

# Semi-supervised detection of optics errors in beamlines

Jonathan Edelen, Nathan Cook, Christopher Hall (RadiaSoft)

Kevin Brown, Yuan Gao, Vincent Shoefer, (BNL)

April 9<sup>th</sup> 2025

MaLAPA 2025: Geneva

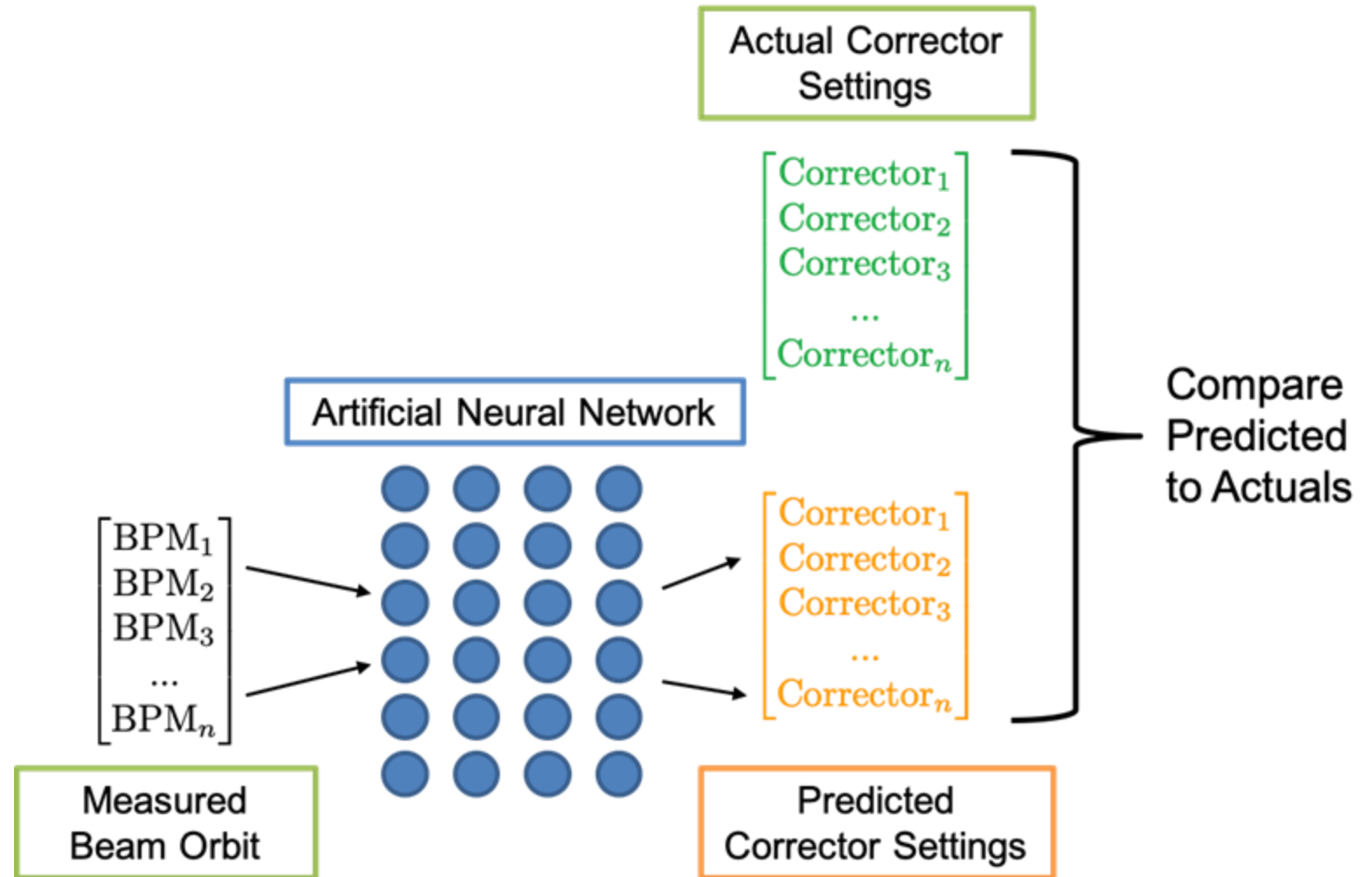
This material is based upon work supported by the U.S. Department of Energy, Office of Science, Office of Accelerator R&D and Production award number DE-SC0023641

