Error Detection in Linacs with Machine Learning Techniques

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FAST/IOTA Collaboration Meeting

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Fermilab

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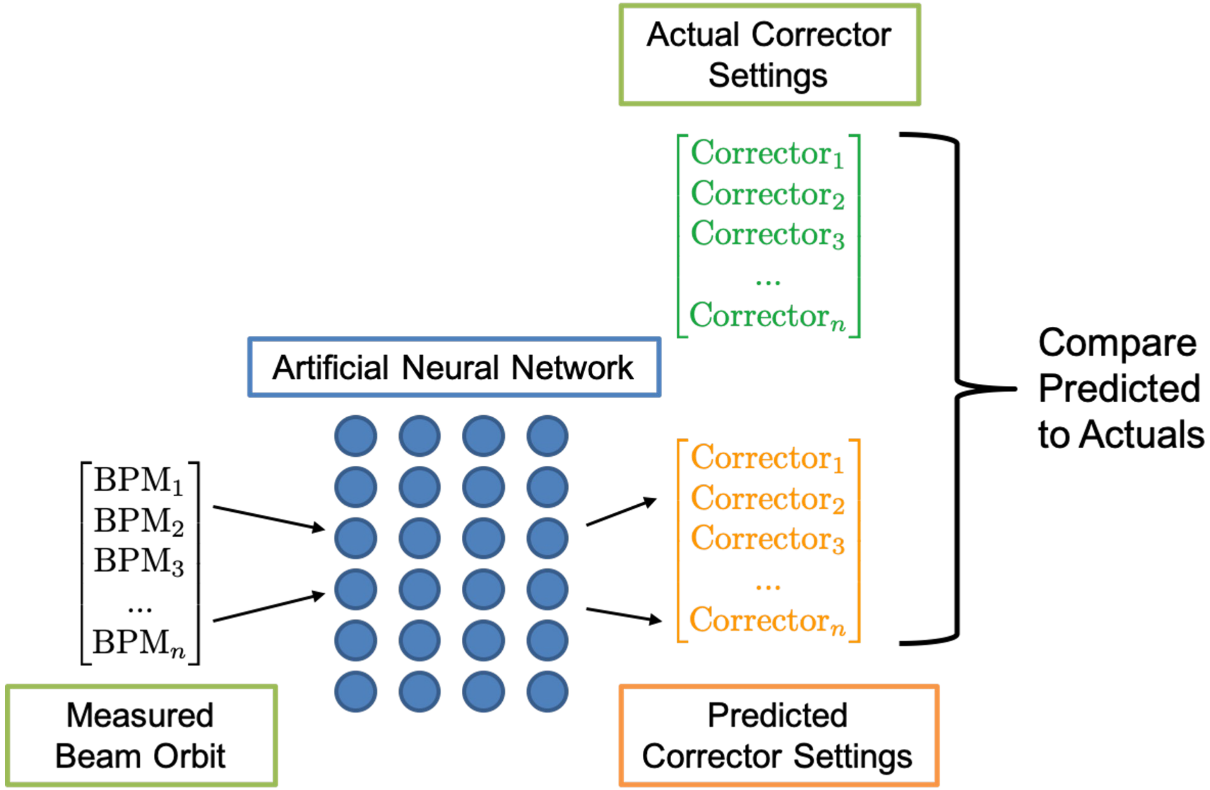
U.S. DEPARTMENT OF ENERGY | Office of Science

Outline

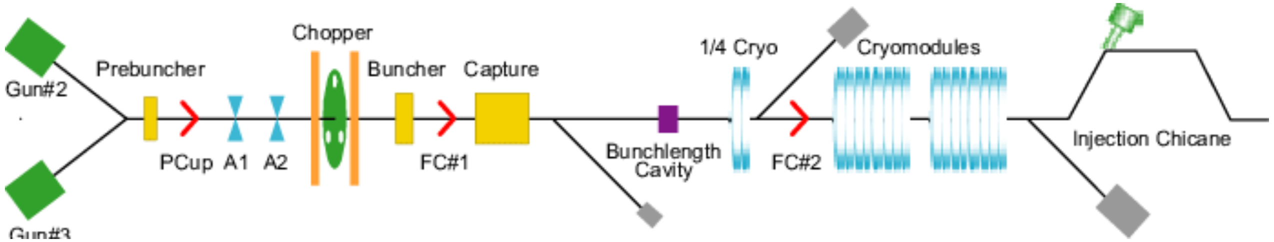
- Machine learning methods
- Initial demonstration at Jlab
- Transitioning to FAST
- Initial results
- Conclusions

Inverse models as a diagnostic tool

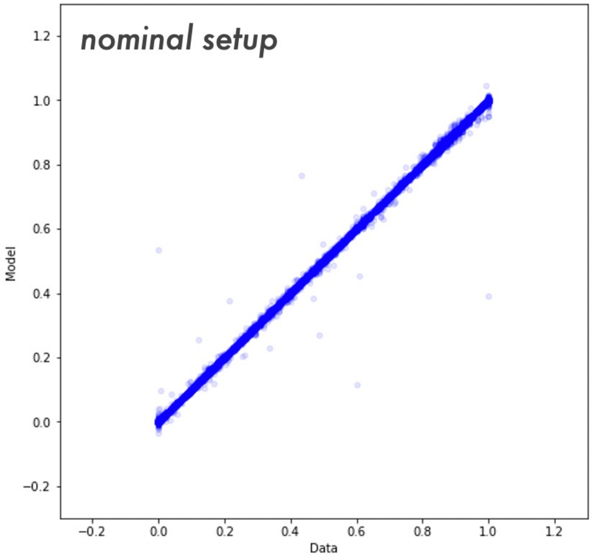
- Inverse models as a diagnostic in a supervised fashion
  - Direct comparison between predicted settings and actual settings informs operations of a potential anomaly
- Inverse models as a diagnostic in an unsupervised fashion
  - Assumptions
    - model errors are caused by other beamline elements
    - each beam-line element will have a unique error signature
- Inverse models for tuning
  - Minimize error between predicted settings and actual settings by varying quads
  - Right: model error as a function of quad strength error

