Neural Networks for Anomaly Detection in LINACs, Injectors, and Transfer Lines

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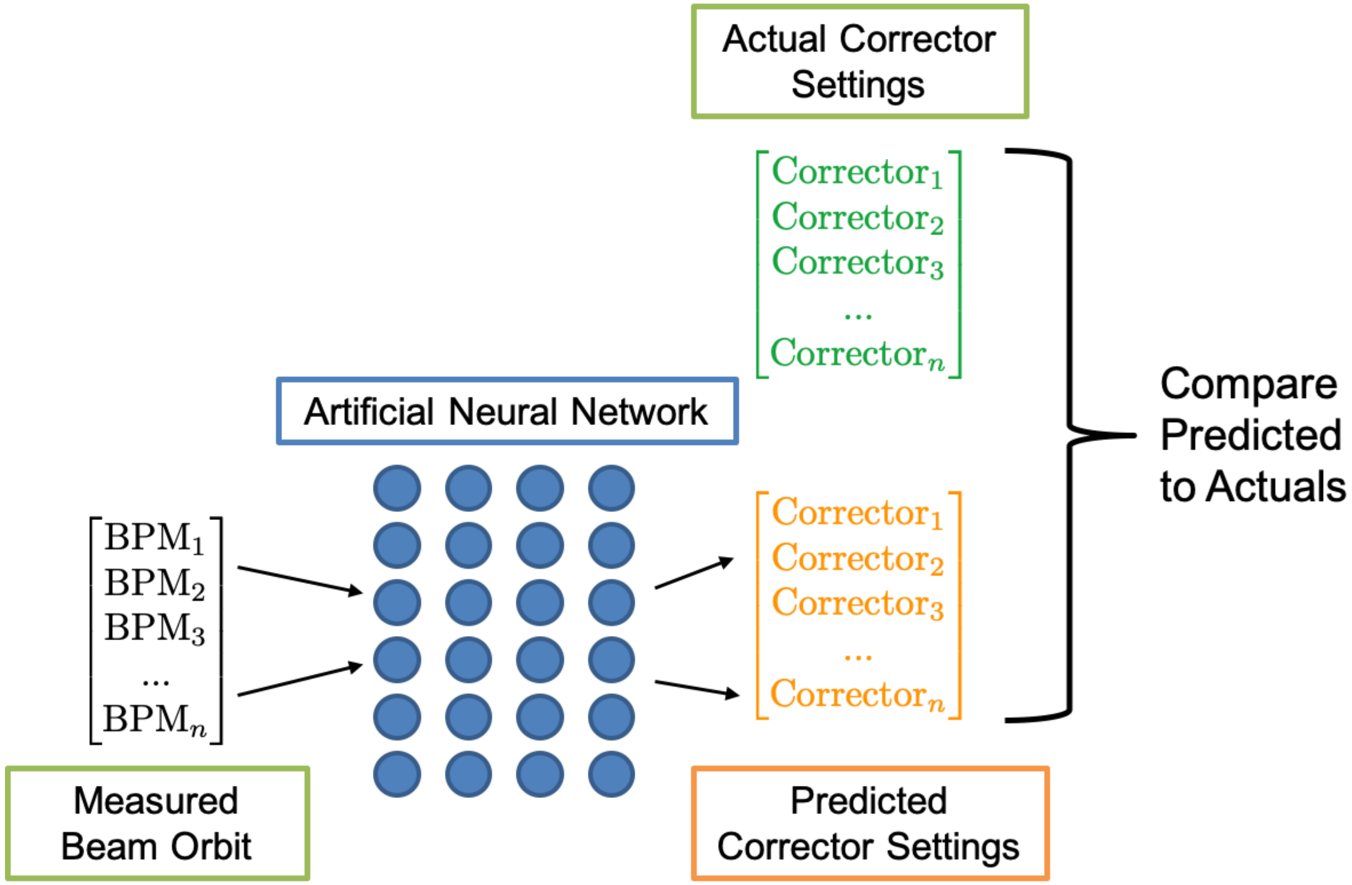
Inverse models for anomaly detection

- Inverse models as a diagnostic in a supervised fashion
  - Direct comparison between predicted settings and actual settings informs operations of a potential anomaly with that magnet



Inverse models for anomaly detection

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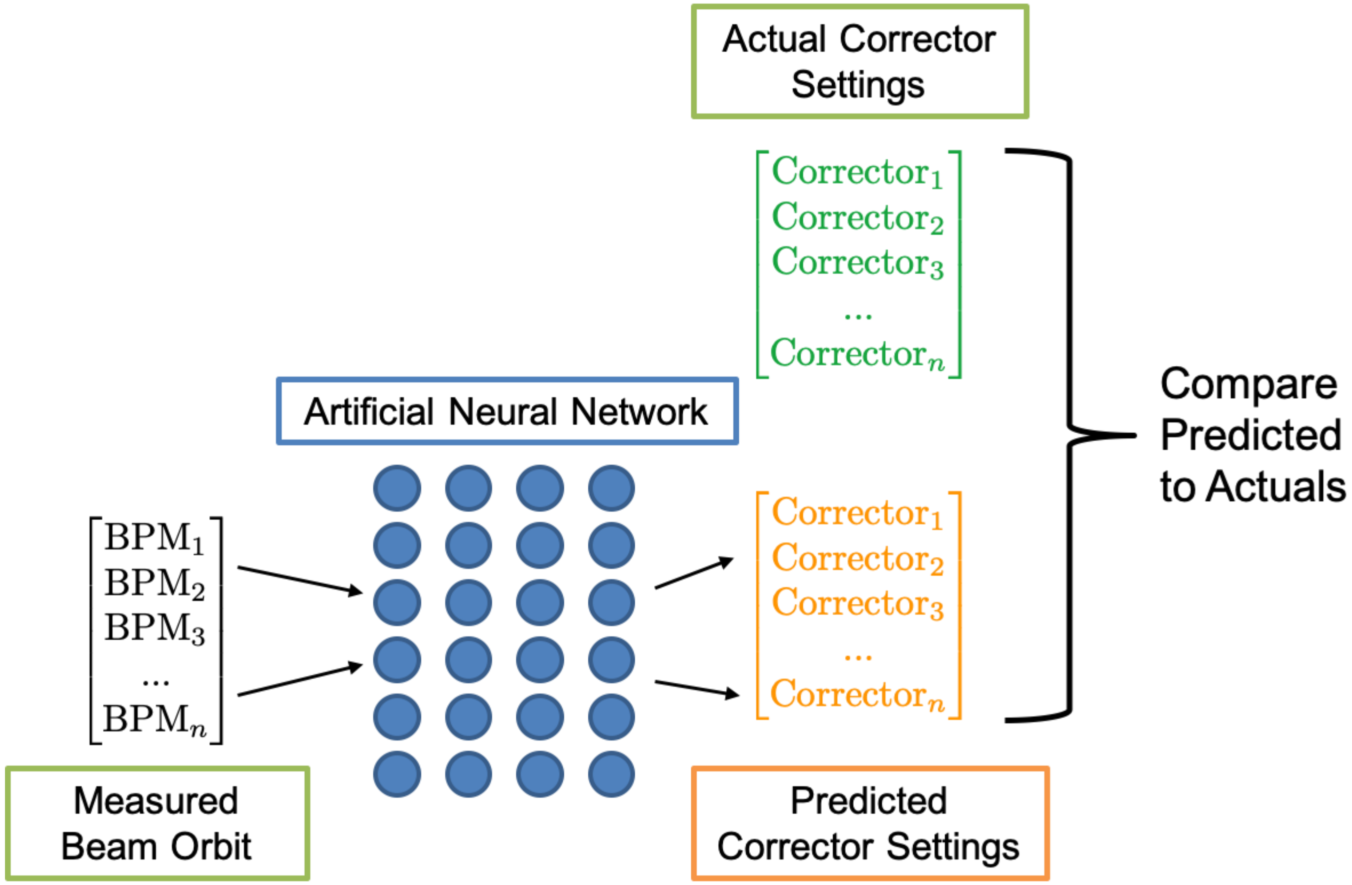
- Inverse models as a diagnostic in an unsupervised fashion
  - Assumptions
    - model errors are caused by other beamline elements
    - each beam-line element will have a unique error signature



