Machine Learning for Optic Correction in the LHC

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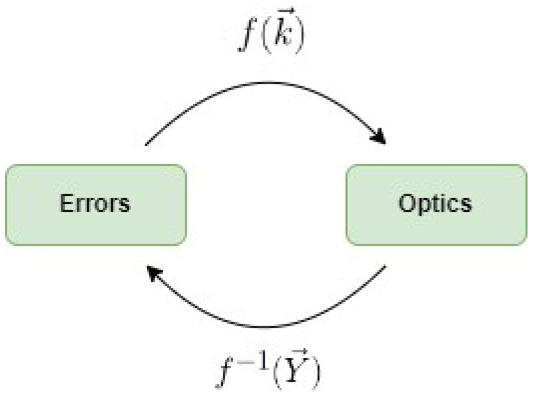
Introduction

Actual methods for quadrupole magnetic error correction consist on knob tuning, response matrix …

- Problems, no information on the actual magnet errors
- Correcting the optics, but not the actual magnet errors!



Machine learning promises multiple new ways to manage quadrupole errors

- The effect of magnet errors on optics can be calculated using simulation software
- ML can be used to model the relation between optics and errors regardless on how complex

$$\vec{Y} = f(\vec{k})$$

$$\vec{k} = f^{-1}(\vec{Y})$$

$$\vec{Y} = (\beta_x, \beta_y, \mu_x \ldots)$$

Methods: Data pipeline

Generating random quadrupole strength errors and calculating the corresponding twiss parameters for data generation

$$\vec{k}$$

$$\vec{Y} = (\Delta\beta_x, \Delta\beta_y, \Delta\mu_x \ldots)$$

Possible improvements to data generation include using MAD-NG or adding noise

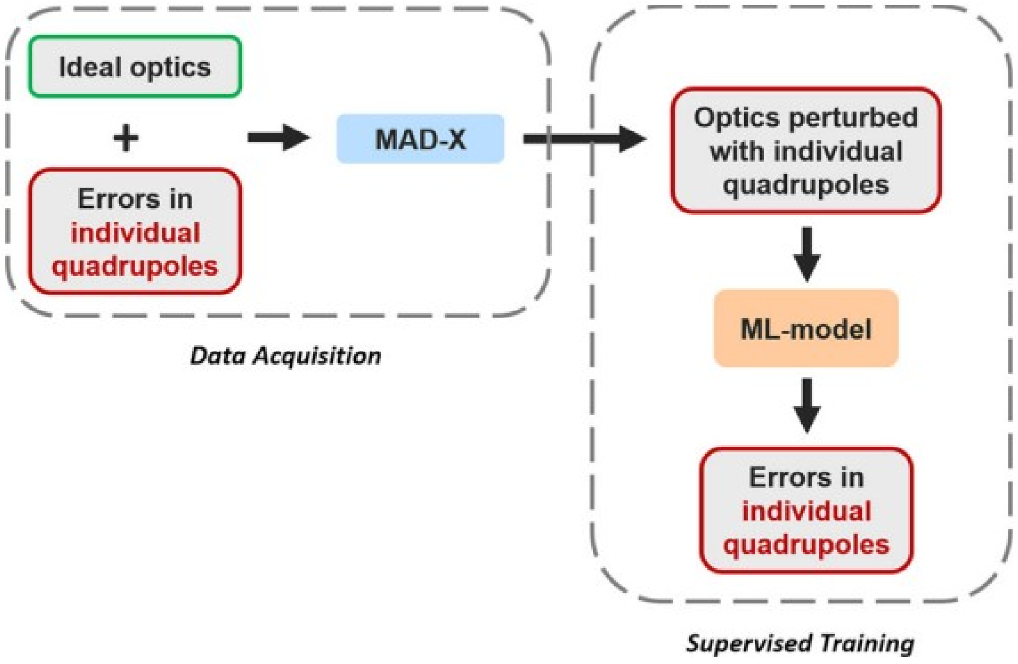


Fig 1. Data pipeline

Methods: ML Model

Ridge and Linear Regression:

$$Loss = Error(Y - \widehat{Y}) + \lambda \sum_{1}^{n} w_i^2$$

Least squares regression with L2 regularization

Bagging:

Training using ten different subsets of data and averaging the results.