# Overview

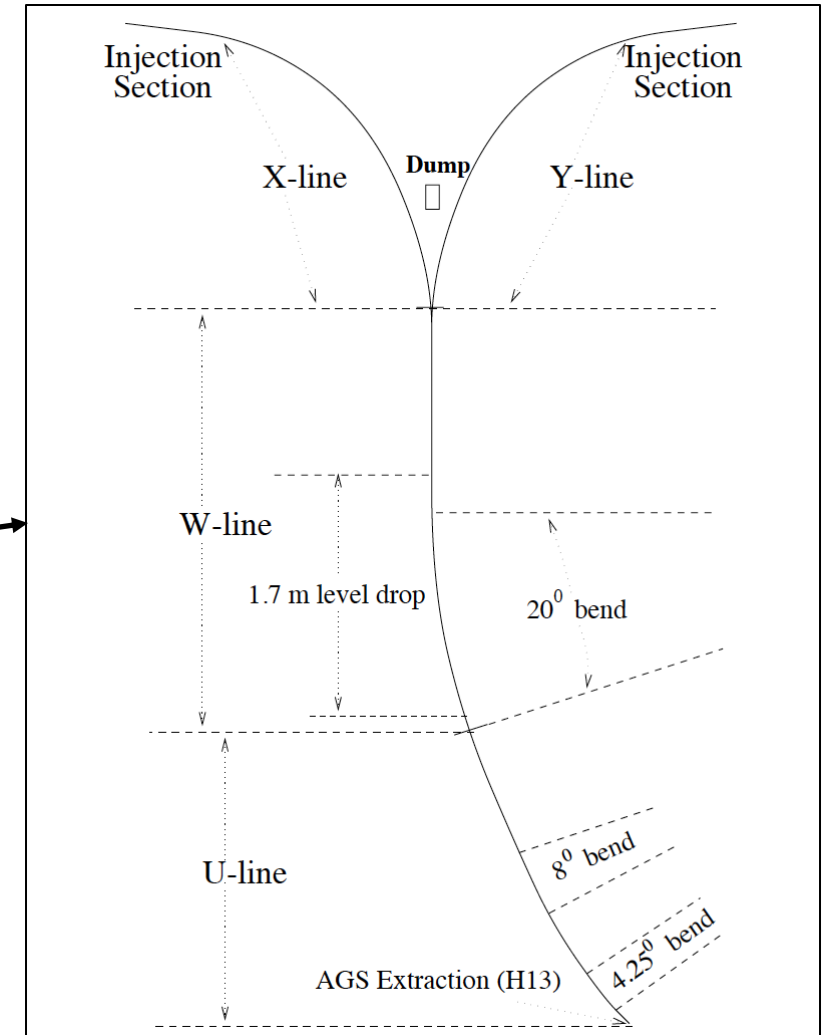
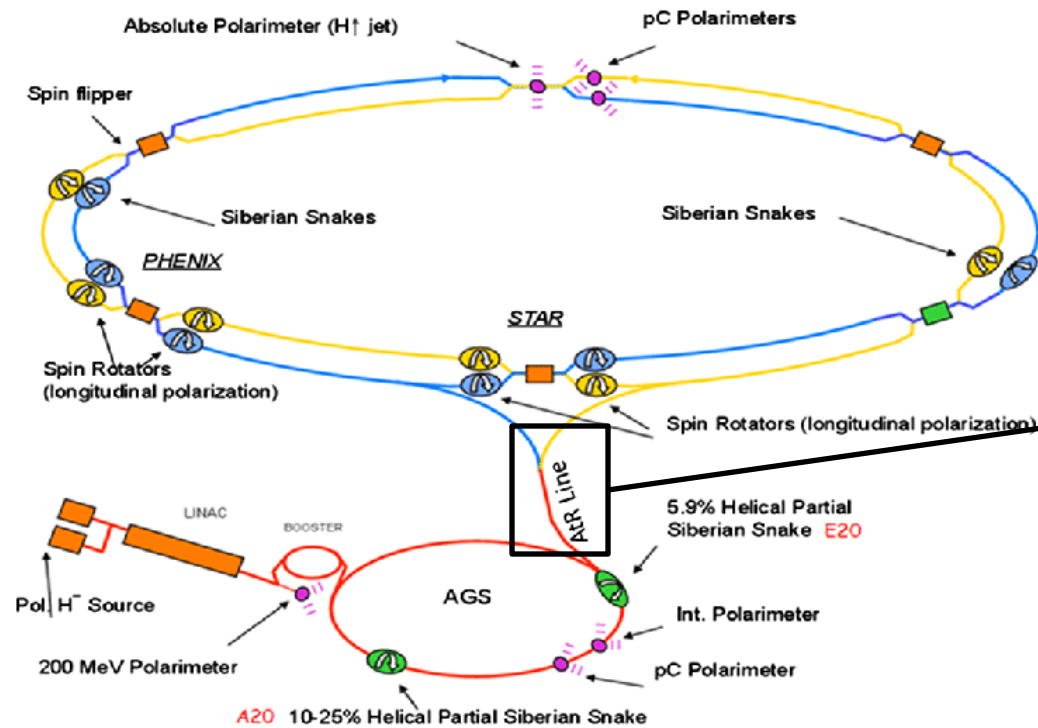
- Development of inverse models for anomaly detection
- Testing ML and linear models on a FODO cell and their robustness to nonlinearities
- Evaluating detection of quadrupole errors on a model of the ATR line at BNL
  - Does an error exist?
  - Can we identify the specific error?
- Testing our approach on measurements

# 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 as a diagnostic in an unsupervised fashion
  - 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



# The AGS to RHIC Transfer Line at BNL



*Relativistic Heavy Ion Collider complex. Right AGS to RHIC transfer line. Our simulations are focused on the UW section of the transfer line.*

# A Toy Problem: FODO Lattice

Data Generation (MAD-X simulations)

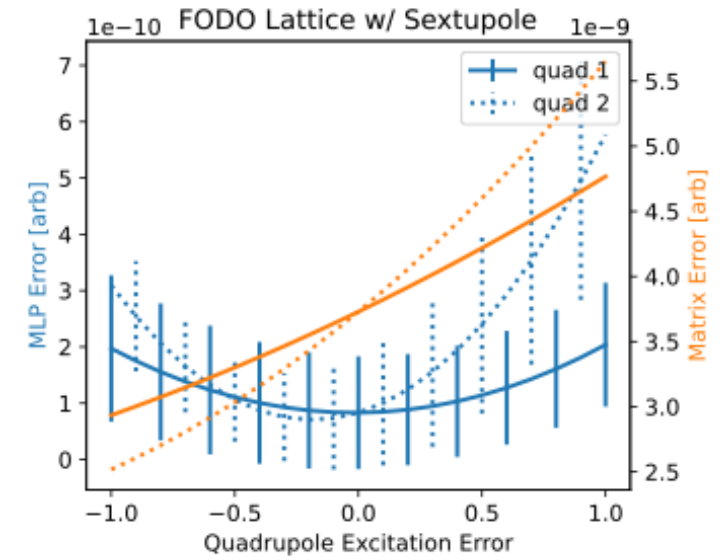
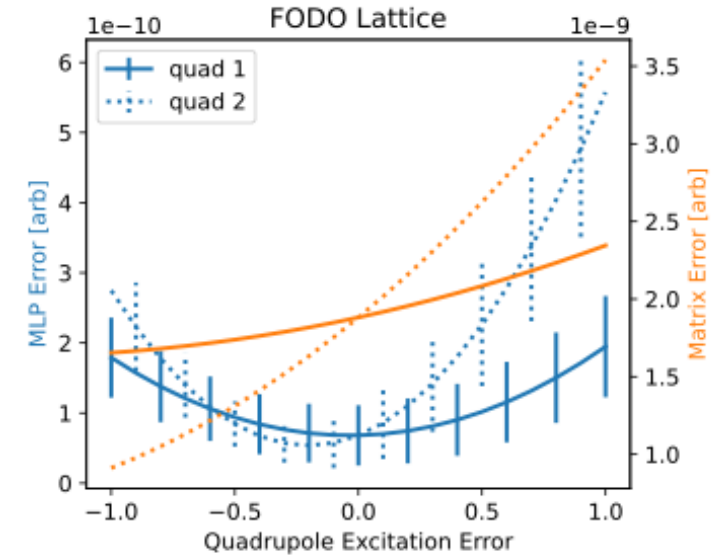
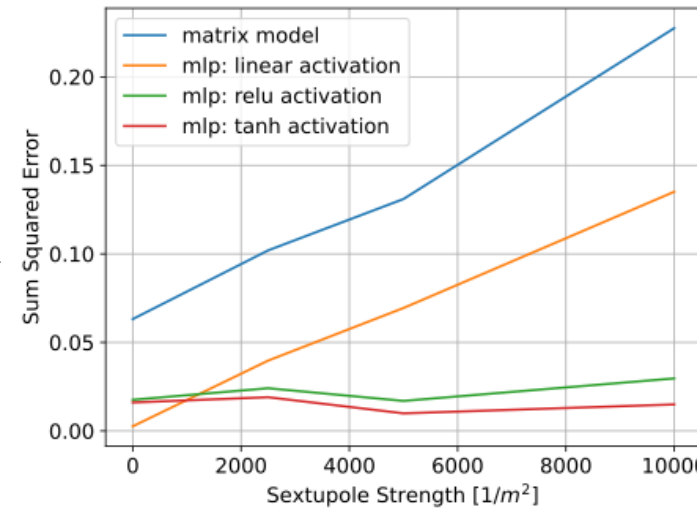
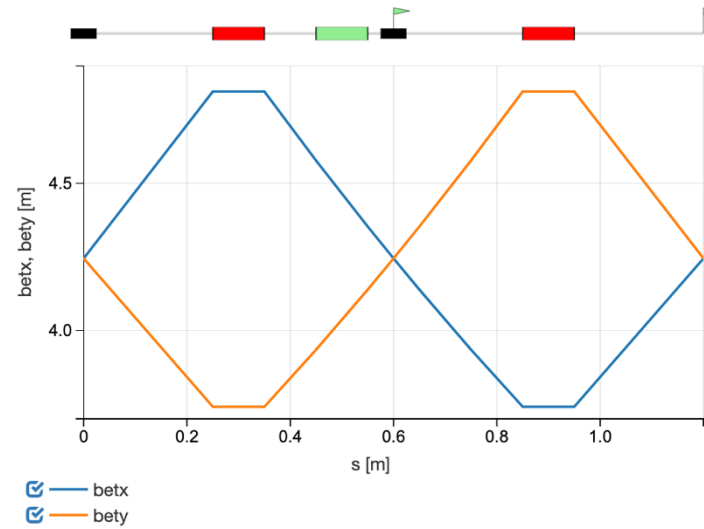
- randomly vary corrector strengths
- fixed quadrupole configuration
- record BPM data