Inverse models for anomaly detection

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  - Assumptions
    - model errors are caused by other beamline elements
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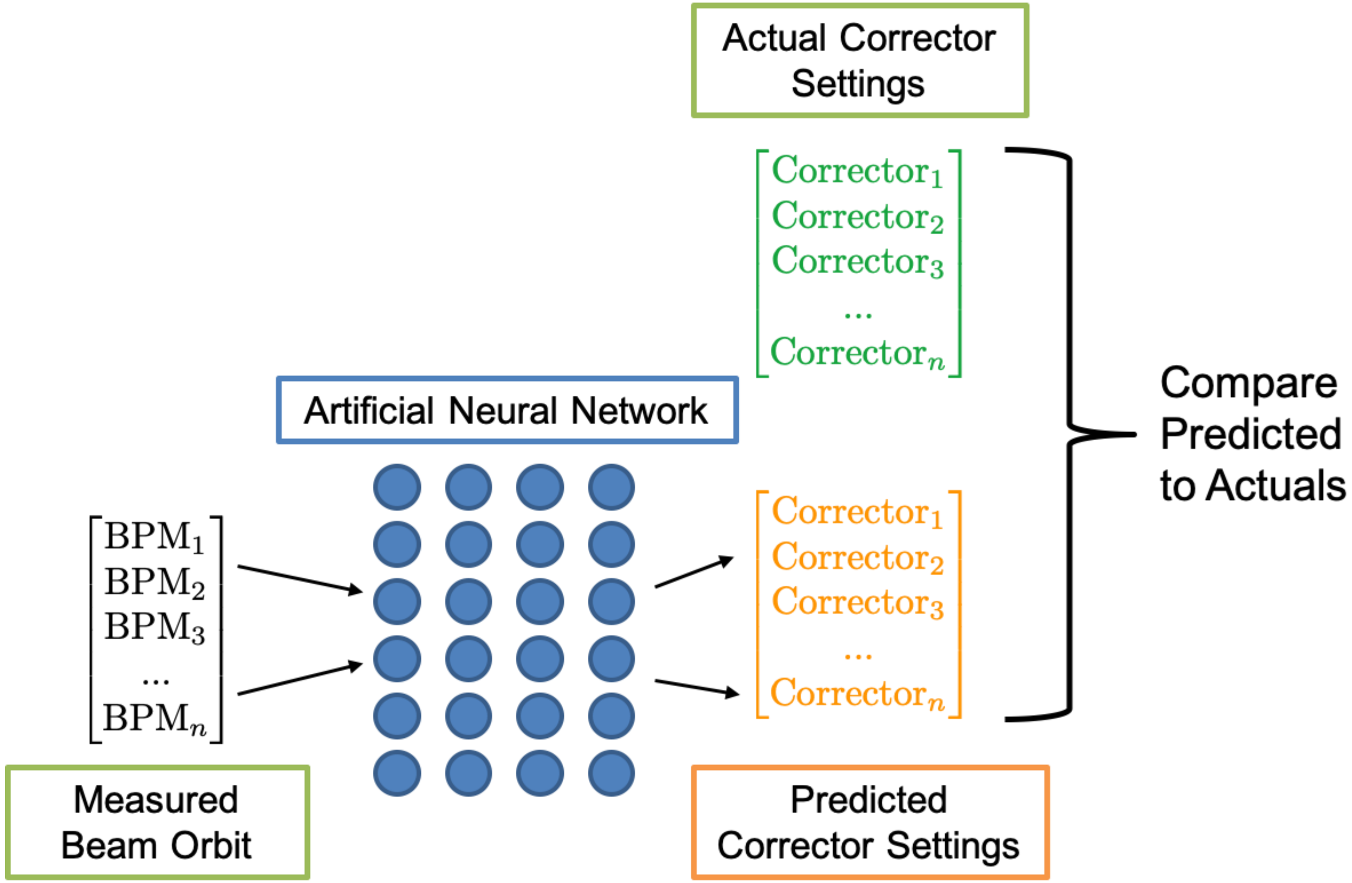
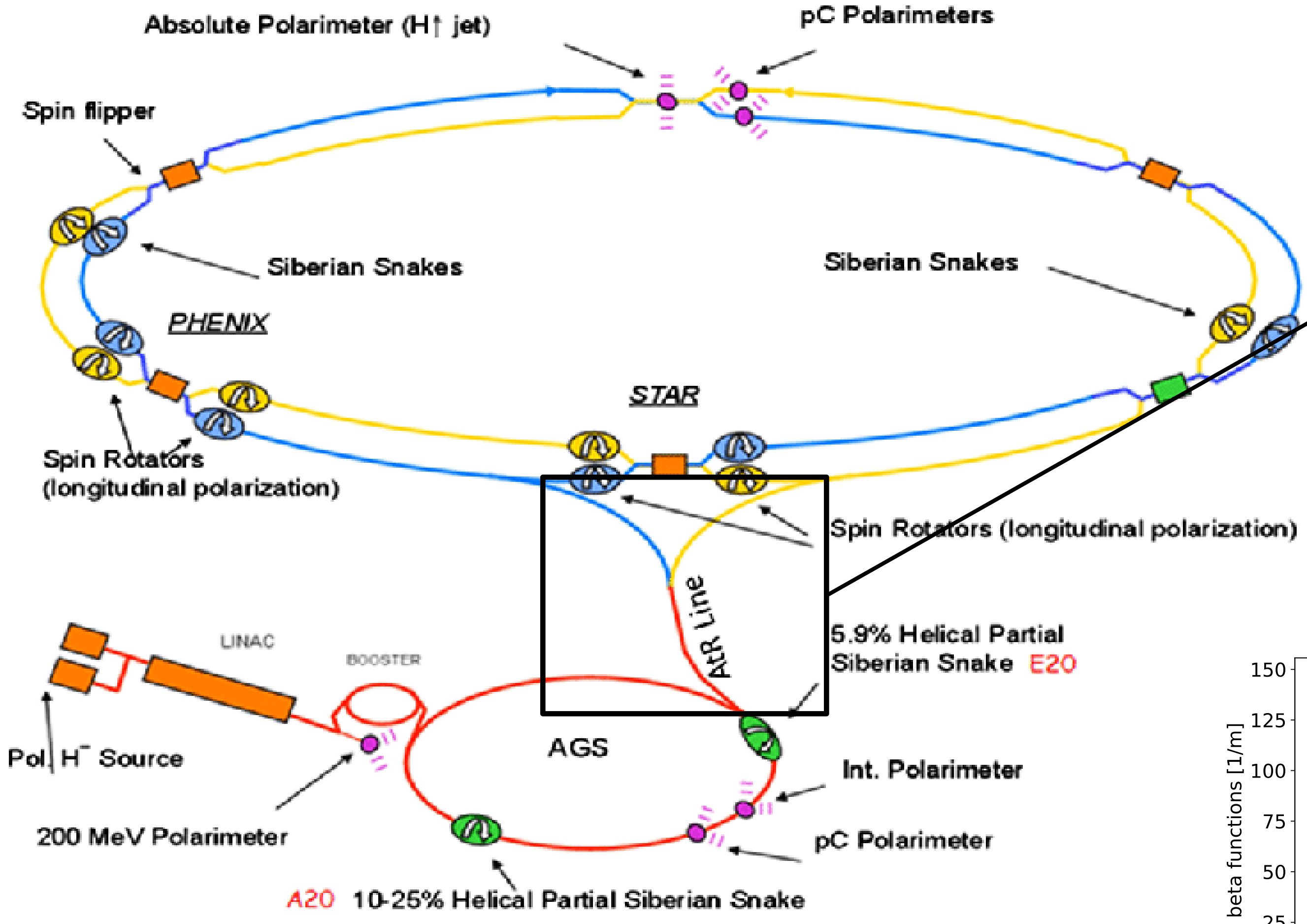
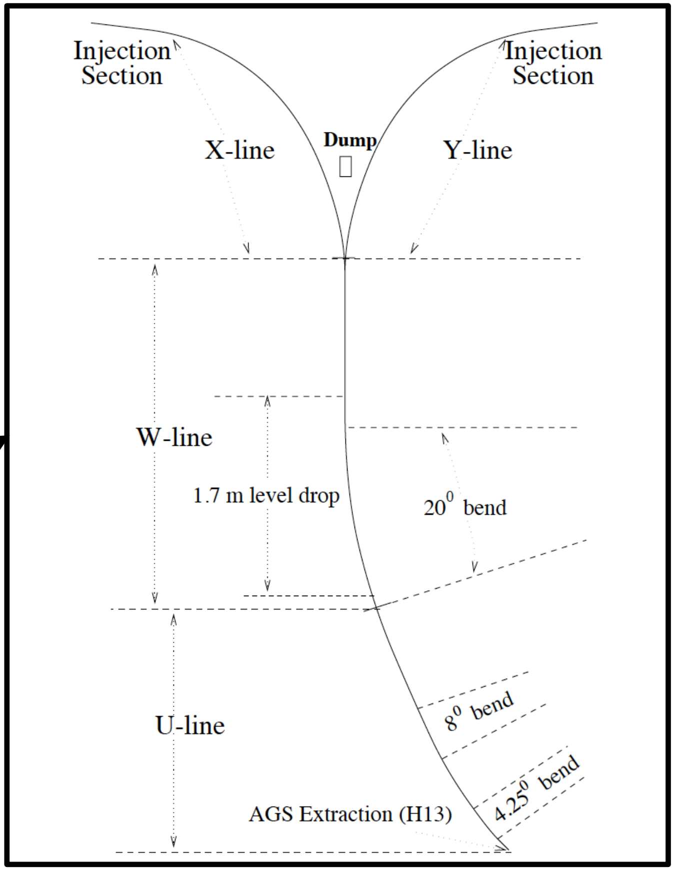
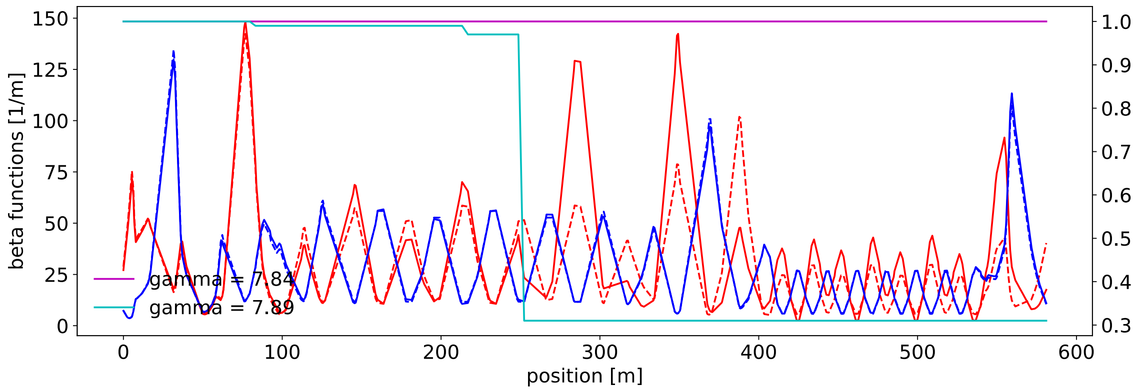
- Inverse models for tuning
  - Minimize error between predicted settings and actual settings by varying quads
  - Right: model error as a function of quad strength error