This methods decreases variance of the model and overfitting

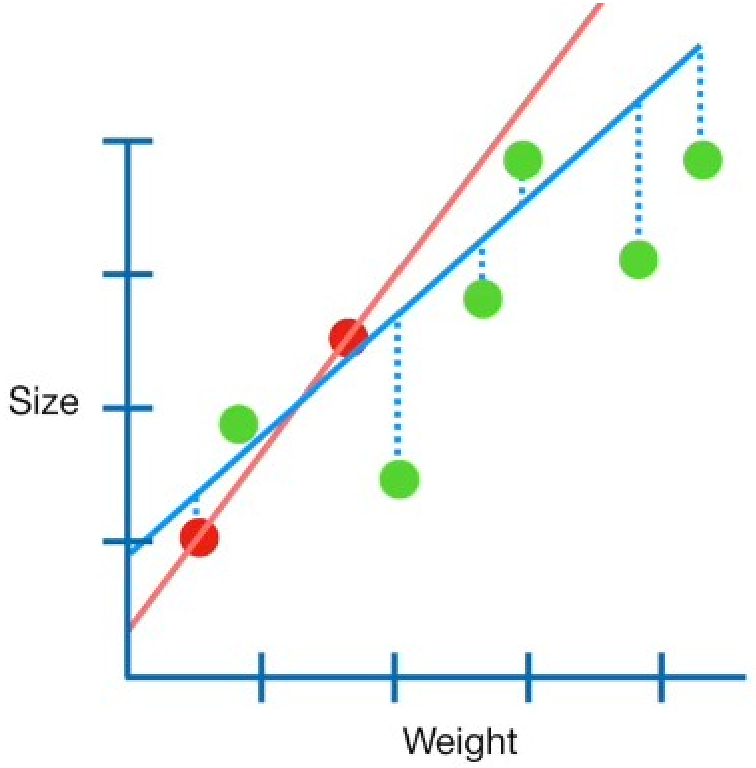


Fig 2. Example Ridge regression

Results: Error Simulation

Elena used 2016 40 CM optics so the whole MADX script had to be updated, repurposing error generation

- 80k Samples using 2023 30 CM optics, errors seem to be too big for this optics 15% of twiss failed!
- 80k Samples with 2023 45 CM, in this case 1-2% of twiss fail