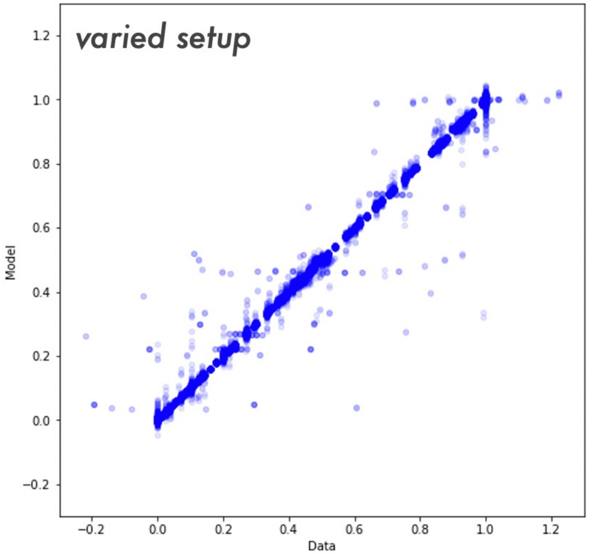


Inverse Model Anomaly Detection at CEBAF



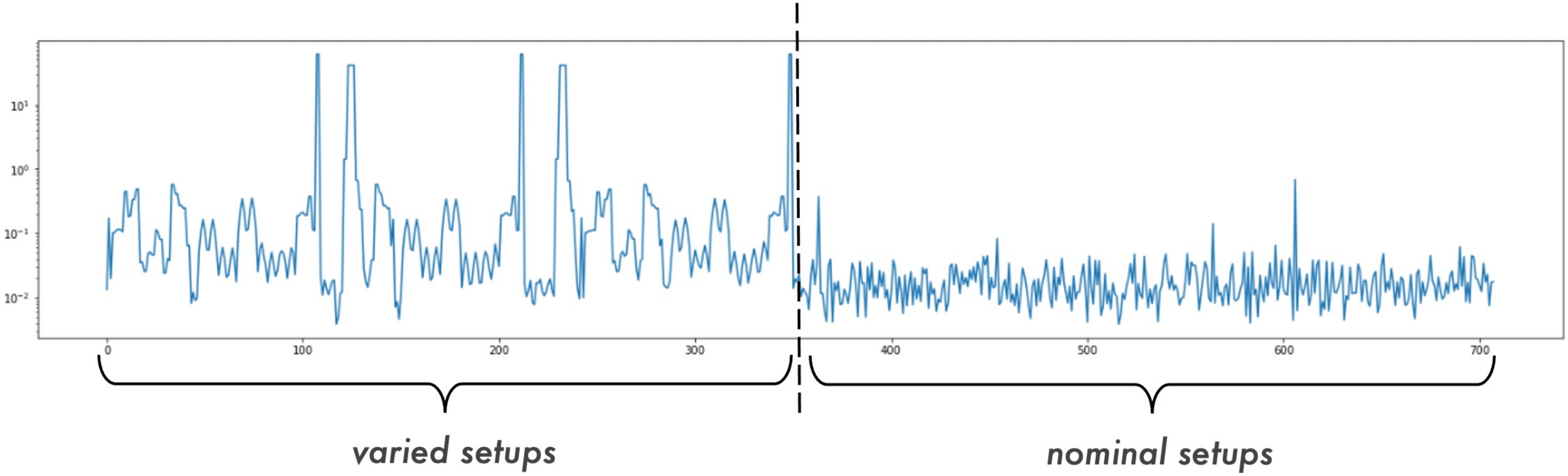
- Data collected during two different operational modes.
  - During normal operations
  - During a dedicated machine study
- Inverse model trained to predict settings from readings
  - Left: Model prediction vs the ground truth for the validation data from the nominal setup
  - Right: Model prediction vs the ground truth for the test data





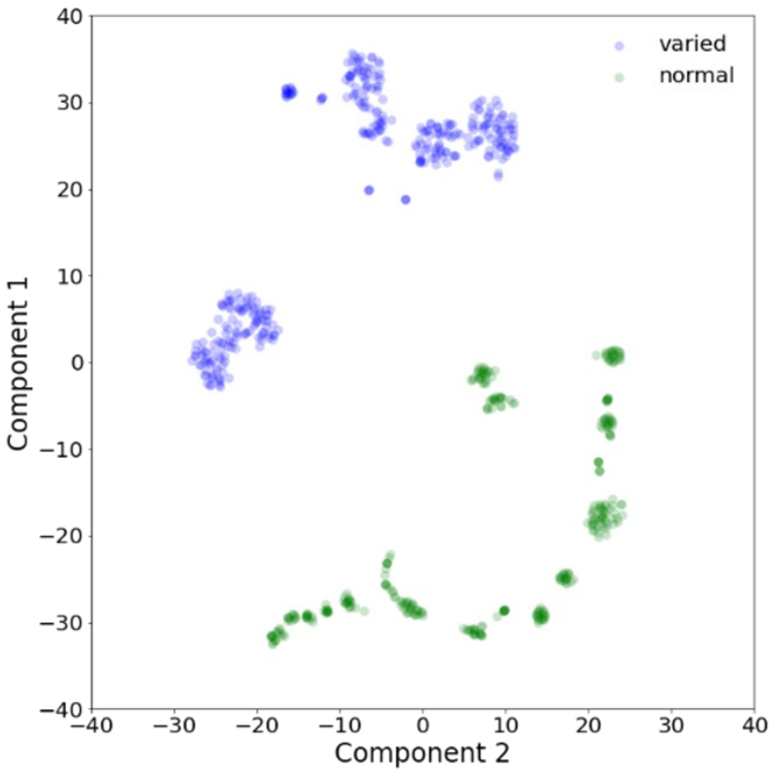
Establishing error thresholds

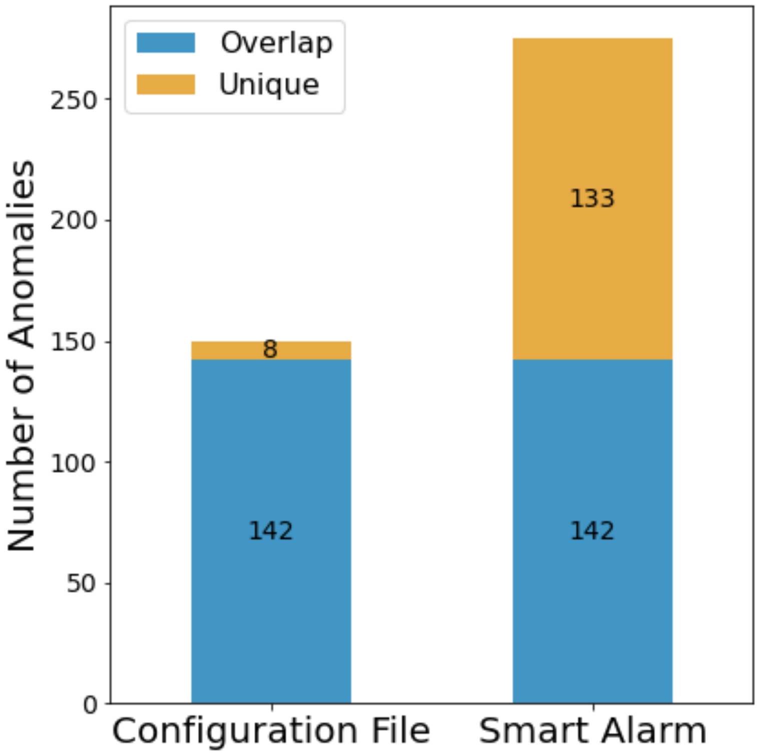
- RMS error of the predicted settings by parameter for the machine study (left) and the nominal setup (right).



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





Transition to the FAST LINAC

- Objective(s):
  - Near term: Develop model that can effectively detect anomalies in an explainable fashion → 60% complete
  - Longer term: Utilize anomaly detection tools to assist in automatic tuning of the machine

- Experimental plan:
  - Collect data during "normal" operational conditions
  - Train machine learning model on data archive
  - Test machine learning on study data where parameters are intentionally varied
  - Evaluate effectiveness at detecting anomalies
  - Develop uncertainty metrics for machine learning model
  - Deploy and test software during experimental run