Model Learning (25 model ensemble)

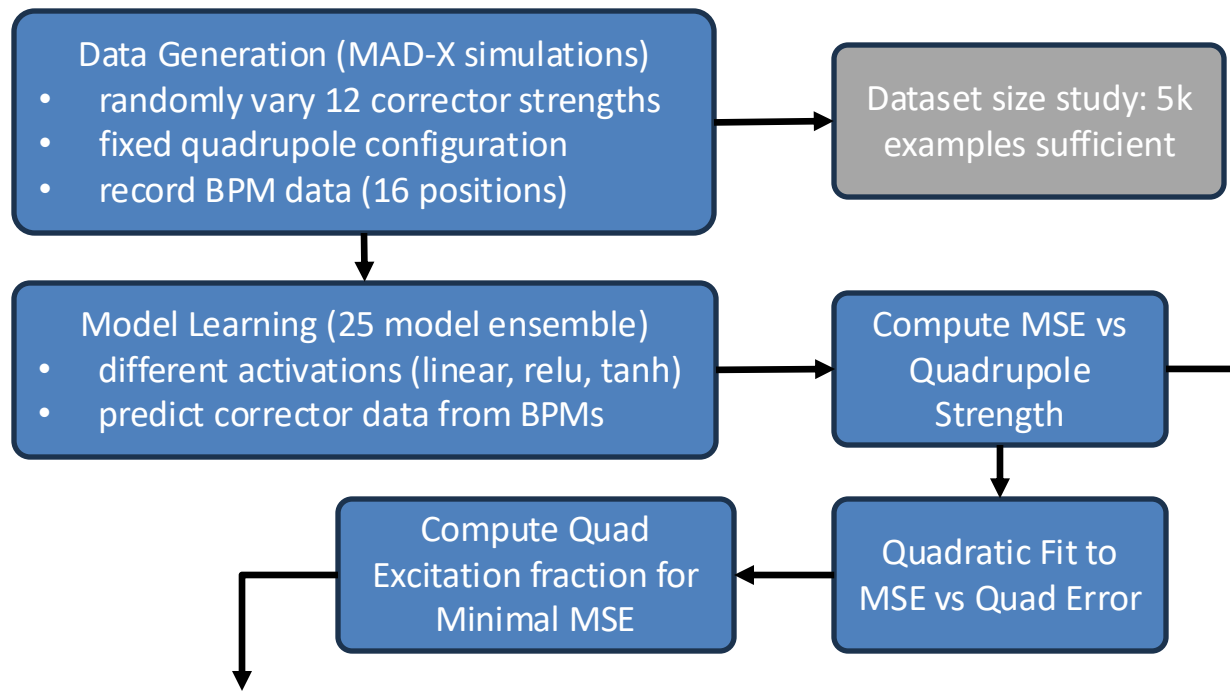
- different activations (linear, relu, tanh)
- predict corrector data from BPMs