All results shown are for 2023 30 CM optics

Results: Error Simulation

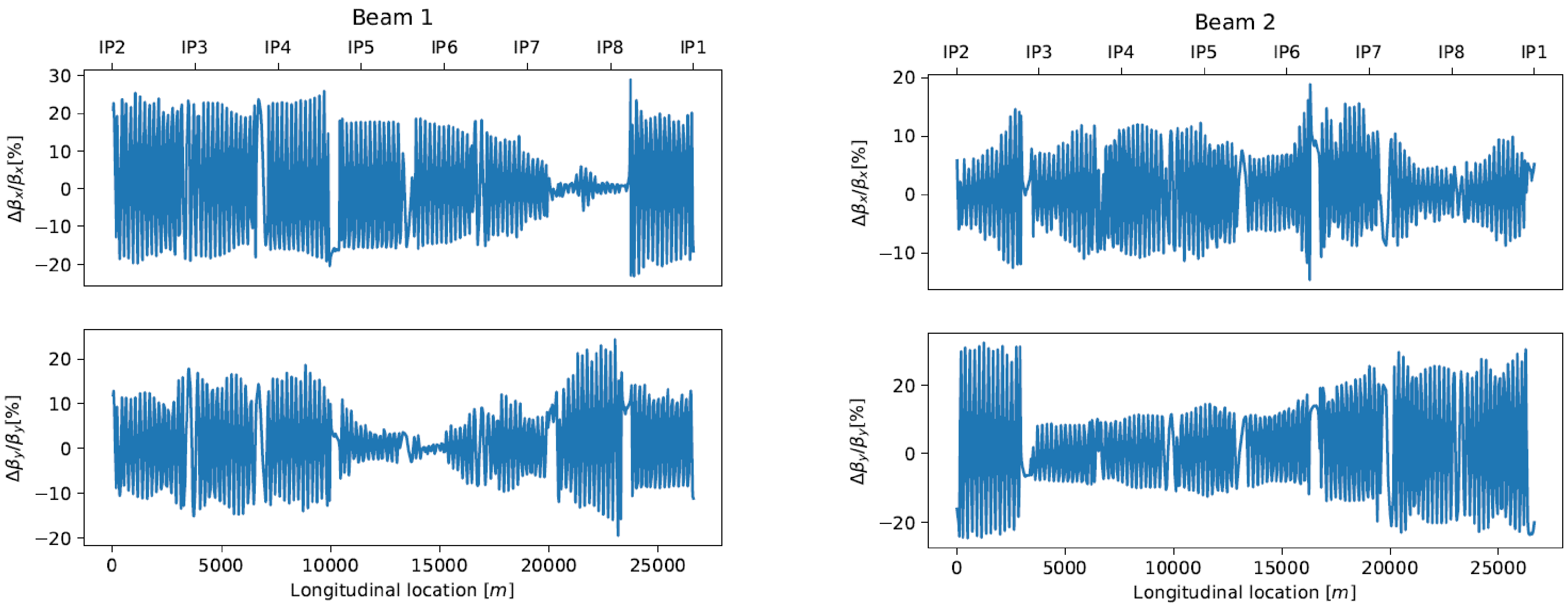
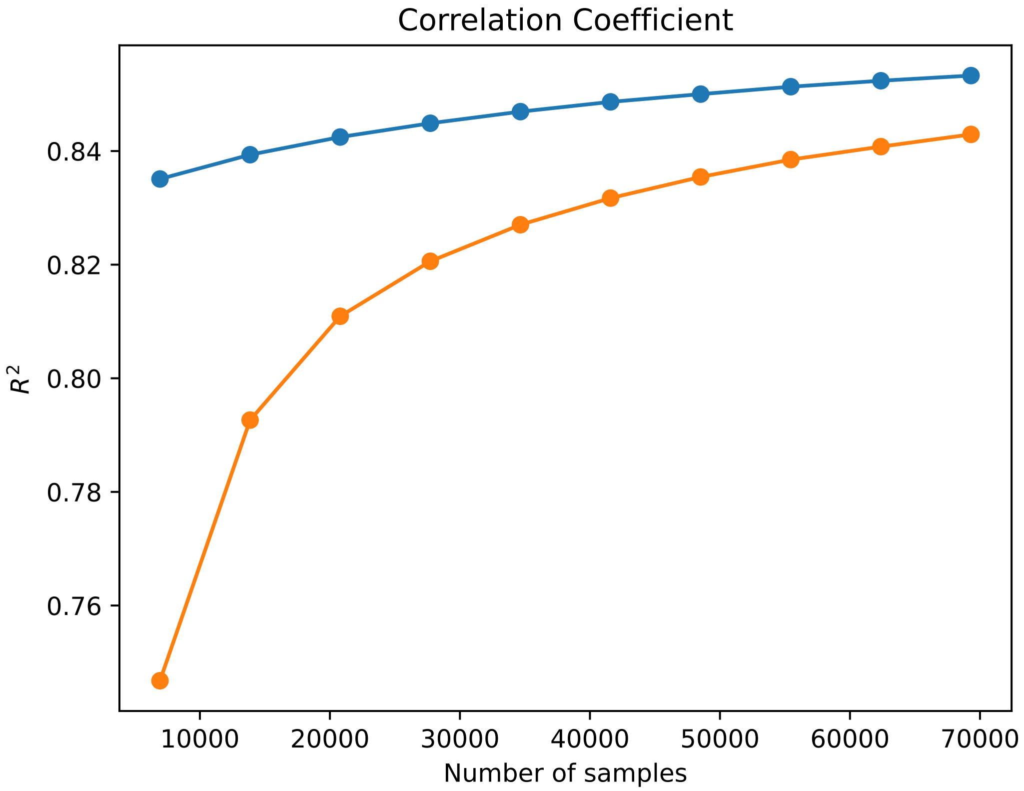