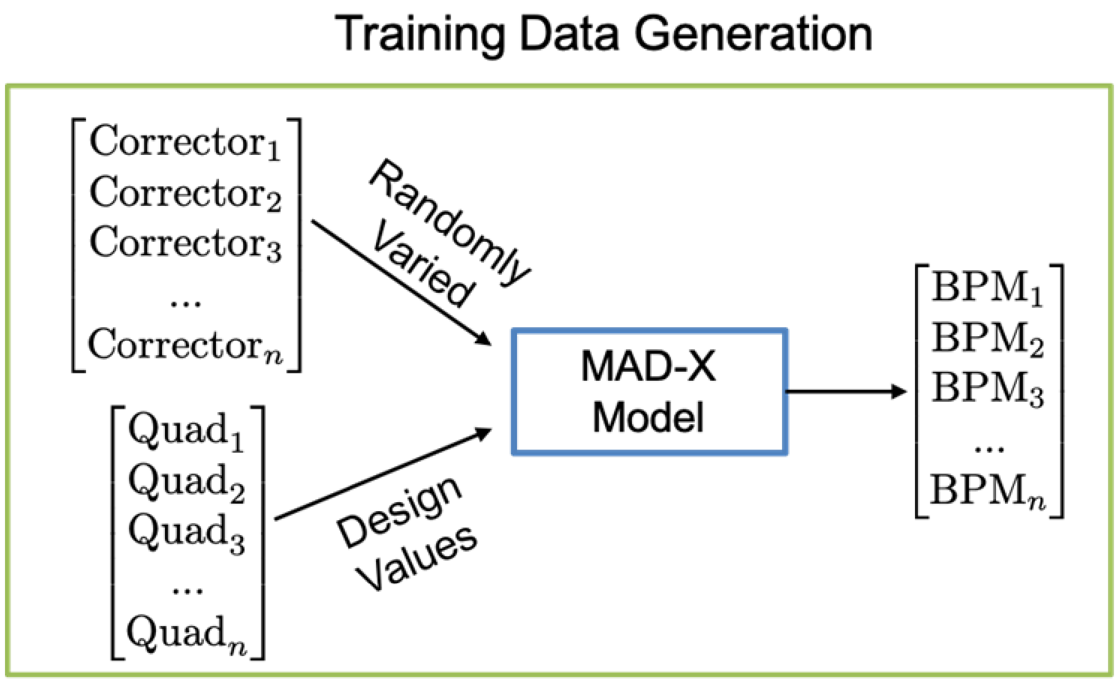
AGS to RHIC transfer line

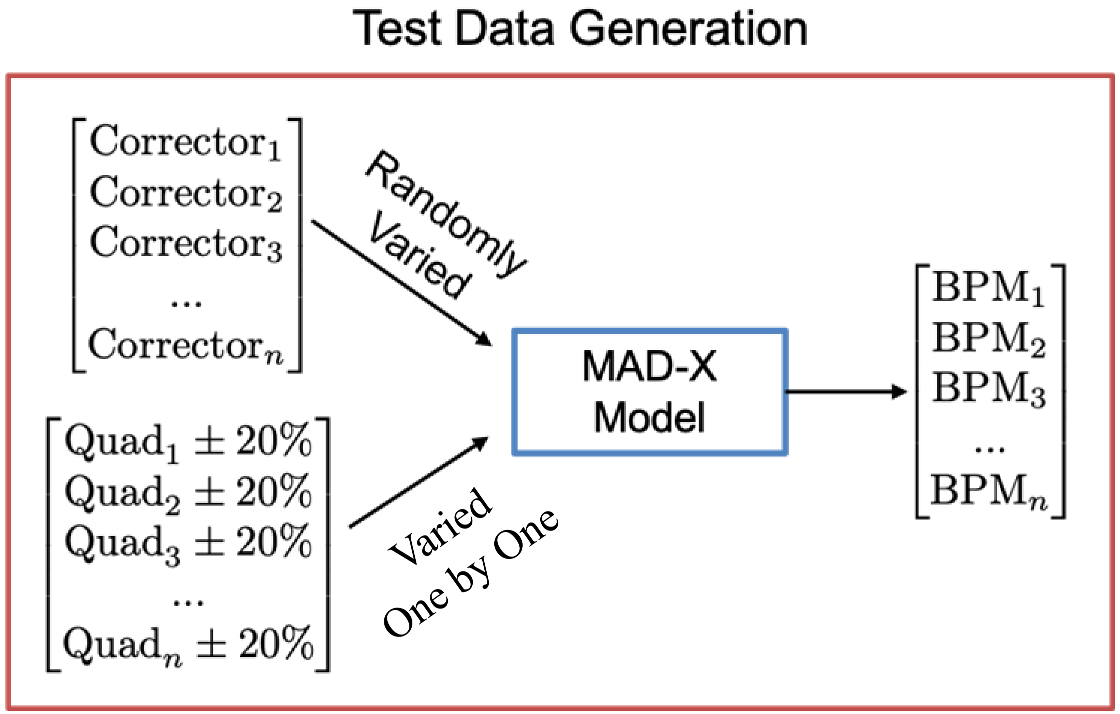






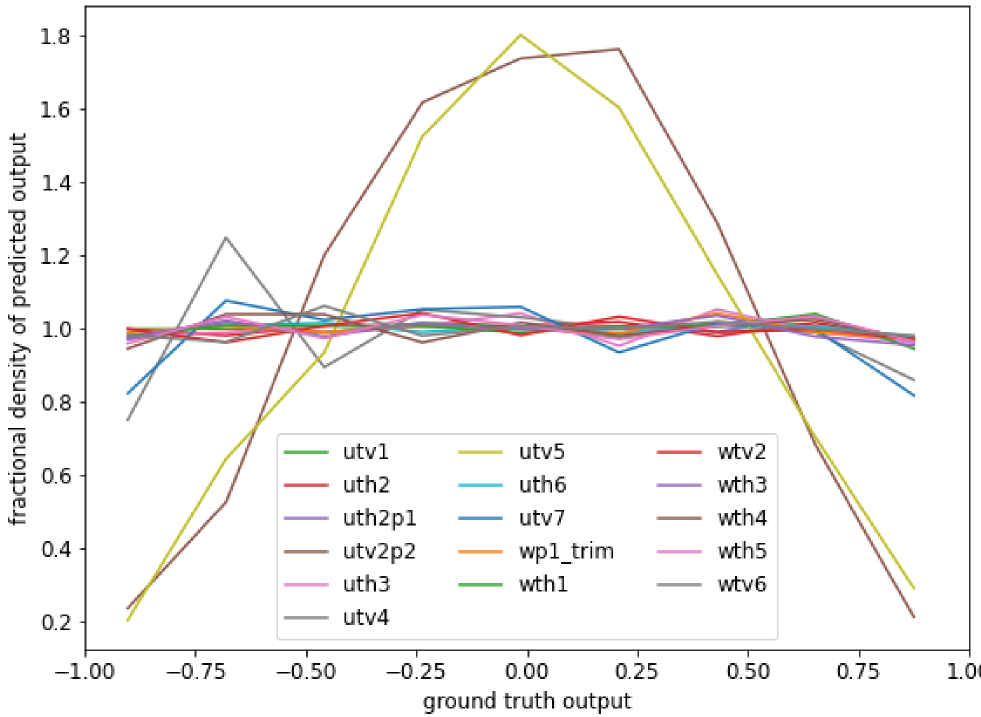
Data generation principles

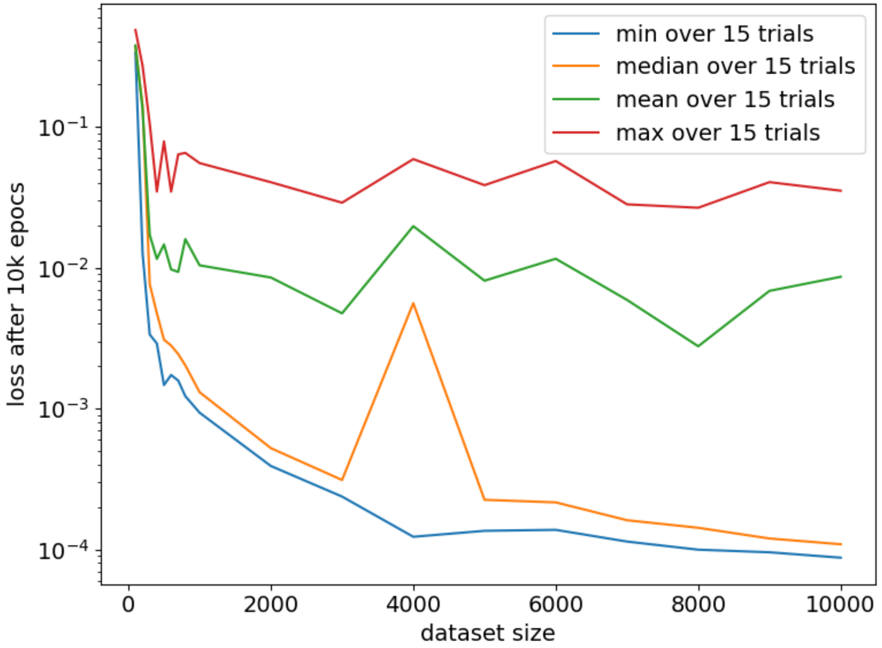


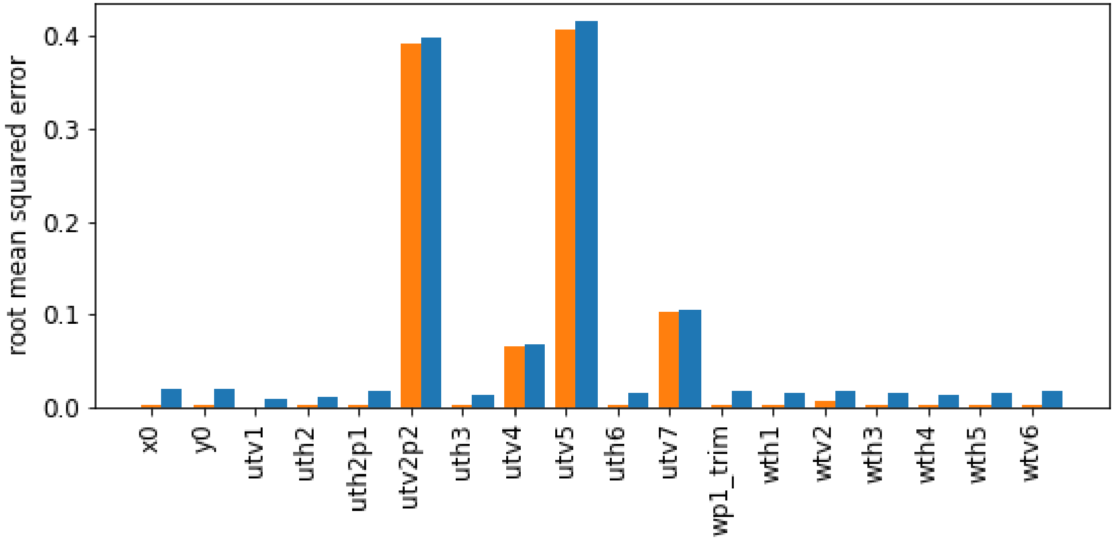


AGS to RHIC transfer line study

- Model training for the AGS to RHIC transfer line
  - Top Right: Fractional density of model error as a function of ground truth for each magnet
  - Bottom Right: RMS error as a function of magnet type
  - Bottom: model loss as a function of the dataset size