Compute MSE on validation data as we vary the sextupole strength

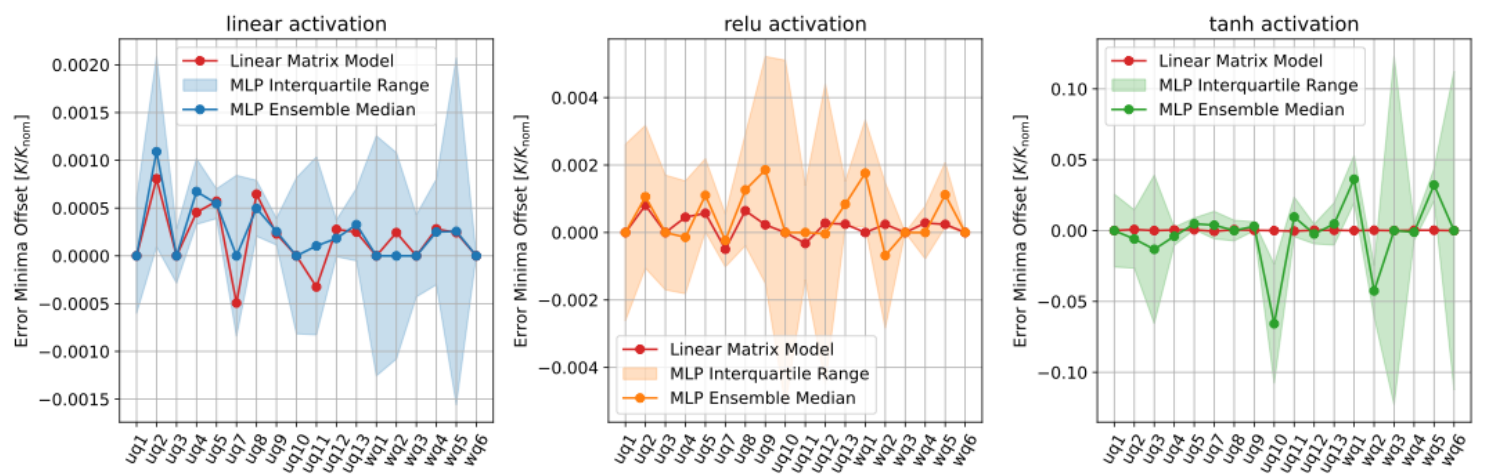
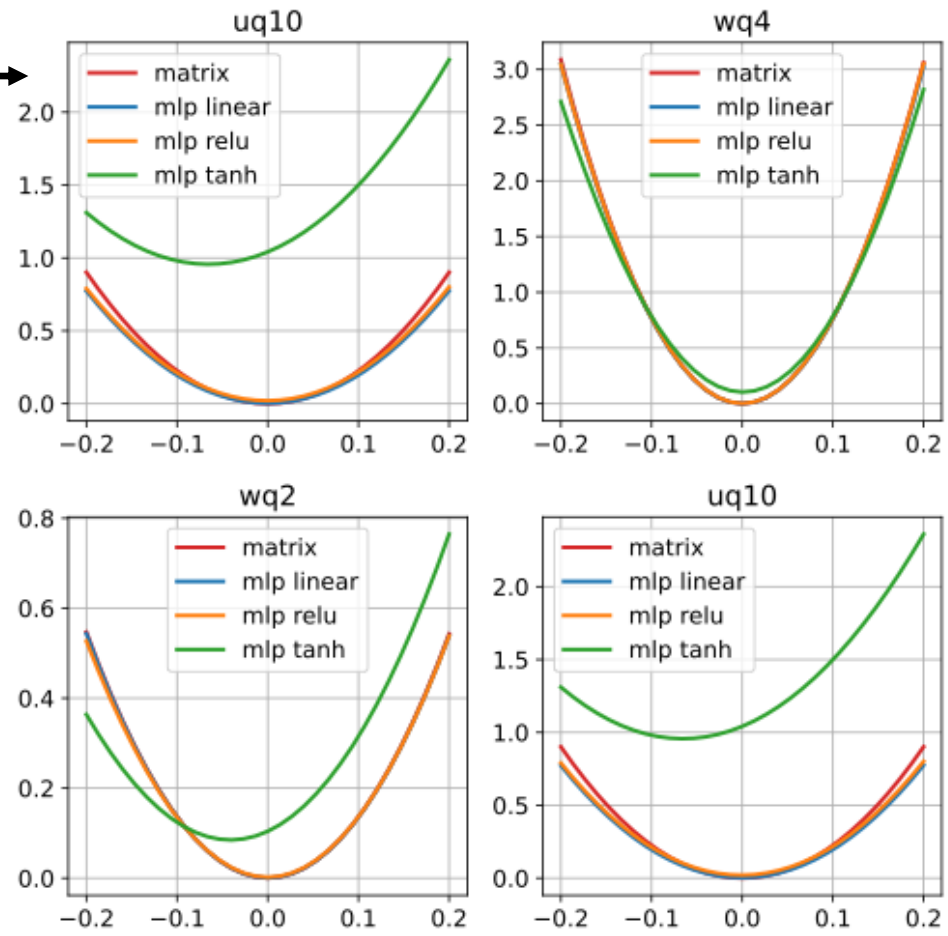
Compute MSE vs Quadrupole Strength for linear and nonlinear lattice



# Evaluating Quadrupole Error Detection Capabilities for the ATR Line



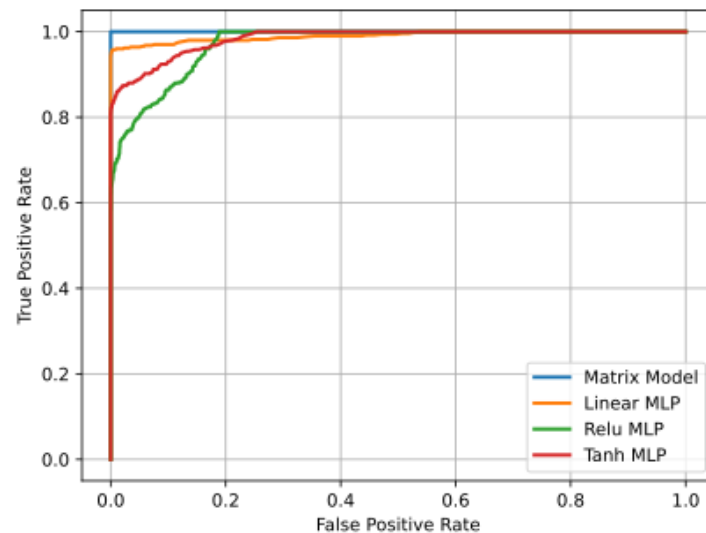
Mean squared error as a function of quadrupole excitation error for a random subset of the 19 quadrupoles in the UW Line. Note: Fixed random corrector settings for the test set.



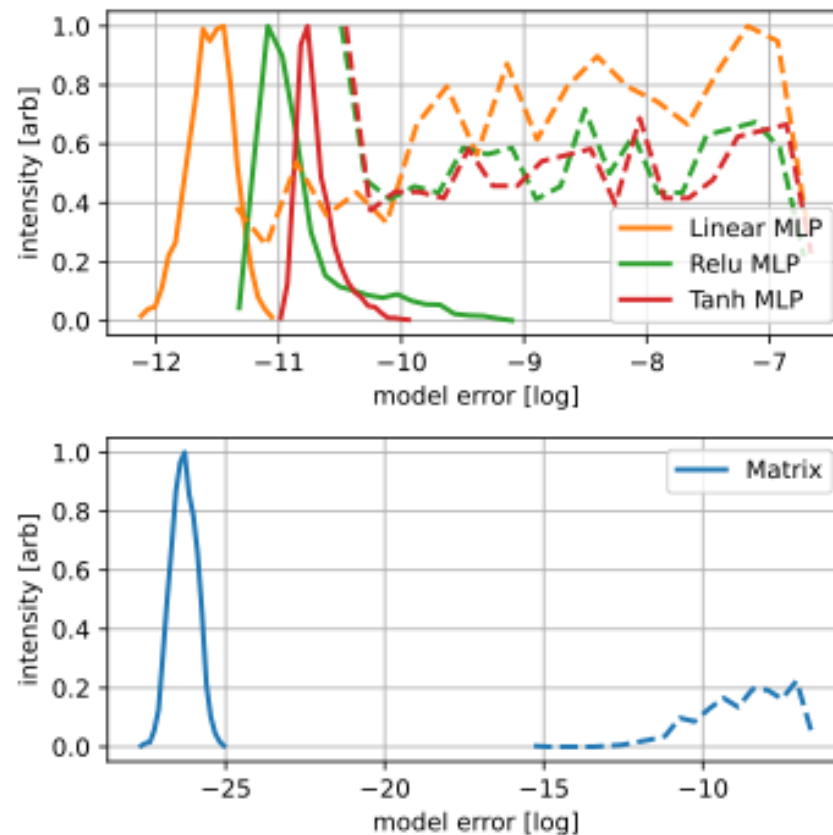
# Evaluating Quadrupole Error Detection Capabilities for the ATR Line