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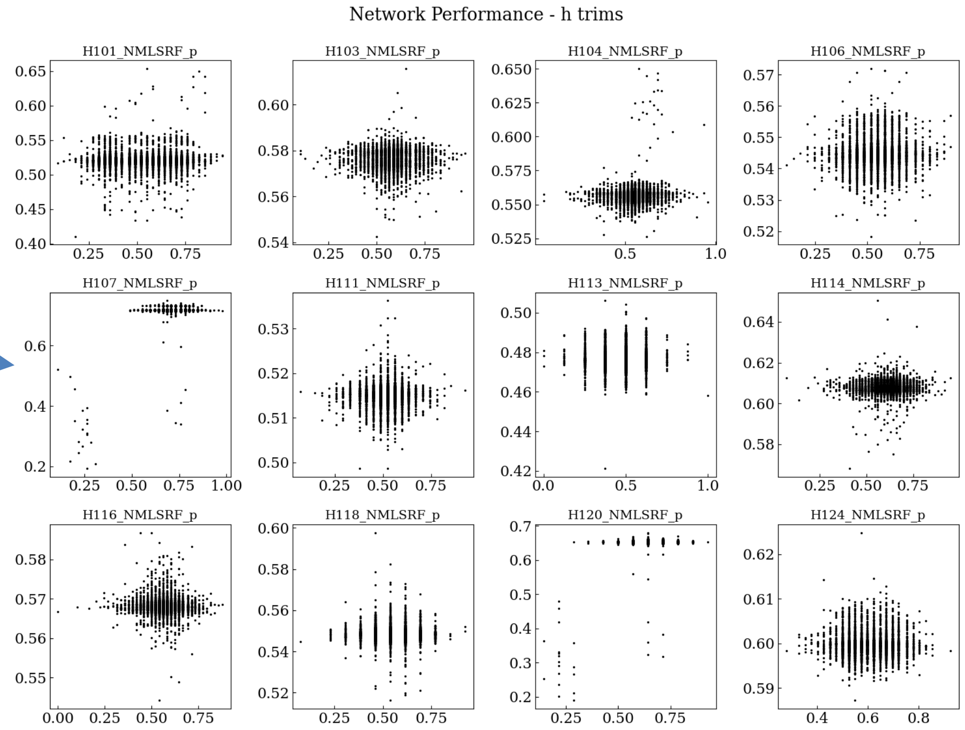
    - Model learning not adequate
    - Troubles with data alignment
    - Identified potential logger issues



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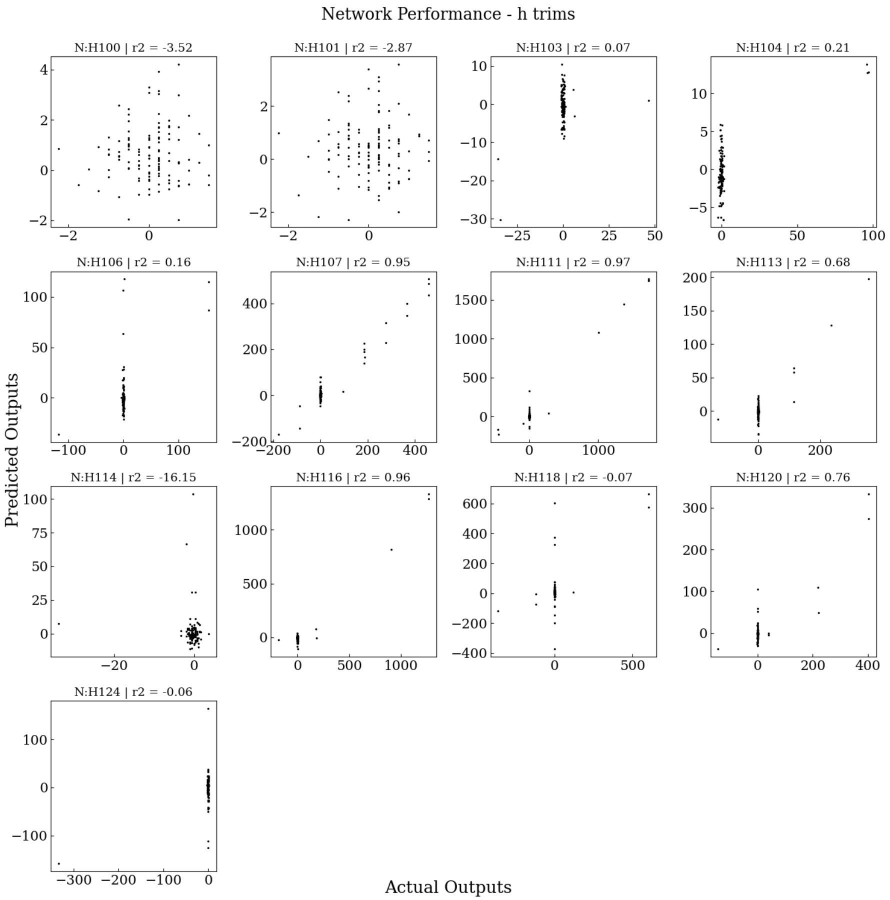

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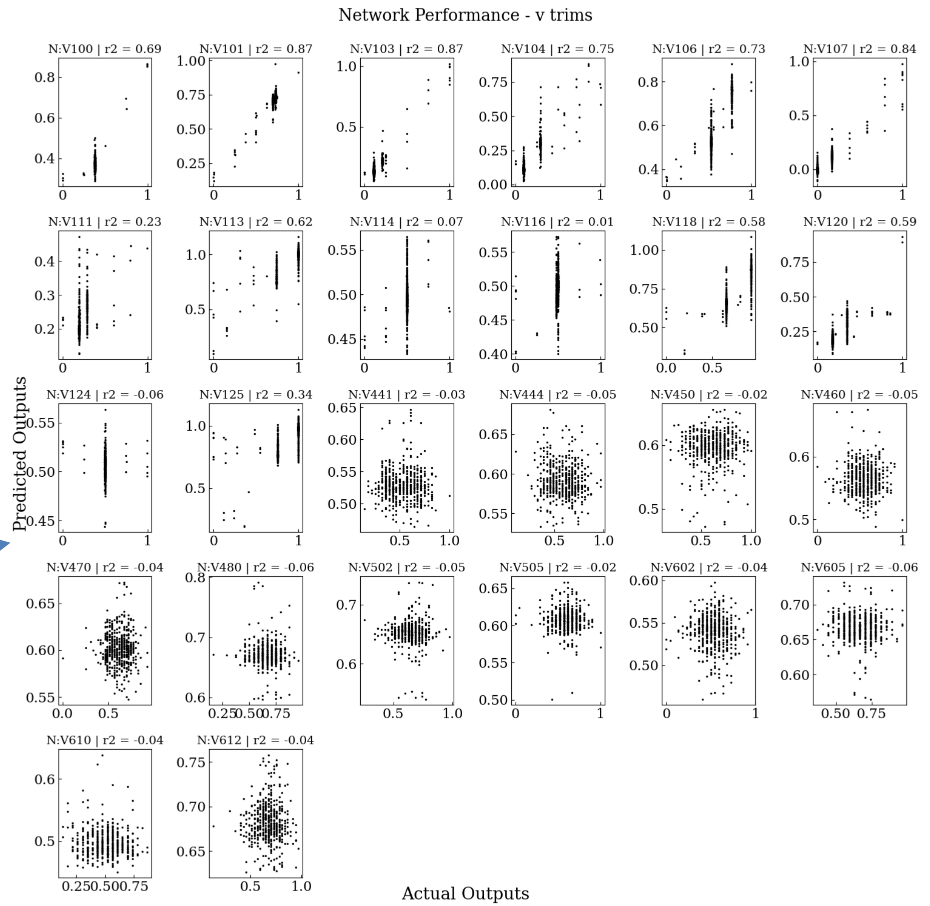