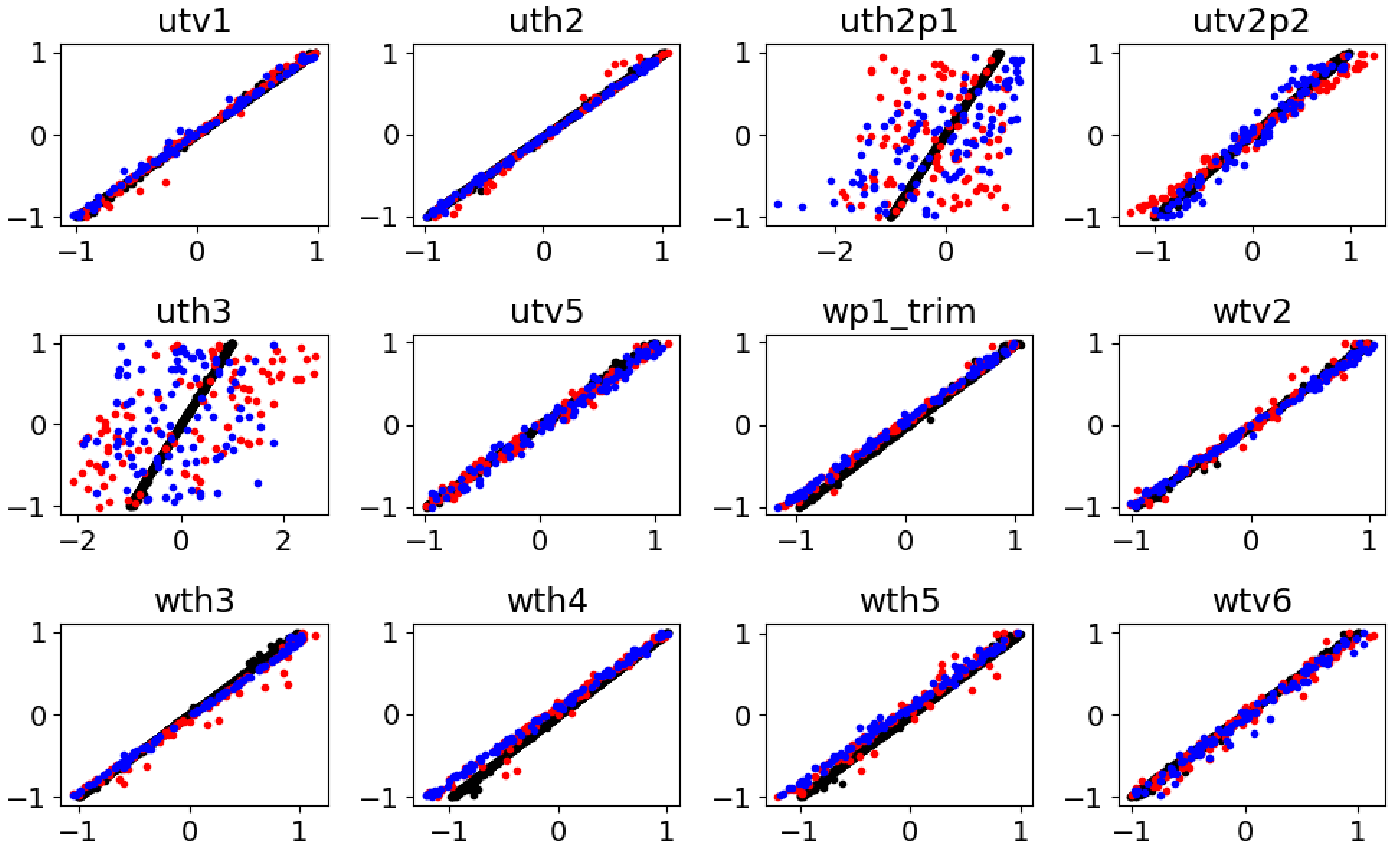






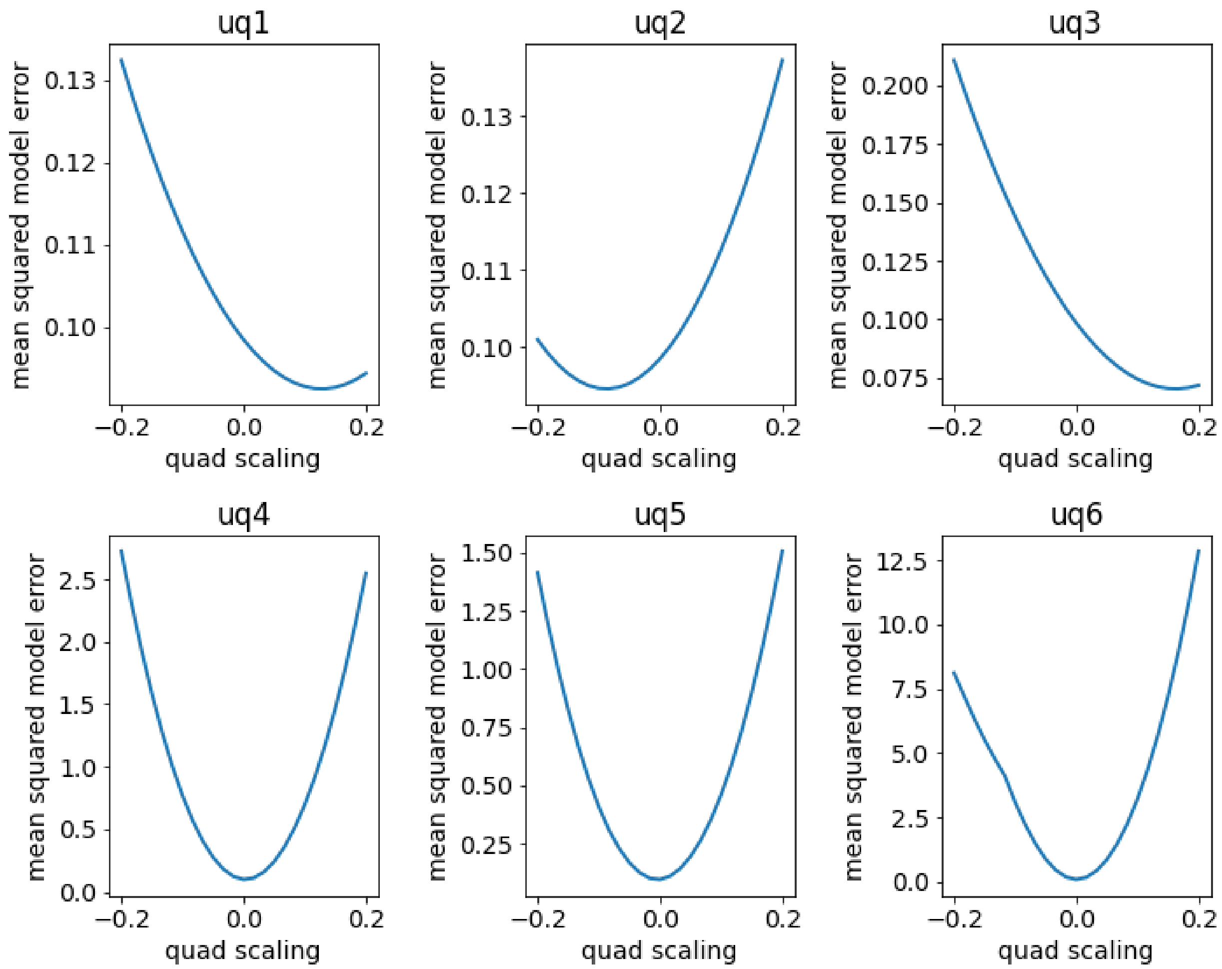
AGS to RHIC transfer line study

- Right: Predicted corrector settings vs the ground truth for the validation set
  - Black: without quadrupole errors
  - Red: a single quadrupole error of -20%
  - Blue: a single quadrupole error of +20%



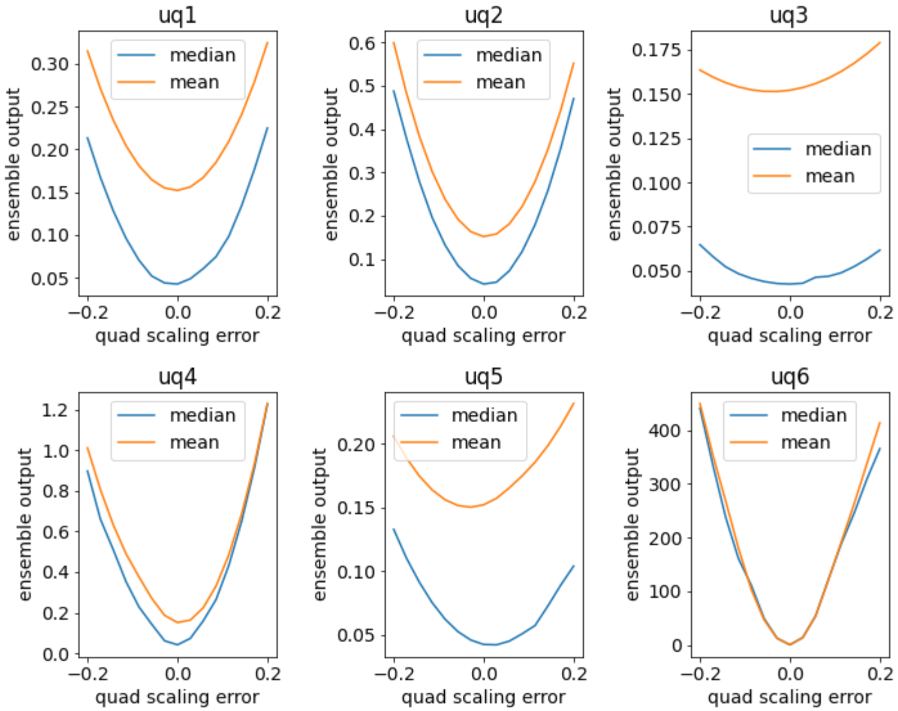