- Test set generation:
  - Single set of random corrector settings
  - 500 random single quadrupole excitation errors
- Compute ensemble mean of sum-squared-error
- Histogram plots show no overlap for linear model and some overlap for MLP models
- False positives computed on the validation data
- True positives computed on the test data

	50% TPR	75% TPR	95% TPR
FPR (line)	0%	0%	0.1%
FPR (relu)	0%	2%	16%
FPR (tanh)	0%	0%	13%

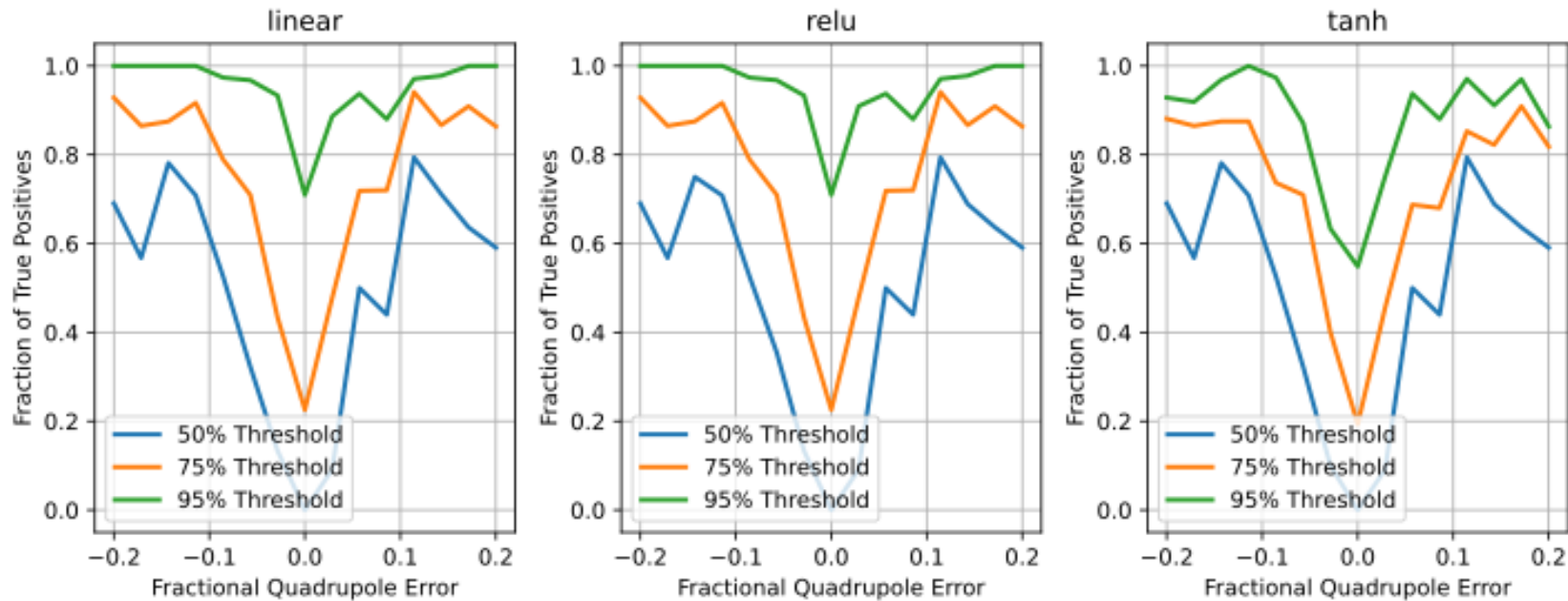


Histograms of validation error (solid) and test error (dashed) for the MLP ensemble (top) and matrix model (bottom)



# Evaluating Quadrupole Error Detection Capabilities for the ATR Line

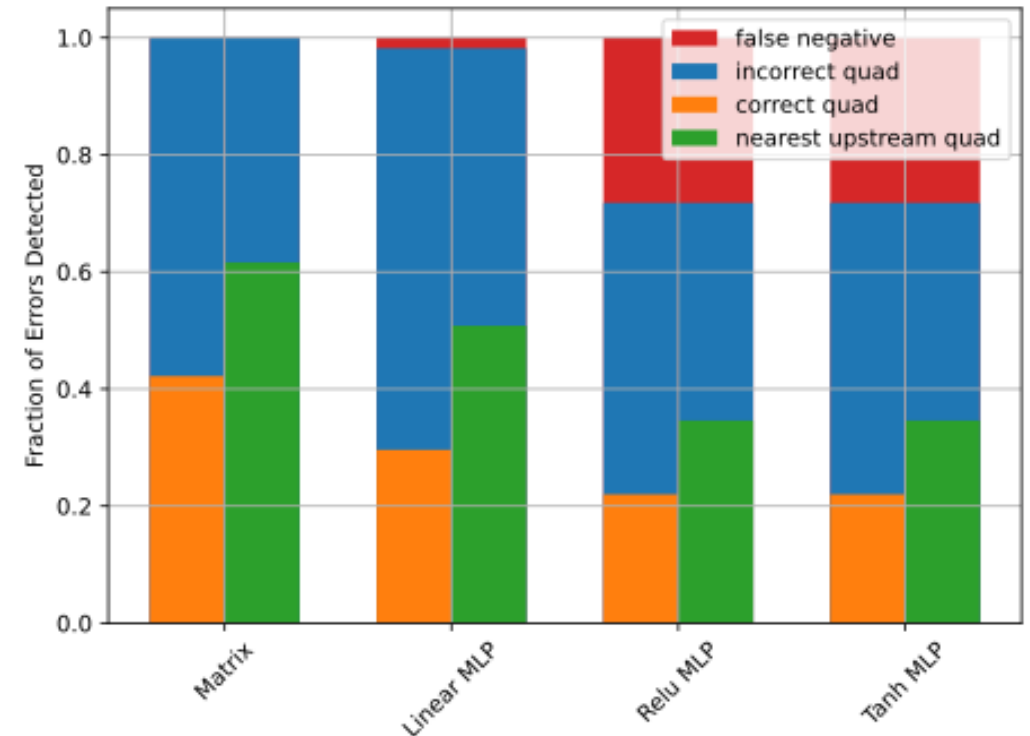
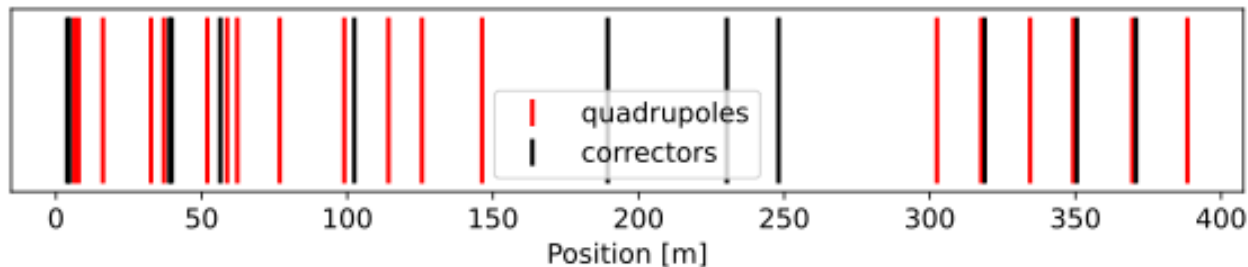
- Fraction of quadrupole errors detected as a function of quadrupole excitation errors for 50% / 75% / 95% categories