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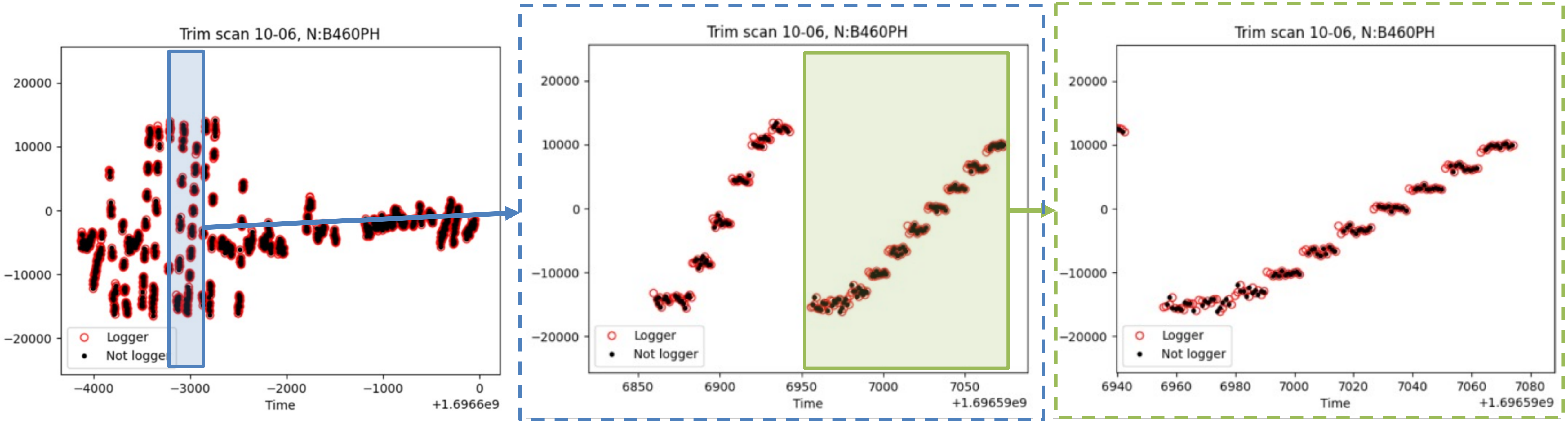
  - Try to see if anomaly detection is possible even with a ~~bad~~ sub-optimal model
  - Success! … sort of

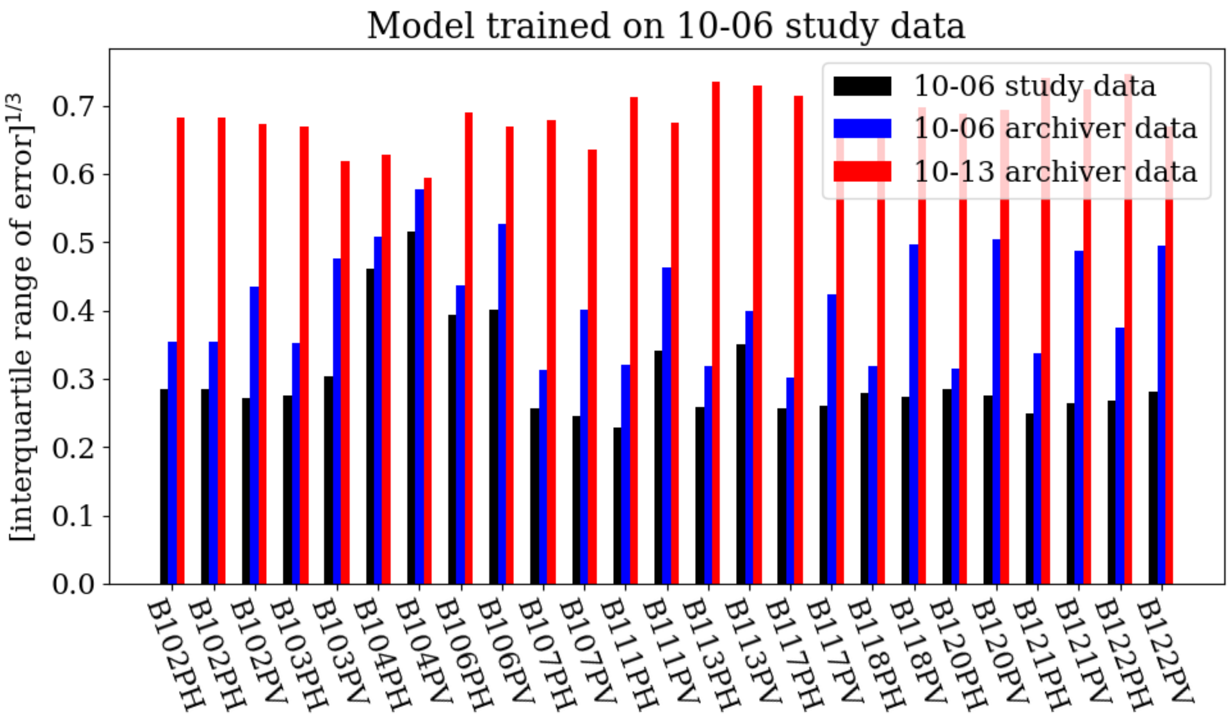
Identifying archiver issues

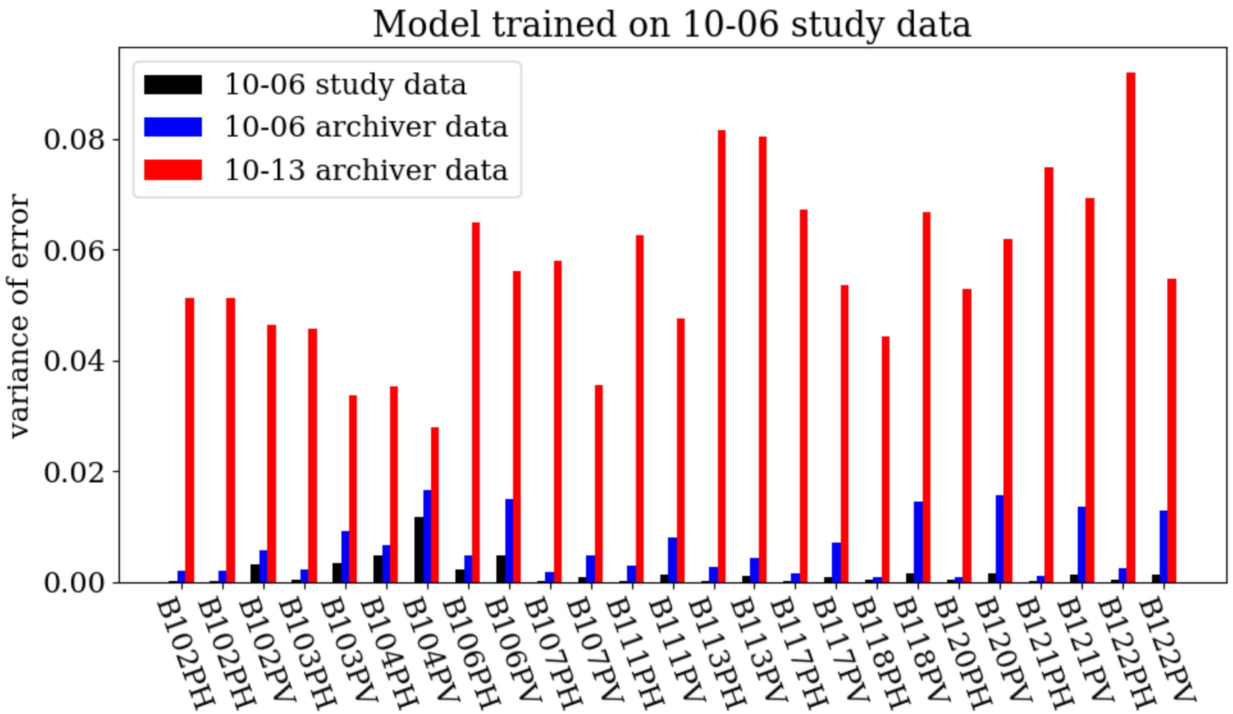
- Time alignment efforts with archive data revealed inconsistencies
  - Comparison of scripted data logging with archiver
  - Study on 10-6 scanned trims and recorded BPMs for model development and testing