Computing the Model Loss as Quadrupoles are Varied

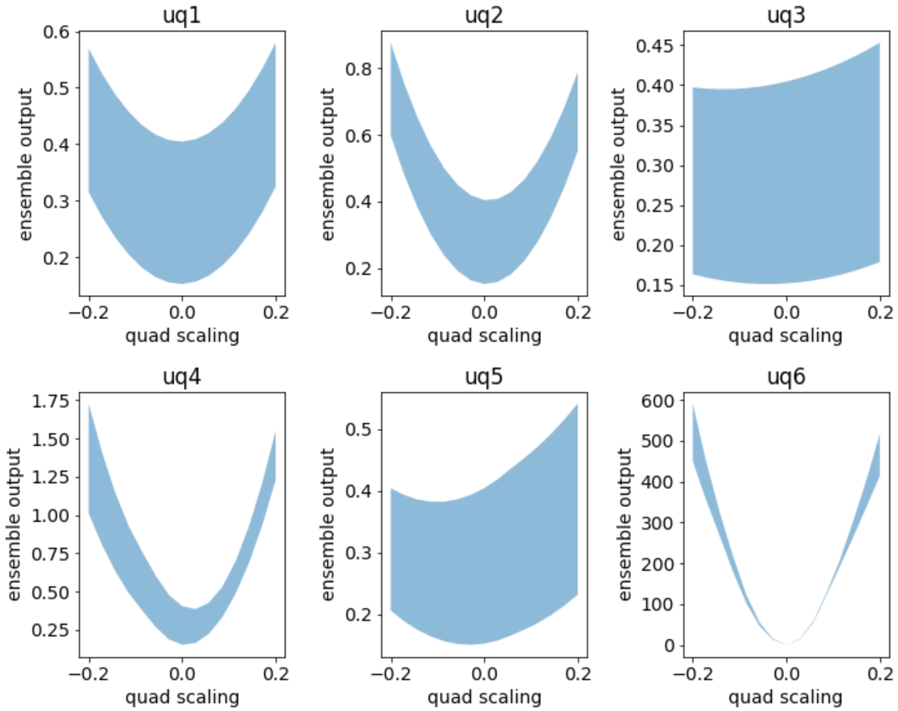
- Model trained for 100k epochs
- Individually varied the quads over a range of plus or minus 20% excitation
- All quads show sensitivity except uq6
- Many quads have minima at 0.0 with some offset
  - Longer training time can improve this
  - Ensemble methods may be more efficient