# Unsupervised Single Quadrupole Error Detection

- Can we identify which quadrupole had an error
  - Ensemble mean of sum squared error not appropriate
  - Compute ensemble mean of squared error
    - Model outputs error for all 12 correctors
    - 12 correctors and 19 quadrupoles!
  - Threshold for error detection set based on peak validation set error
  - Find nearest up-stream quadrupole to peak corrector error
    - This works 20%~40% of the time (depending on the model)
  - Is the quad error between two correctors
    - 20% improvement

	Correct	Nearest Upstream	False Negative
Matrix	42%	62%	0%
Linear MLP	30%	51%	2%
Relu MLP	22%	50%	28%
Tanh MLP	22%	50%	28%

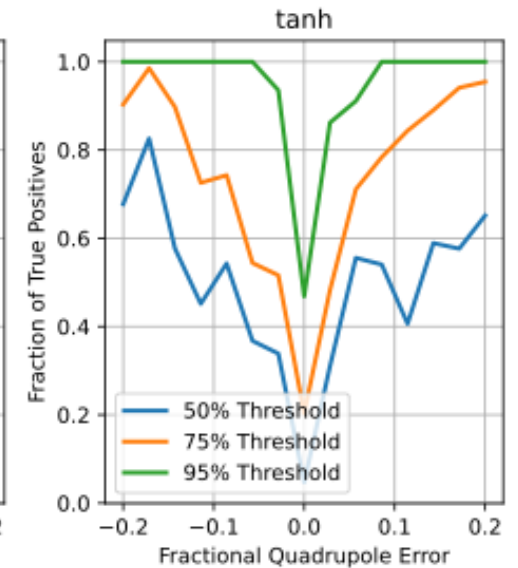
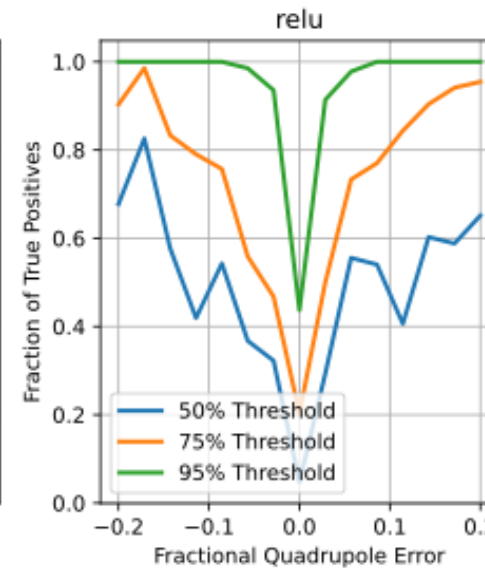
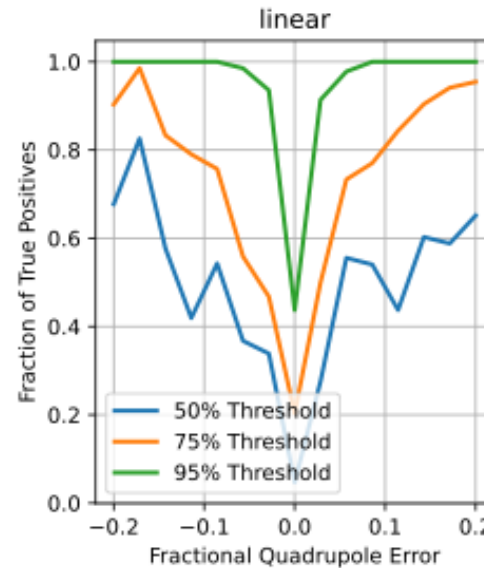
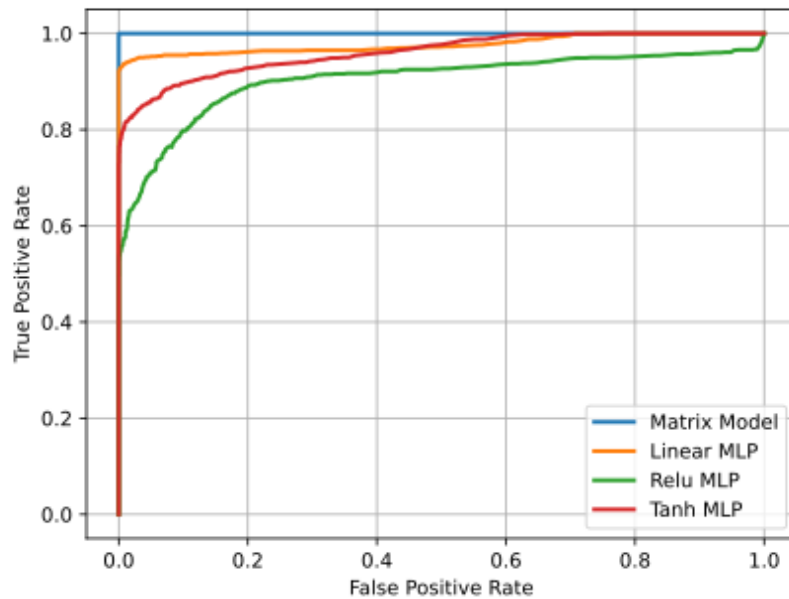
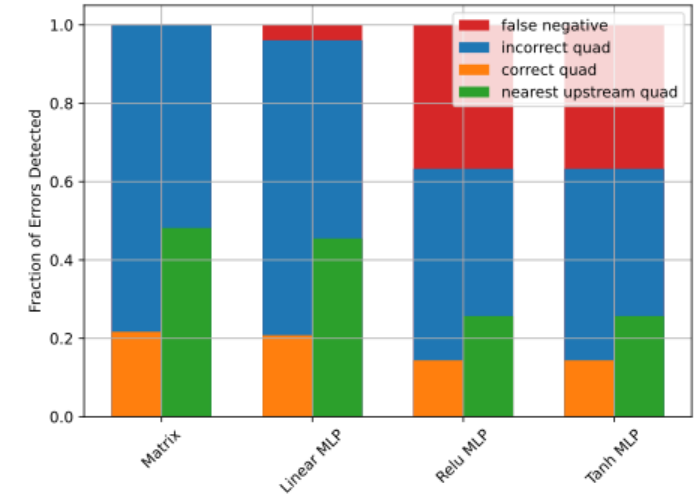


