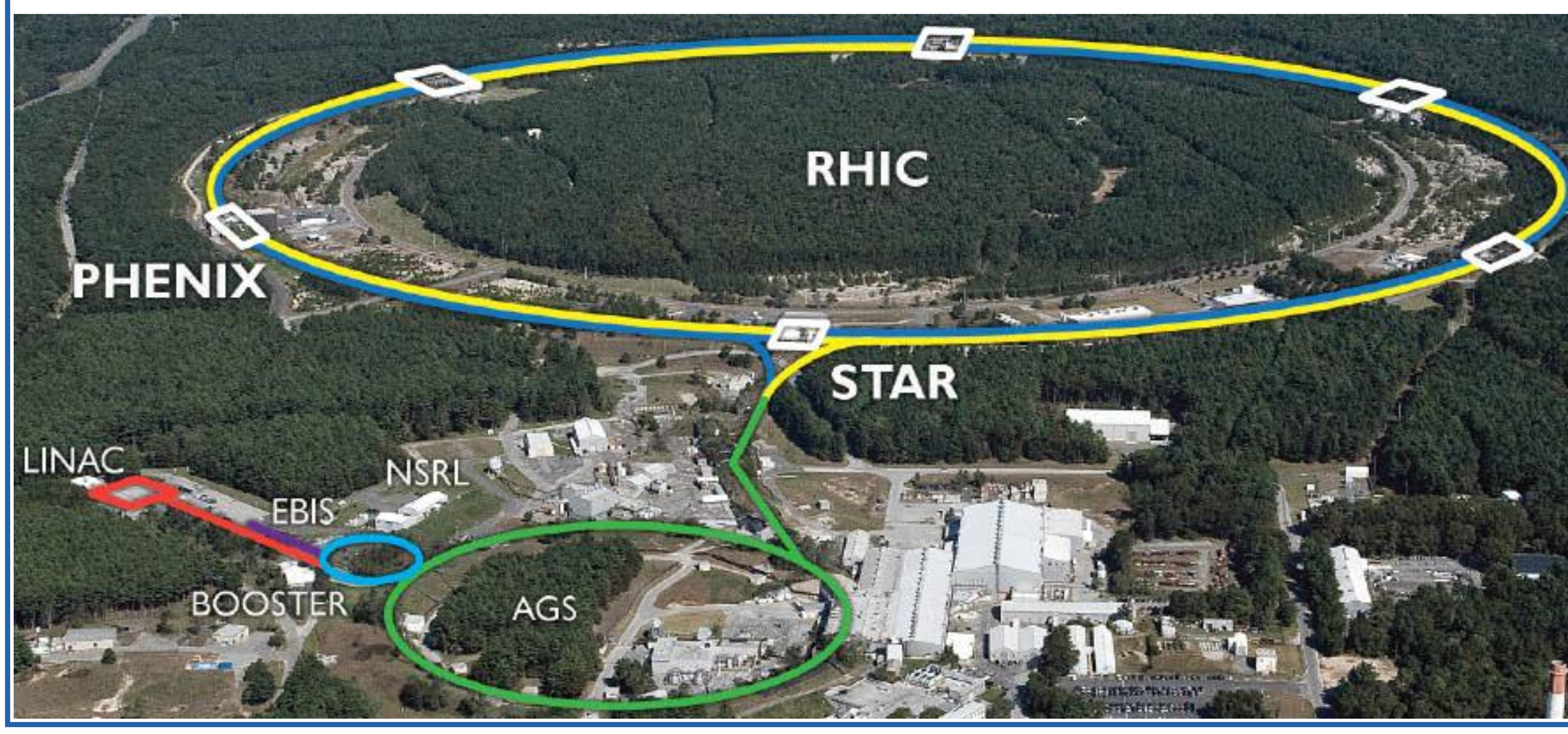
Our current methods combine all of these files into a HDF5 format, such that the data is easily parsable and can have a multitude of different selections for a variety of parameter training and classification. In the figure below, we are showing the PS data from a single quench event from on of the fills of RHIC. Here you can see that as the system senses a quench the currents begins to drop to zero as the magnets are turned off in a controlled manner.





Background

Quench protection systems are used to prevent potentially catastrophic failures in superconducting magnet systems. There is an extensive protection system in place at Brookhaven National Laboratory (BNL). The conventional systems have two primary mechanisms, actively monitoring the resistance of the superconducting cable and providing a relief system for the cryogenic system. We are developing our algorithms on quench data from magnets in the Relativistic Heavy Ion Collider (RHIC), see figures on the right. The conventional quench protection system constantly monitors the voltages and currents of the power supply (PS) on the ring to insure the resistances are below a threshold.