Initial model training results

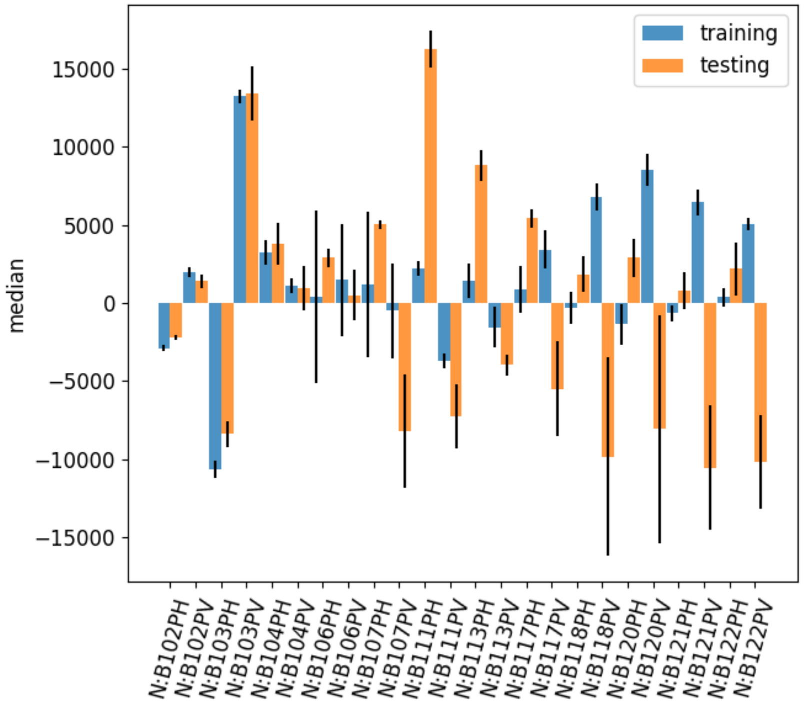
- We trained a model on only the 10-06 study data. Then, we applied that model to the archiver data and study data. The following plots show the error of the model predictions.
  - Note, we are considering an archiver timeframe on 10-06 when dedicated study data was collected and an archiver timeframe on 10-13 when no dedicated study was run.

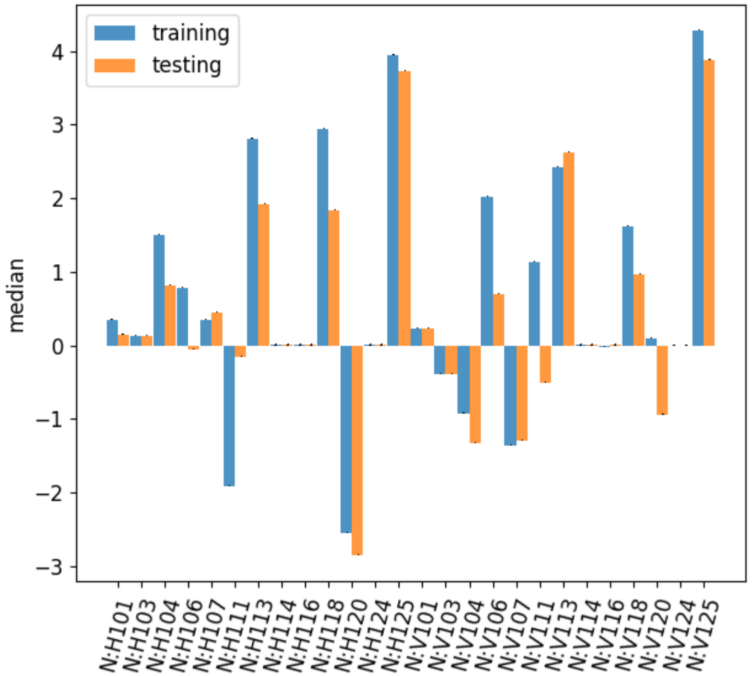


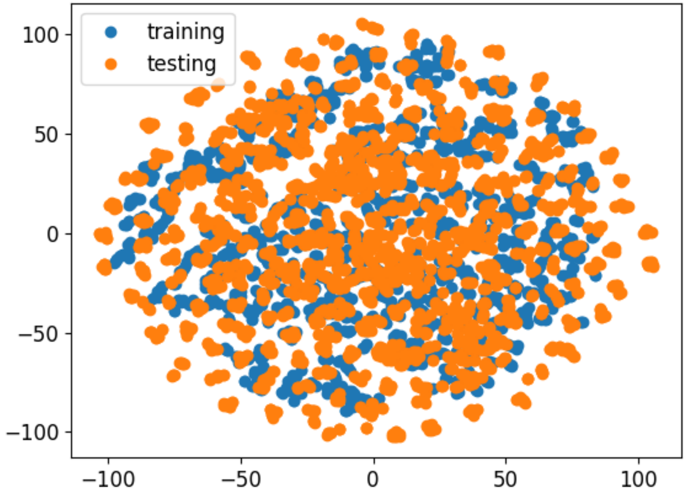


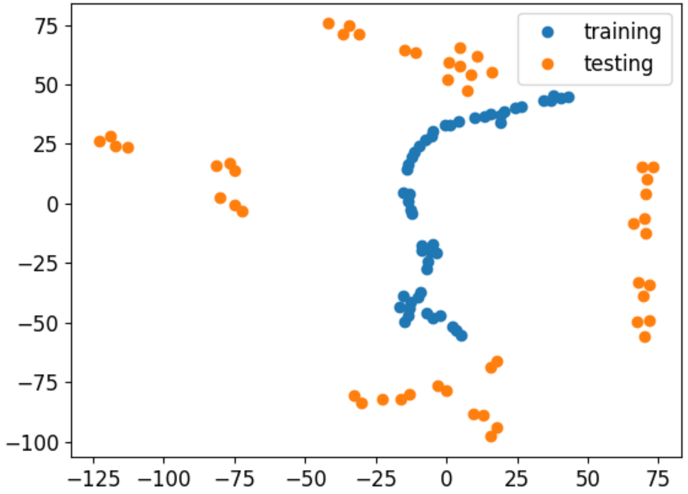
Understanding the training and testing data

- Training data collected from the data logger between studies ~ Oct 13
- Testing data collected from script during machine studies on Oct 6
- Bar plots showing the median and interquartile range
  - BPMs (bottom left): Correctors (bottom right)
- T-sne dimensionality reduction
  - Example-by-example (right top)
  - Model parameters (right bottom)