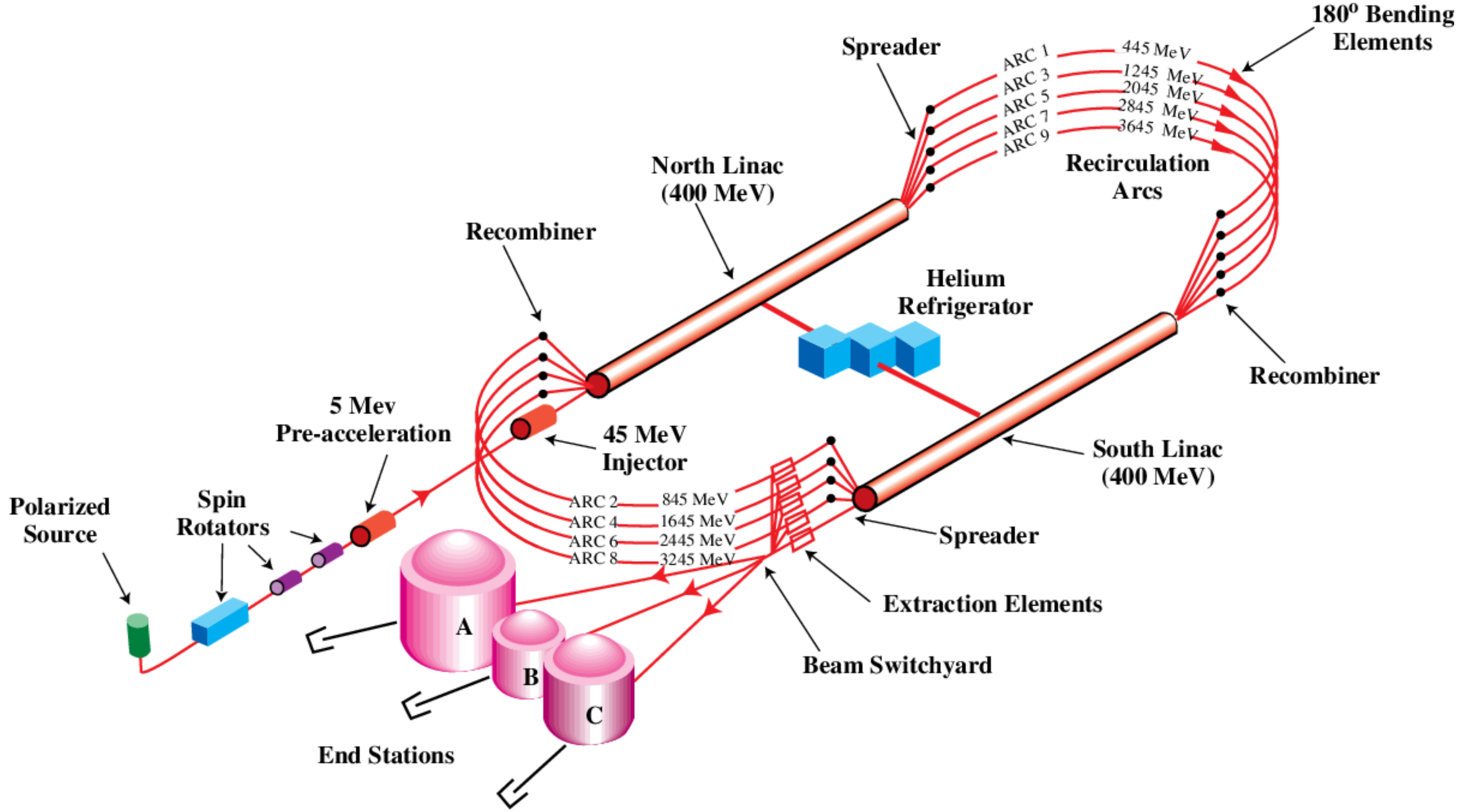
Consider an Ensemble of Models

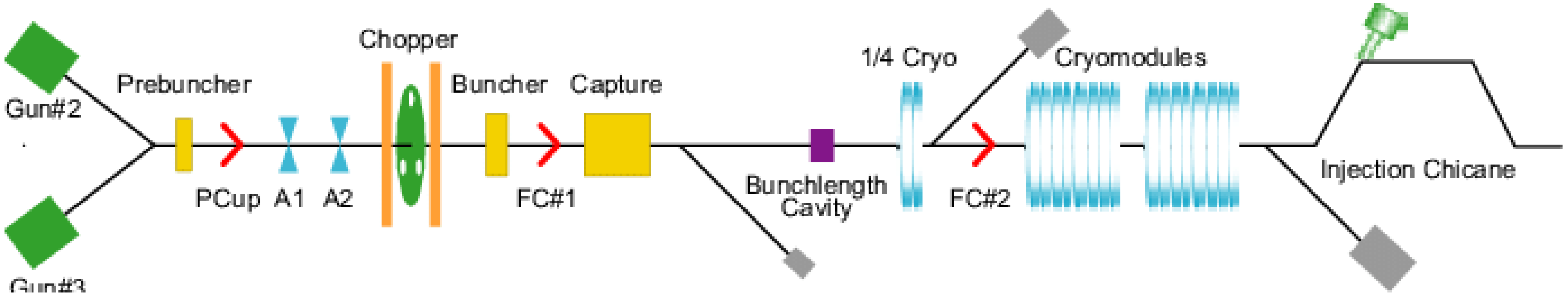
- 23 models with random initializations: consider median and mean for output of the ensemble
- Examine the ensemble output as you vary the quad strengths
- Left: Ensemble output as a function of quad strength variation / Right: Ensemble output with ensemble variance
  - Note clearly defined minima at or very close to 1.0 for all cases except uq6
  - This is an improvement over slide 16 where some quads do not have well defined minima





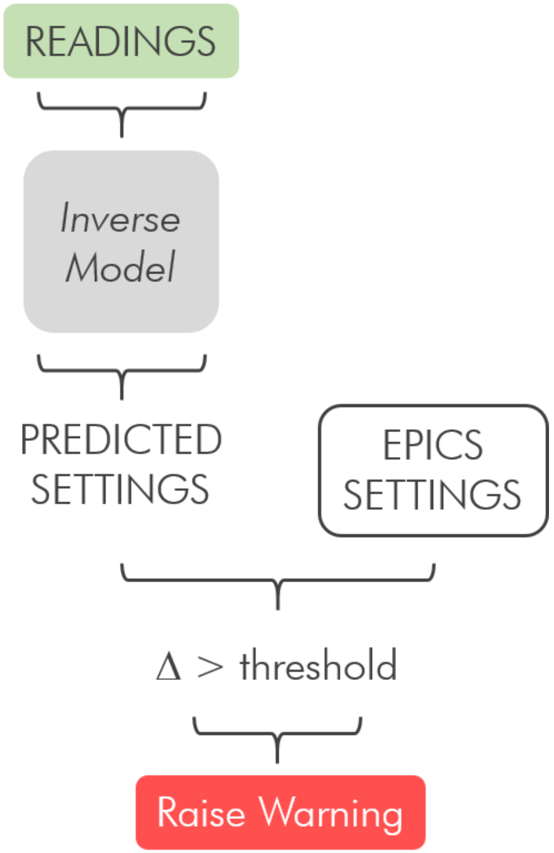
Overview of the CEBAF Injector





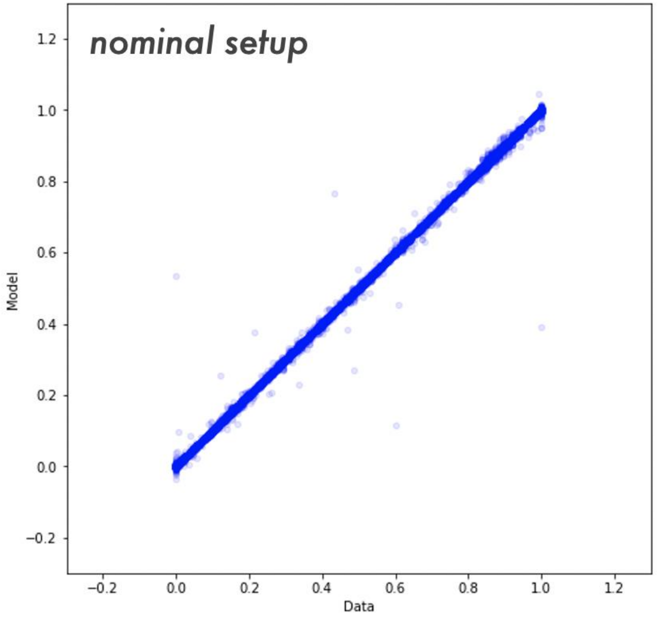
A Smart Alarm System for the CEBAF Injector