# Unsupervised Single Quadrupole Error Detection

- Repeat study with 1k examples

- Random corrector settings
- Random quadrupole errors

	Correct	Nearest Upstream	False Negative
Matrix	22%	48%	0%
Linear MLP	21%	46%	4%
Relu MLP	14%	26%	37%
Tanh MLP	14%	26%	37%

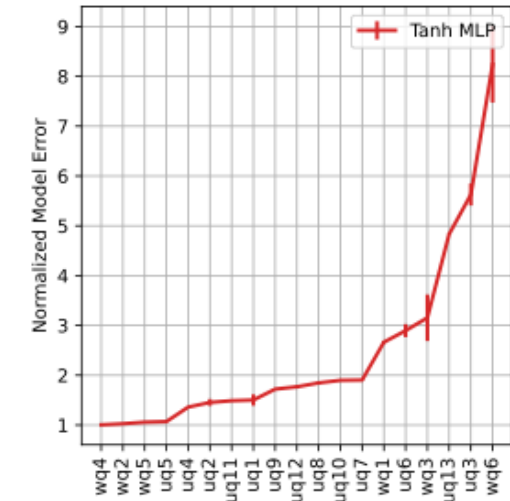
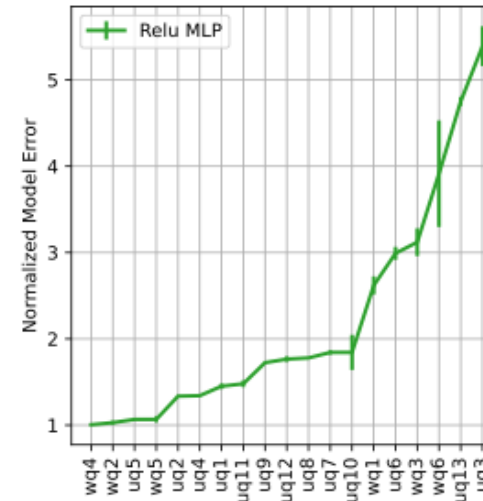
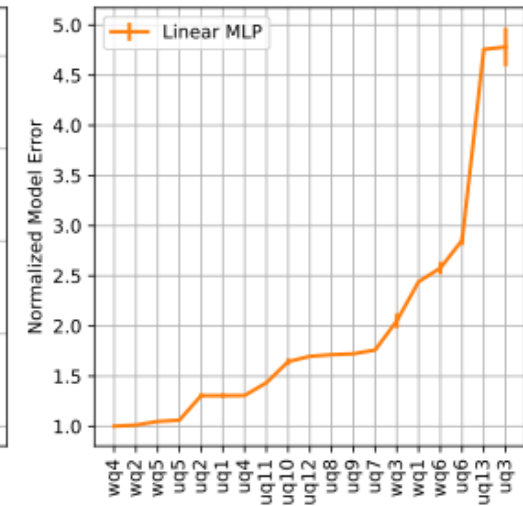
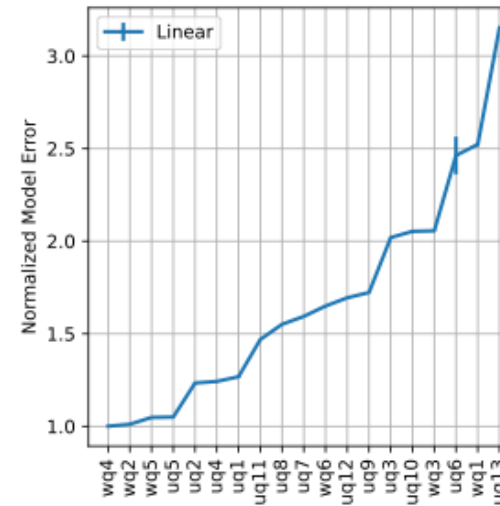


# Supervised Single Quadrupole Error Detection

## Calibration Data

- Plus-minus max quadrupole excitation error (25 x 38 x 12)
- Compute ensemble mean (38 x 12)
- Normalize ensemble mean to peak corrector error (38 x 12)
- Sum normalized error (38)
- Average and peak to peak (19)

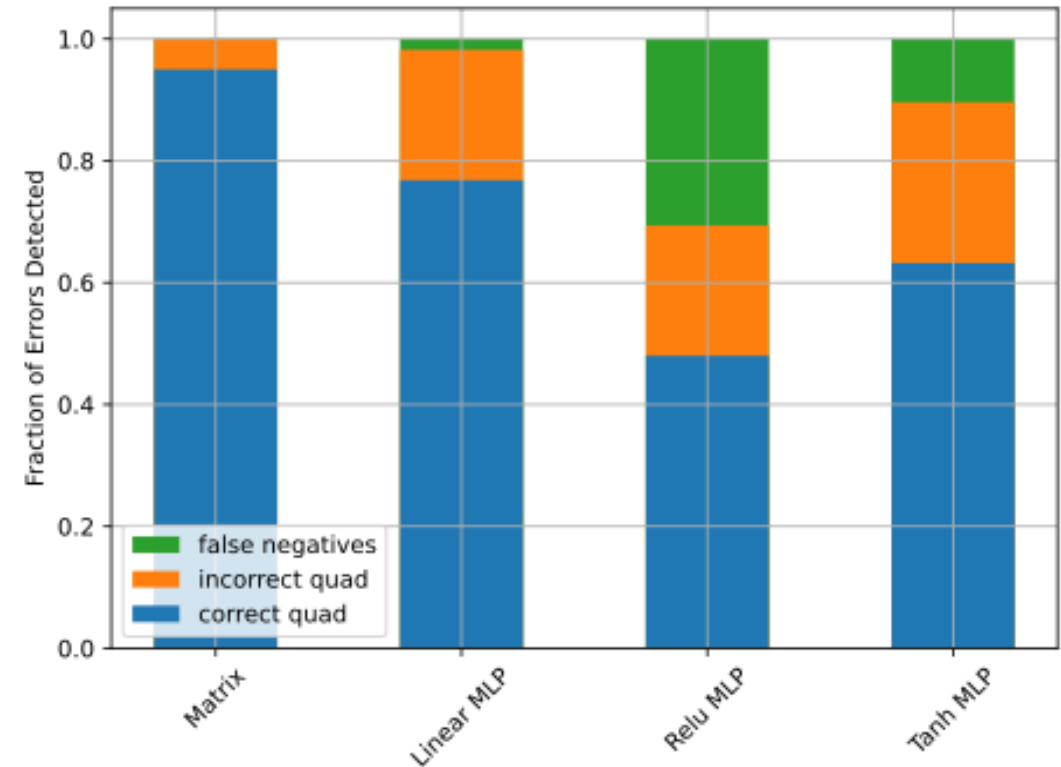
- Sum of the normalized error is unique(ish) for each quadrupole excitation
  - Cannot comment if they are linearly independent
  - Peak-to-peak variance in the calibration error makes it difficult to discriminate between some quads