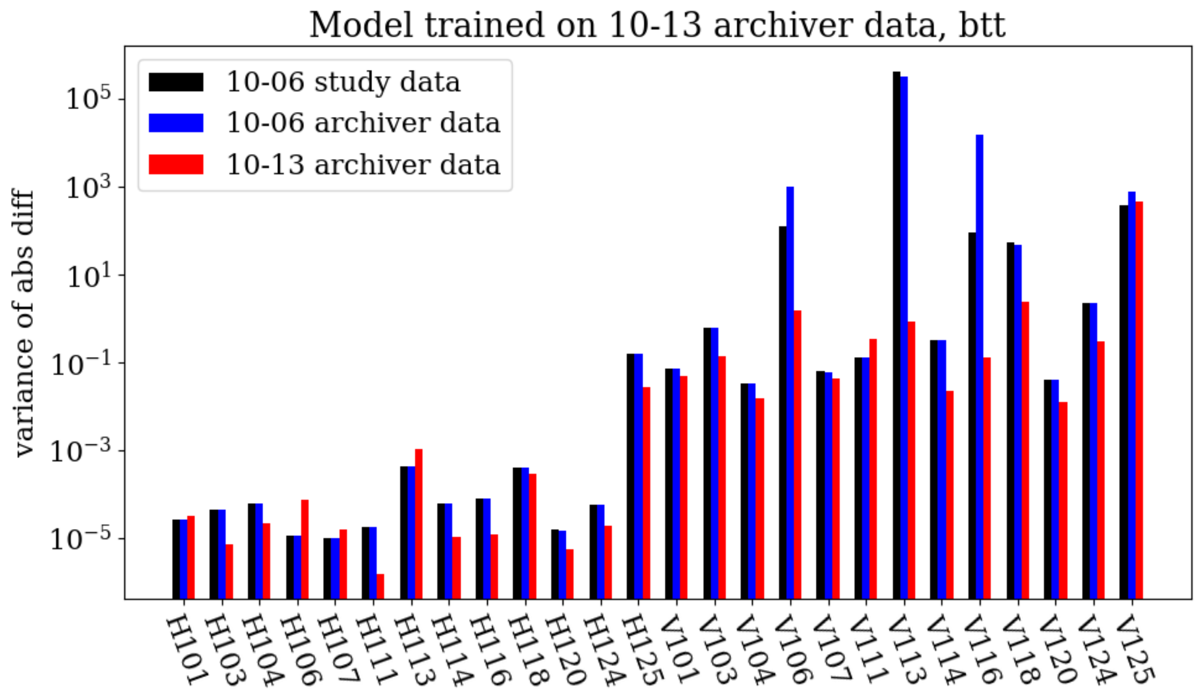


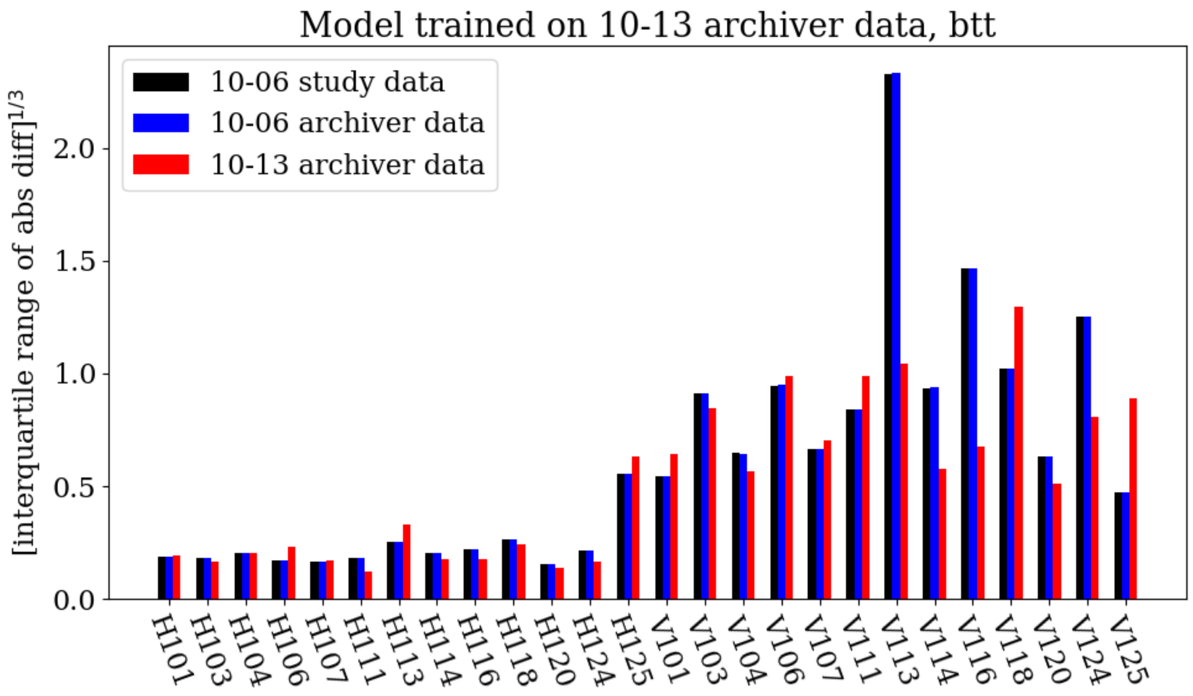




Initial machine learning studies

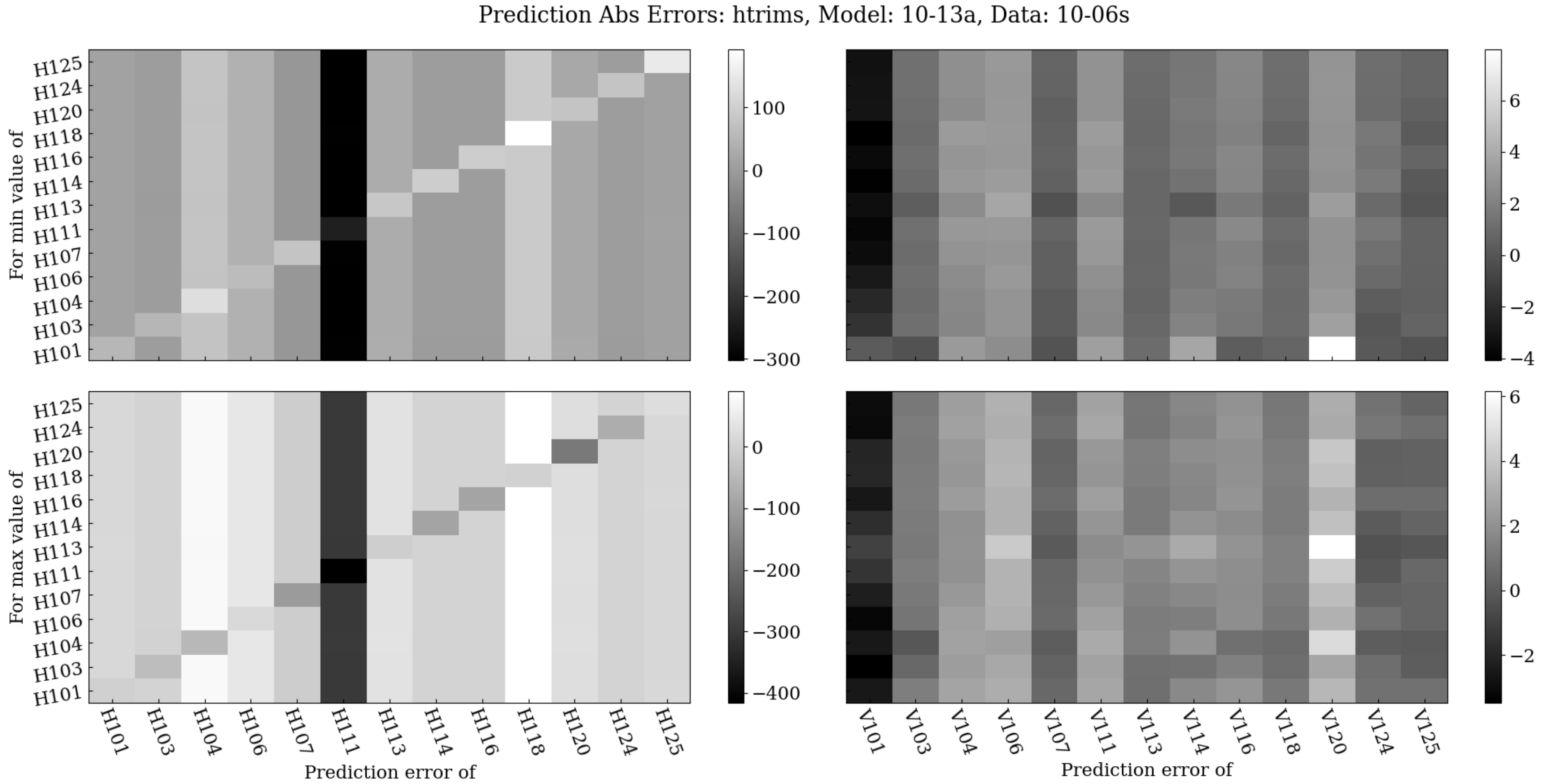
- Model is trained on operations data and tested on study data
  - Study was conducted on 6 October: Both scripted data collection and data logger collection