Classification

As a first step, we need to classify all of the data. As mentioned above the data recorded by the quench trigger could either be from a real quench event or be a fake event that was triggered by some other event or none at all. A simplistic method for labeling the magnet data as 'good' and 'bad' is to determine the standard deviation of the signals. If the standard deviation is larger than 0.5 the magnet is classified as 'bad', otherwise the magnet is 'good'.

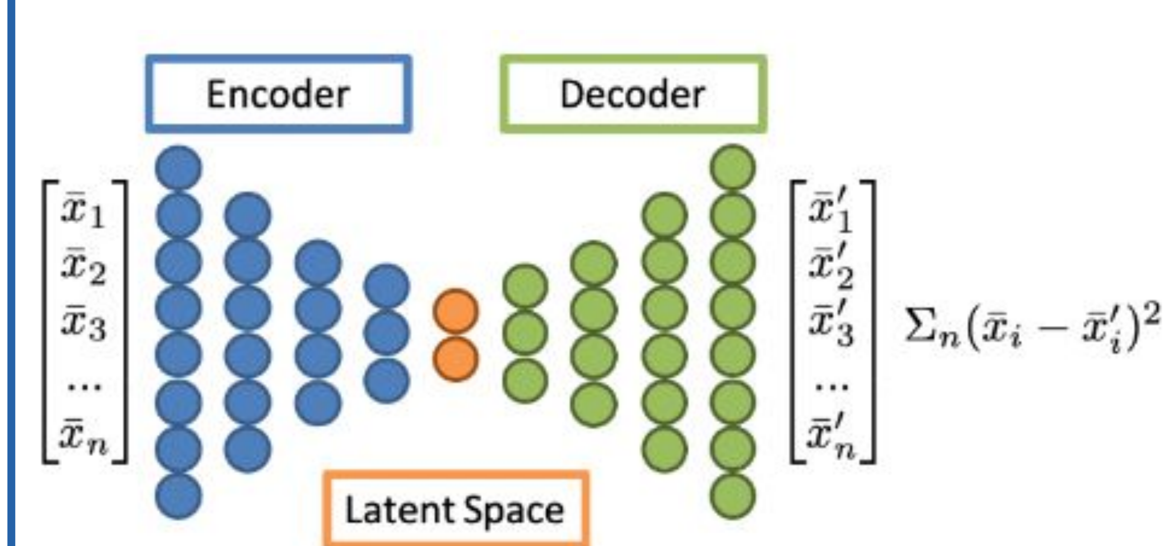
We have made an initial simple classifier that is made up of 3 by 100 node dense layers with a binary classification with a gradient descent optimization. Our initial results show a good match between magnets classified with the standard deviation and magnets evaluated with the classifier. These results have also been evaluated with boosted decision trees to show accurate classification of the data.

Additionally, we have a more complex classification method which can denote the actual magnet which was flagged as the cause of the triggered quench protection system. Along with this, a specific label is added to denote where along the circuitry the quench occurred, beam induced quenches, and fake quenches. This allows for five classifications for possible quenches that we need to be able to identify within the data.

Once we have a robust classification scheme, we will use a neural network based classifier for multi-class identification along with methods for uncertainty classification. This will not only allow us to predict the quench but provide a confidence interval for the prediction. Initial uncertainties will be calculated with ensemble methods by running the models many times with different random initializations, but further methods will use results from different possible classifiers such as logistic regressors. Once we have all of this we can use gaussian process layers on the output neural network to include a confidence interval and the uncertainty can be evaluated by constructing hybrid linear combinations of many quench events. We hope to classify event structures like that of the figure on the left.

Unsupervised Learning

Once we have provided a thorough classification methods, we will develop unsupervised learning techniques with our initial studies will be used as a benchmark. Some methods with be using clustering methods which can identify if quench events have a fundamentally different structure. The use of autoencoders to perform a dimensionality reduction and the ability to explore the latent space representation of the datasets. Depending on the size the latent space can be projected onto a 2-D plane and additional clustering can be applied. Once this has been compared to the benchmark methods, we will develop an uncertainty quantification similar to the supervised learning. We plan to expand to include variational or variational recurrent autoencoders.



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