# Supervised Single Quadrupole Error Detection

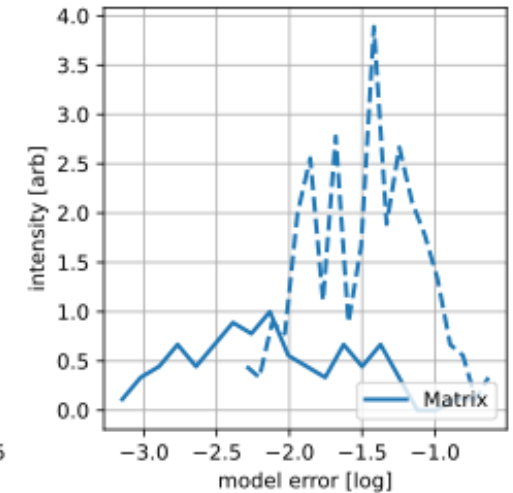
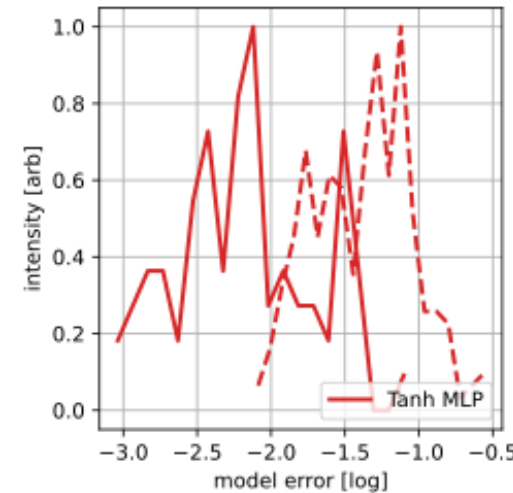
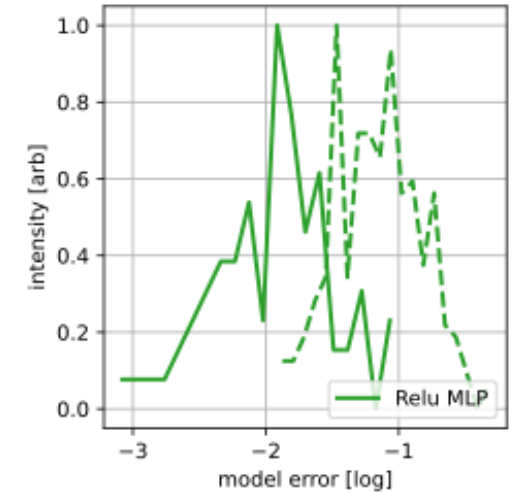
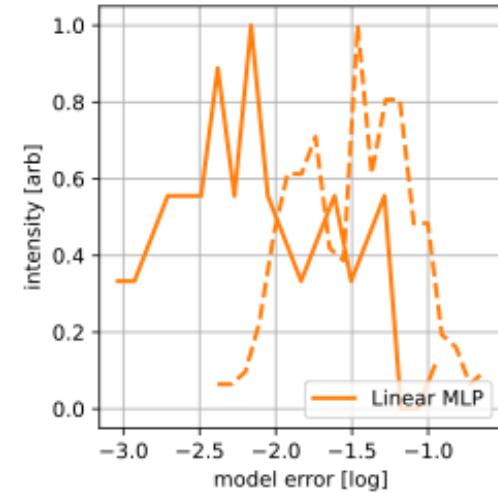
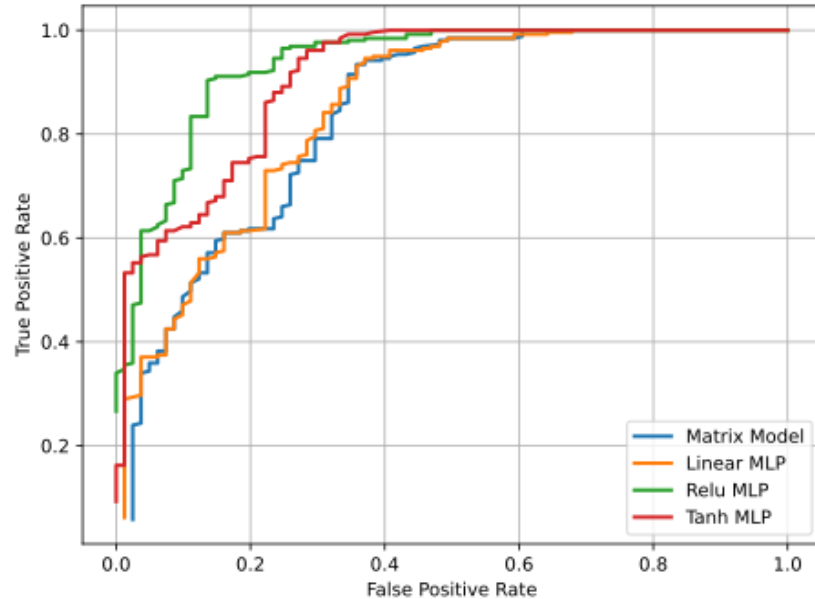
- Can we identify which quadrupole had an error
  - Threshold for error detection set based on peak validation set error
  - Match model error with calibration values

	Correct	Incorrect	False Negative
Matrix	95%	5%	0%
Linear MLP	77%	21%	2%
Relu MLP	48%	21%	31%
Tanh MLP	63%	27%	10%



# Unsupervised Quadrupole Error Detection: Measurement Data

- Collected training data over different RHIC runs – relatively limited dataset
  - Train ensemble of 25 models
- Test data for three quadrupole changes while varying the correctors
- Right: Histogram of model error for the validation set (solid lines) and test set (dashed lines)
- Bottom: ROC curve for test data



# Summary

- Inverse models are a useful tool for anomaly detection.
- Unsupervised techniques can reliably determine *if* a quadrupole error exists but not reliably determine *which* quadrupole it is
  - Supervised techniques can improve single quadrupole error discrimination
- Nonlinear models outperform linear models when transferring to the operational machine
  - A matrix model is optimal for the simulations
  - A relu-MLP was the optimal choice on measurement data

# Disclaimer

This report was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.