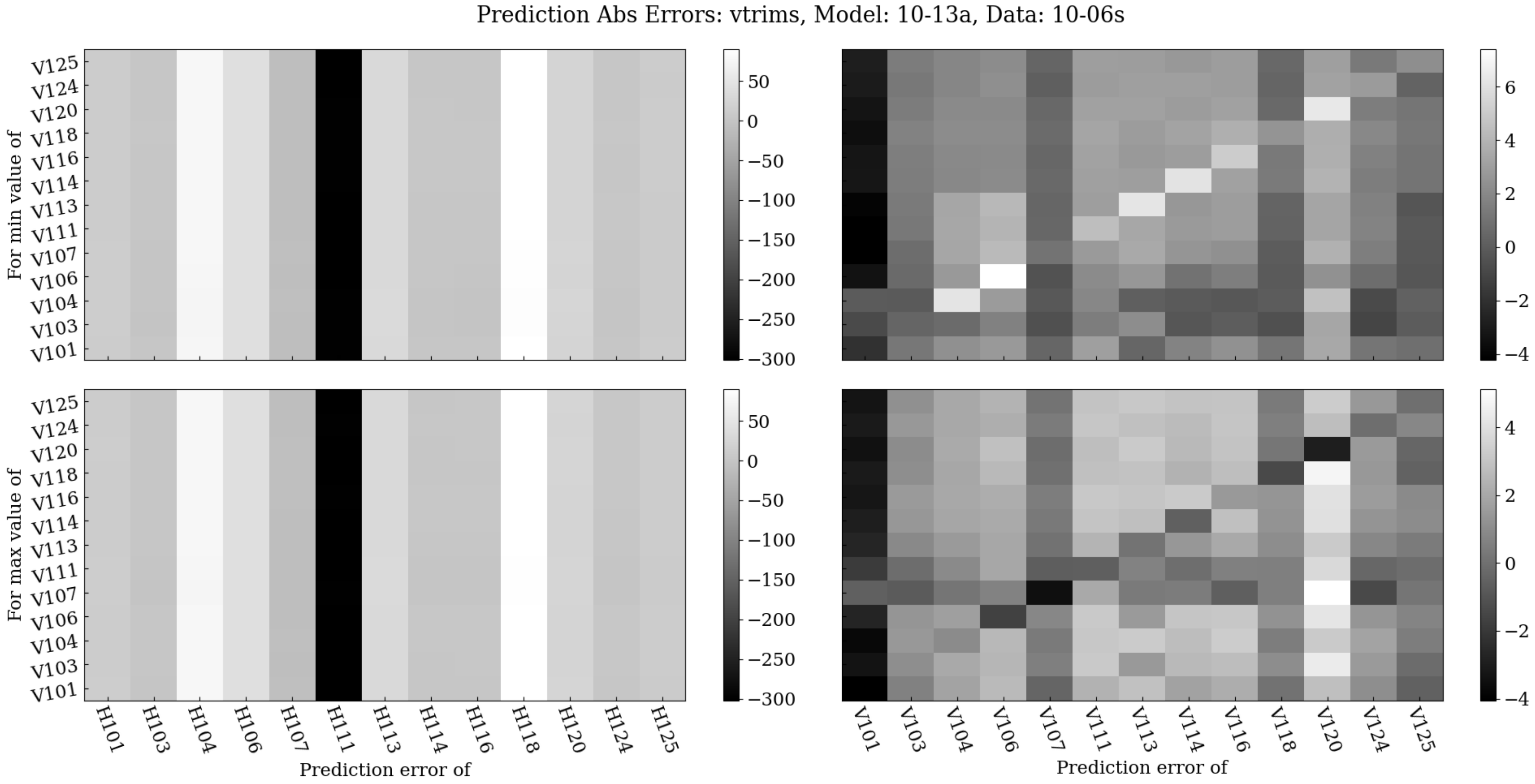
Predicting the trim settings from the BPMs

- Prediction errors for the horizontal trims
  - For the min (left) and max (right) trim setting during the study



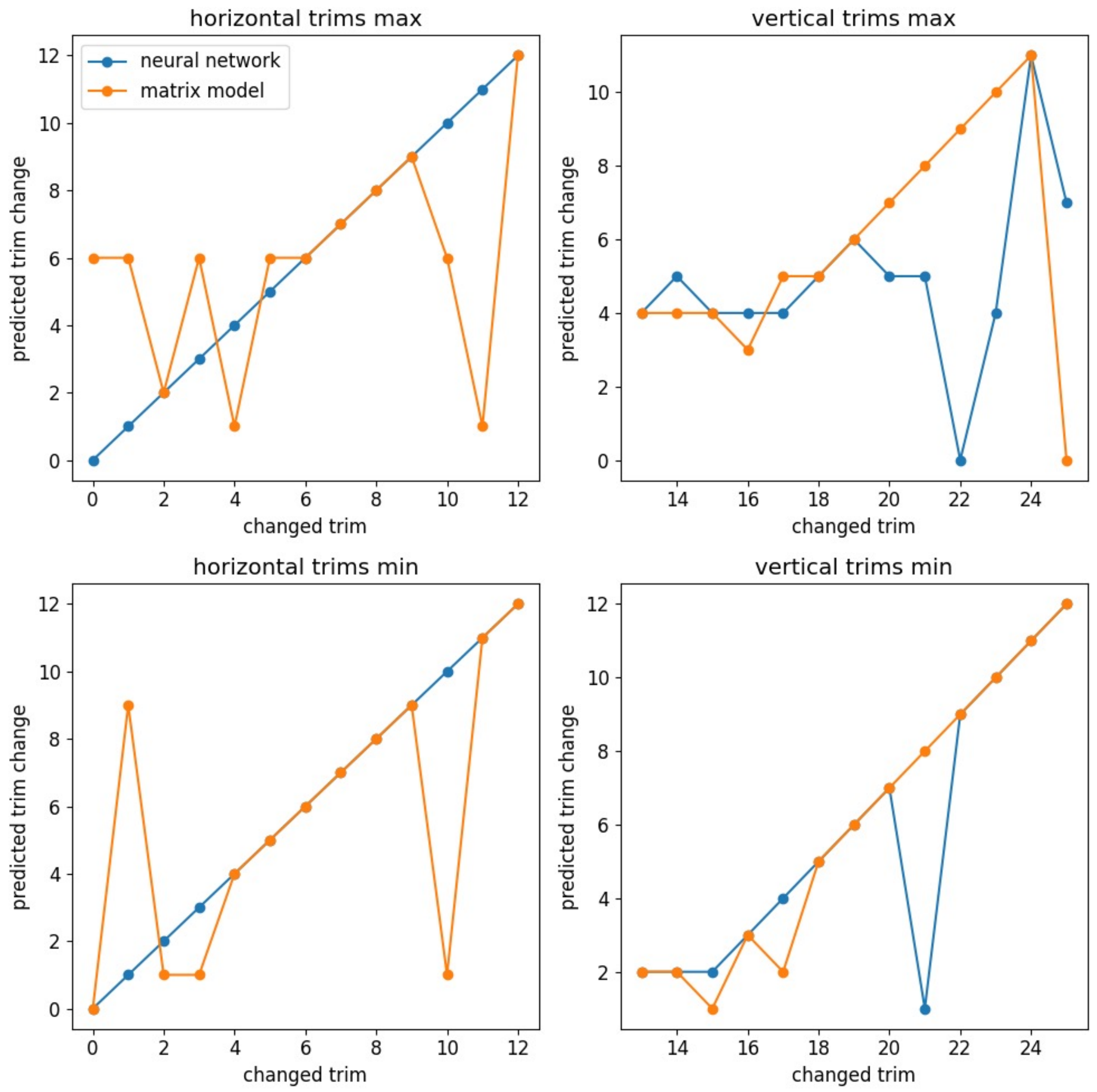
Predicting the trim settings from the BPMs