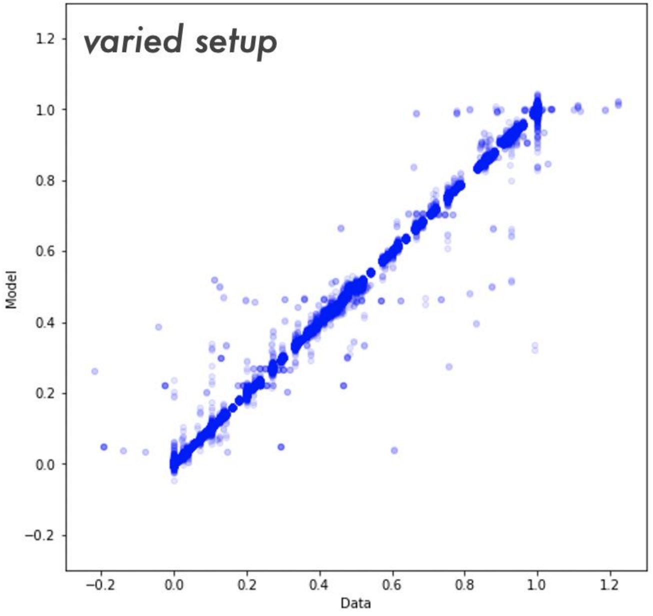
- Alarm systems typically alert operators when there is a problem with the beam
  - Often does not provide much information on what caused the alarm
  - Diagnosing the problems is time consuming for operators
- Use machine learning to automate the root-cause-analysis effort
  - Autoencoders quantify similarities or differences between machine states
  - Inverse models use actual measurements to predict settings

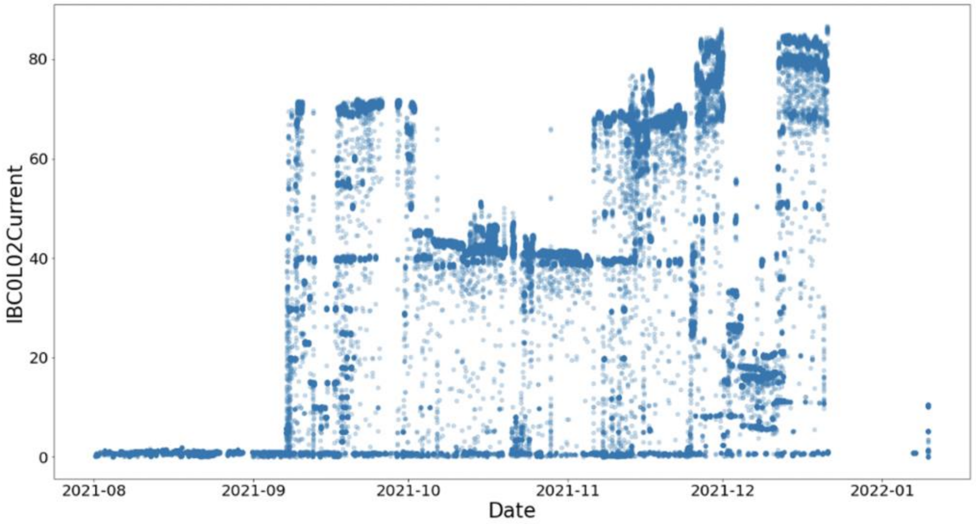


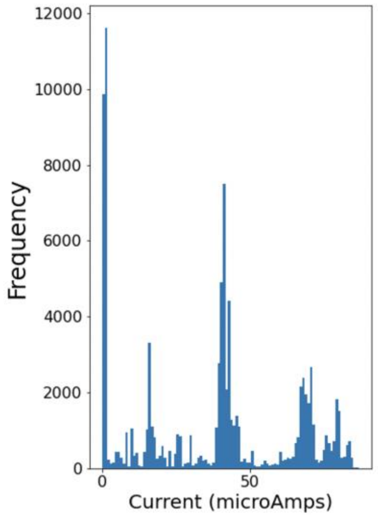
A Smart Alarm System for the CEBAF Injector

- Data collected during two different operational modes.
  - First during normal operations
  - Second during a dedicated machine study where parameters were varied
- Neural network inverse model is trained to predict settings from readings
  - Left: Model prediction vs the ground truth for the validation data from the nominal setup
  - Right: Model prediction vs the ground truth for the test data (study data)