- Prediction errors for the vertical trims
  - For the min (left) and max (right) trim setting during the study



Identification of trim errors

- Use algorithm to identify trim errors
  - Model trained to predict trim settings from BPM readings
  - Compute error between predicted trim setting and actual trim settings
  - Large model offsets make threshold determination challenging
    - The changed trim has a clear signature over non changed trims
    - Subtract the mean error and then find the location with the max residual
  - Compare with linear matrix model



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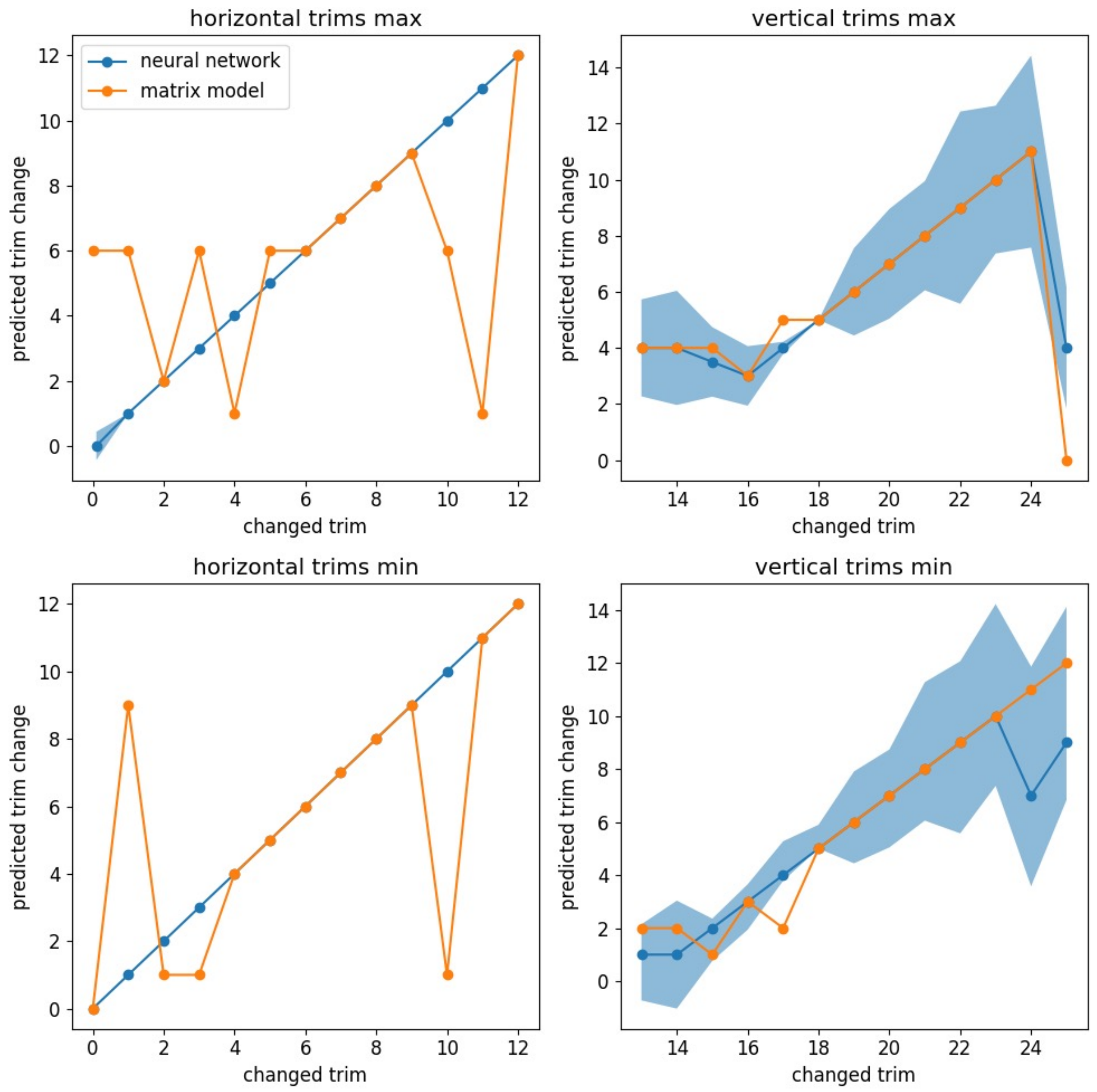
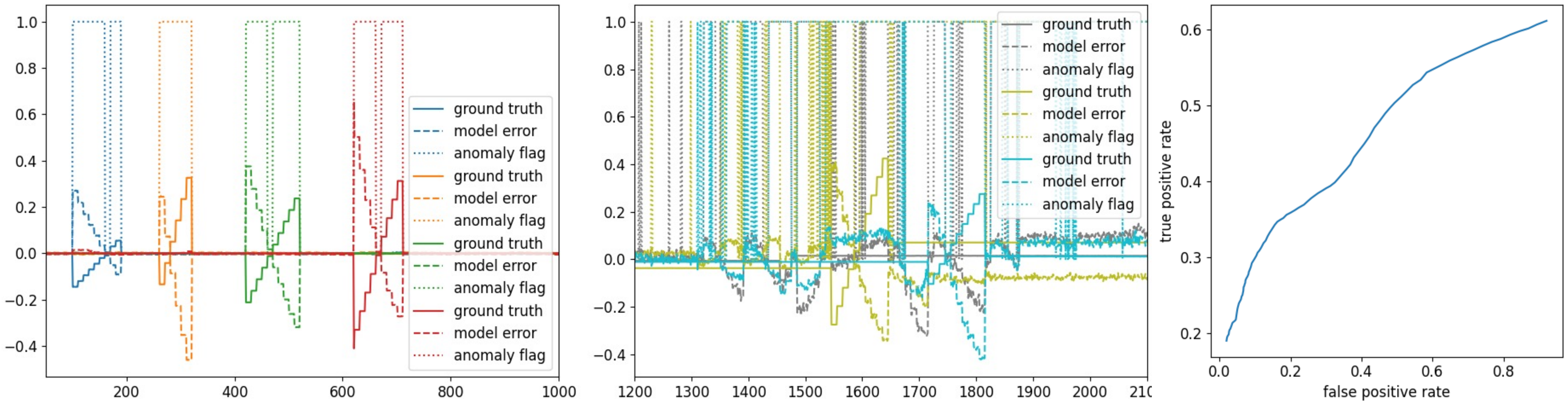
  - Compare with linear matrix model
- Use model ensemble to improve prediction and provide error bars
  - Plots show median prediction with plus minus one standard deviation



Detailed error detection analysis / threshold evaluation

- Evaluate model performance on all test data
  - ROC curve (far right) shows true positive rate vs false positive rate for varying detection thresholds
- Error detection for horizontal trim examples (left) and vertical trim examples (middle)
  - Color coded by which trim is changed
  - Model error in dashed line
  - Anomaly flag in solid line showing that the BPM is correctly identified



Next steps

- Iterate on model learning
  - Try to improve the predictions for baseline model: planned
- Improve detection algorithm
  - Extend to remaining BPMs on the LINAC: planned
  - Expand ensemble to include linear and other models: planned
  - Try Siamese networks for stronger error discrimination: in progress
- Determine deployment path
  - Experiment on proton source?
  - Expand to include more diagnostics?

Conclusions

- Neural network model was able to detect changes in the machine in different operational modes
    - Improvement over matrix model
    - Training data collected during normal operations (no dedicated study required to train the model)

- Need to better understand the data logger issues

- Understand why the method works even with a poor (in my opinion) model

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