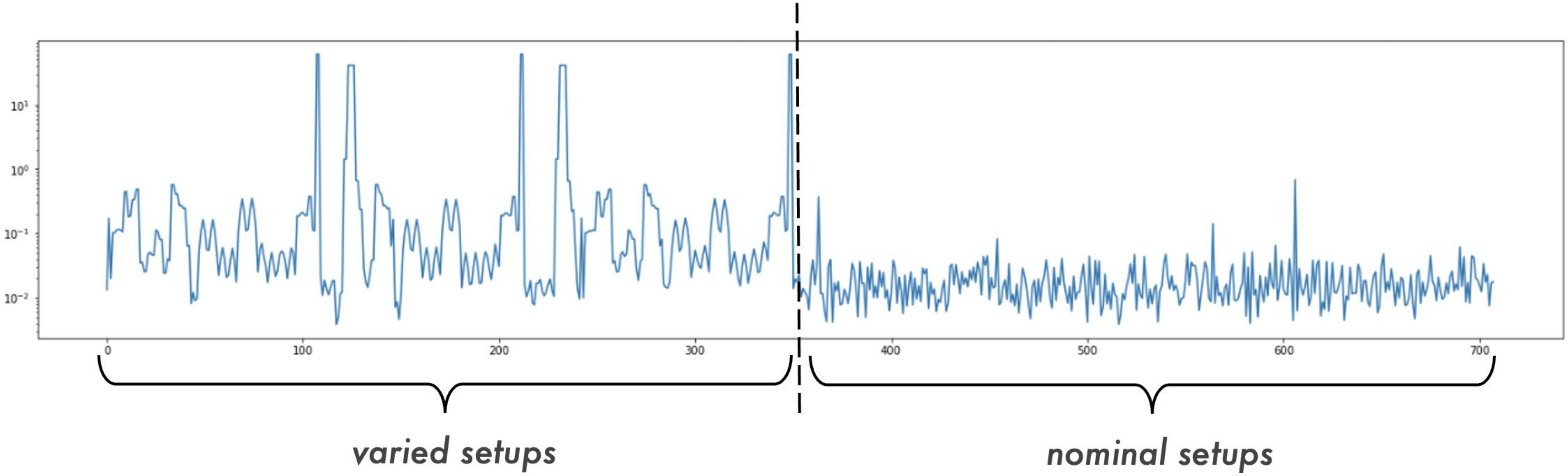






A Smart Alarm System for the CEBAF Injector

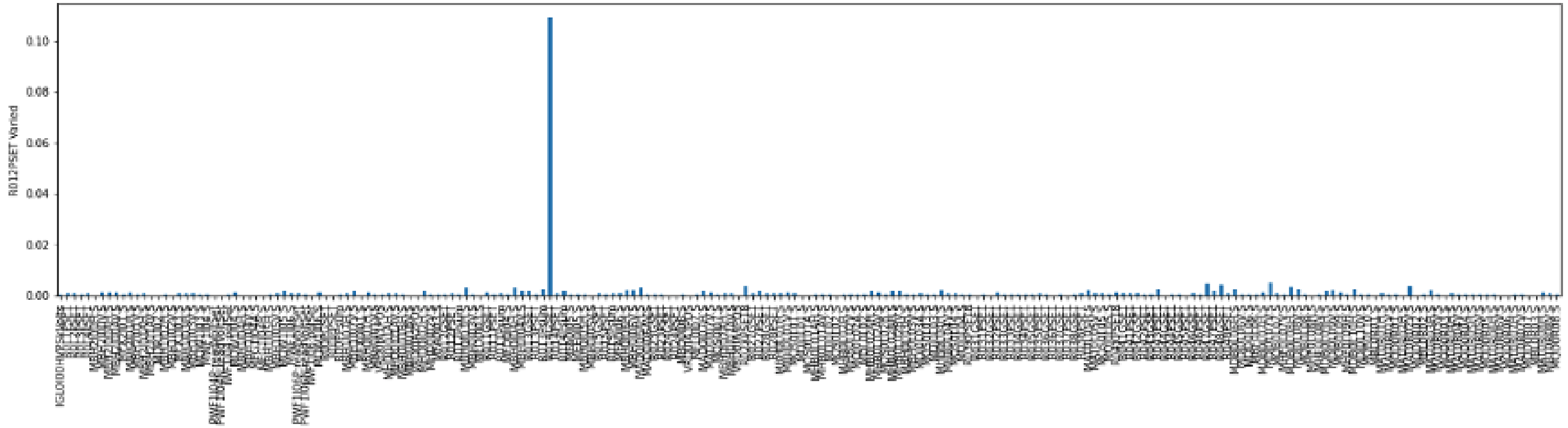
- RMS error of the predicted settings by parameter for the machine study (left) and the nominal setup (right).
- The difference is indicative of the model being able to detect variations in the machine state.
- Thresholds for anomaly detection are established based on performance on the nominal setup



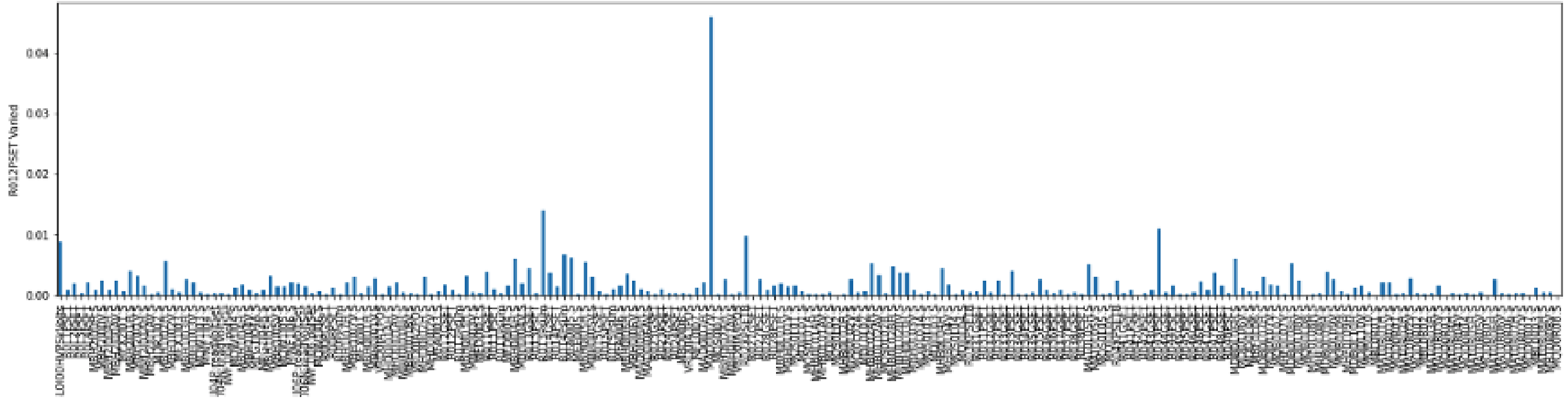
A Smart Alarm System for the CEBAF Injector

- Identifying individual errors using the inverse model
  - Top: model error is a maximum for R014GSET which is the parameter that changed
  - Bottom: model error is maximum for MAD0107V which is the parameter that was changed

R014GSET → 28.28

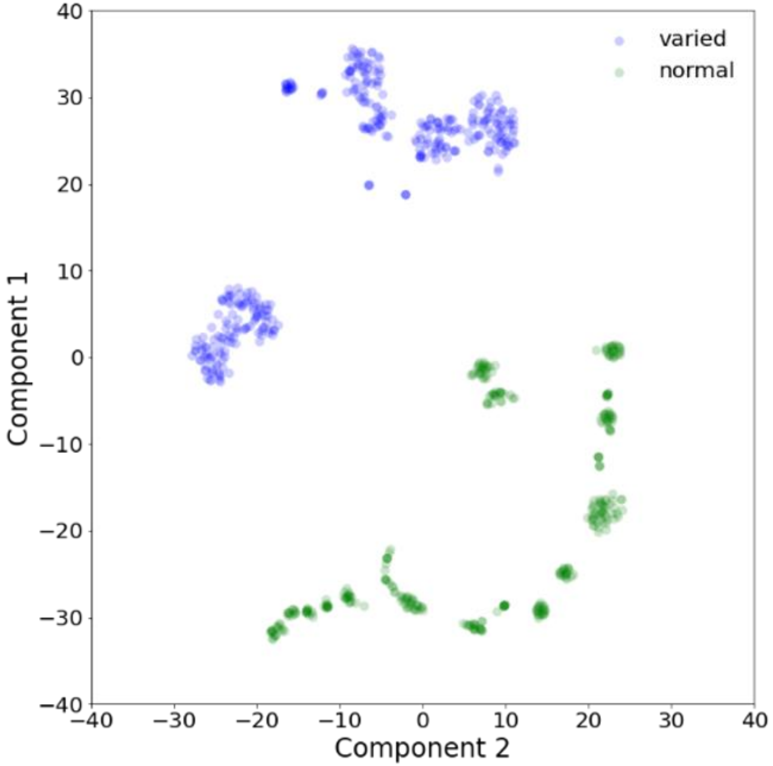


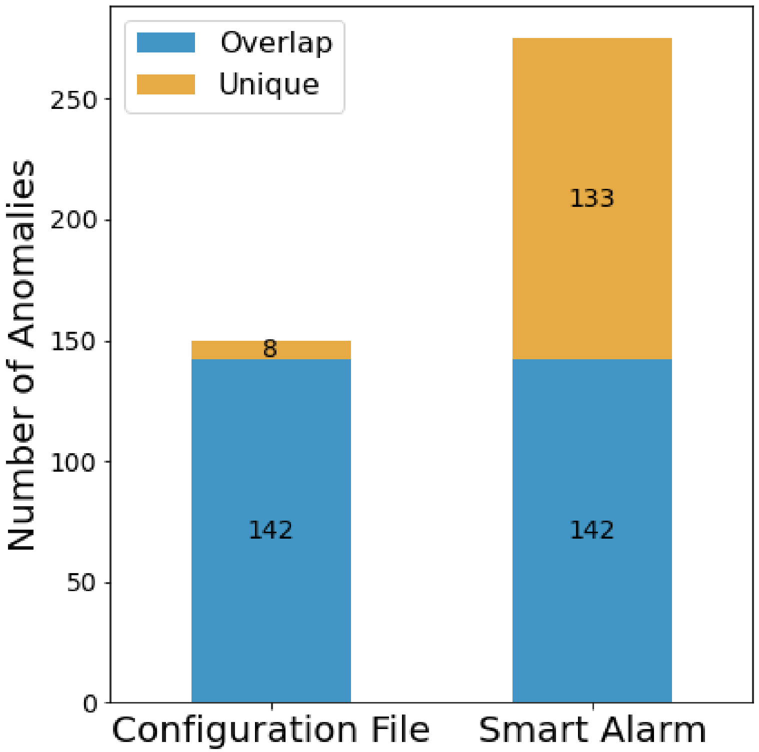
MAD0I07V.BDL → 20.9



A Smart Alarm System for the CEBAF Injector

- Left: T-SNE was used to reduce the dataset dimensionality
  - Operational data is shown in green and the study data in blue
  - The model correctly flagged the study data as anomalous
  - The T-SNE reduction of the data also provides a strong indication that these two datasets are distinct in nature
- Right: Comparison with conventional threshold-based alarming.
  - Threshold misses numerous configurations that would be undesirable by the user program





Conclusions

- Smart alarm system at JLab
  - Algorithm development nearing completion, published (https://iopscience.iop.org/article/10.1088/2632-2153/acb98d/meta)
  - Many thanks to the efforts of Chris Tennant and the JLab team
- Beamline control algorithms at BNL
  - Algorithm development nearing completion, publication in preparation.

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