Fig 3. Example Beta Beating

Results: Model Training



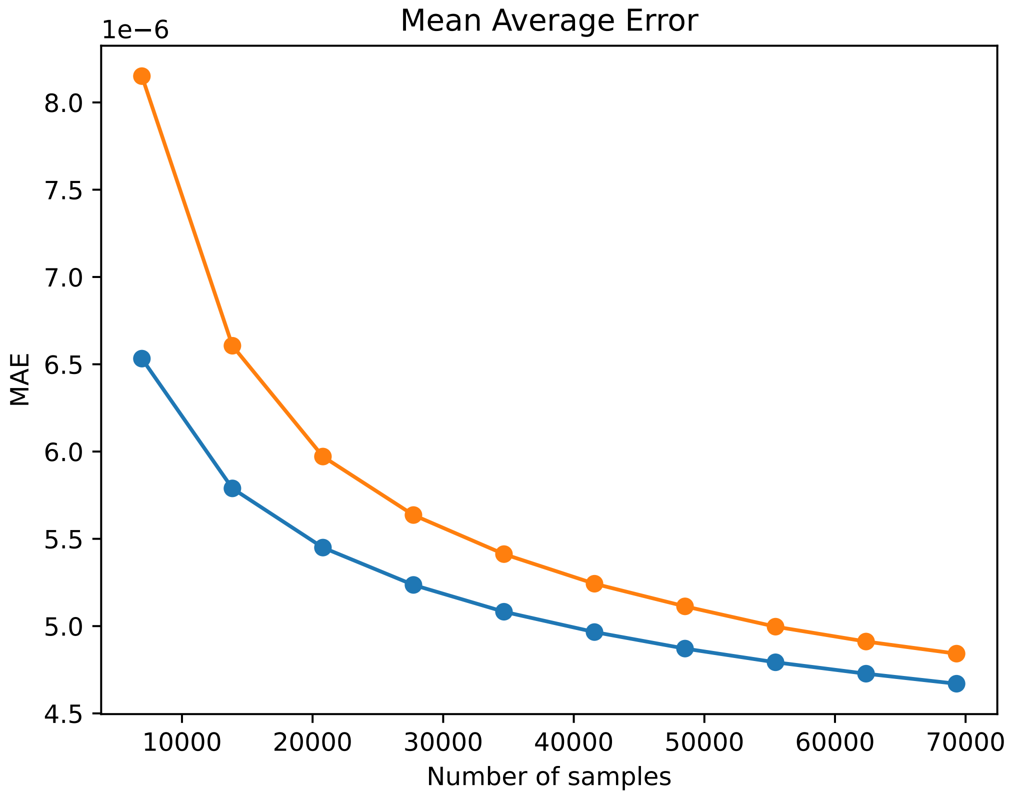


Fig 4. Training for different number of samples

Results: Model Training

Algorithm	Correlation Coefficient: R2	Mean Absolute Error: MAE
Ridge Regression	Train: 0.853 Test: 0.843	Train: 4.67e-06 Test: 4.83e-06
Linear Regression	Train: 0.888 **Test: 0.872**	Train: 3.45e-06 **Test: 3.69e-06**

Decision tree regression: Not worth considering

For 45CM optics results are similar

Results: Example prediction

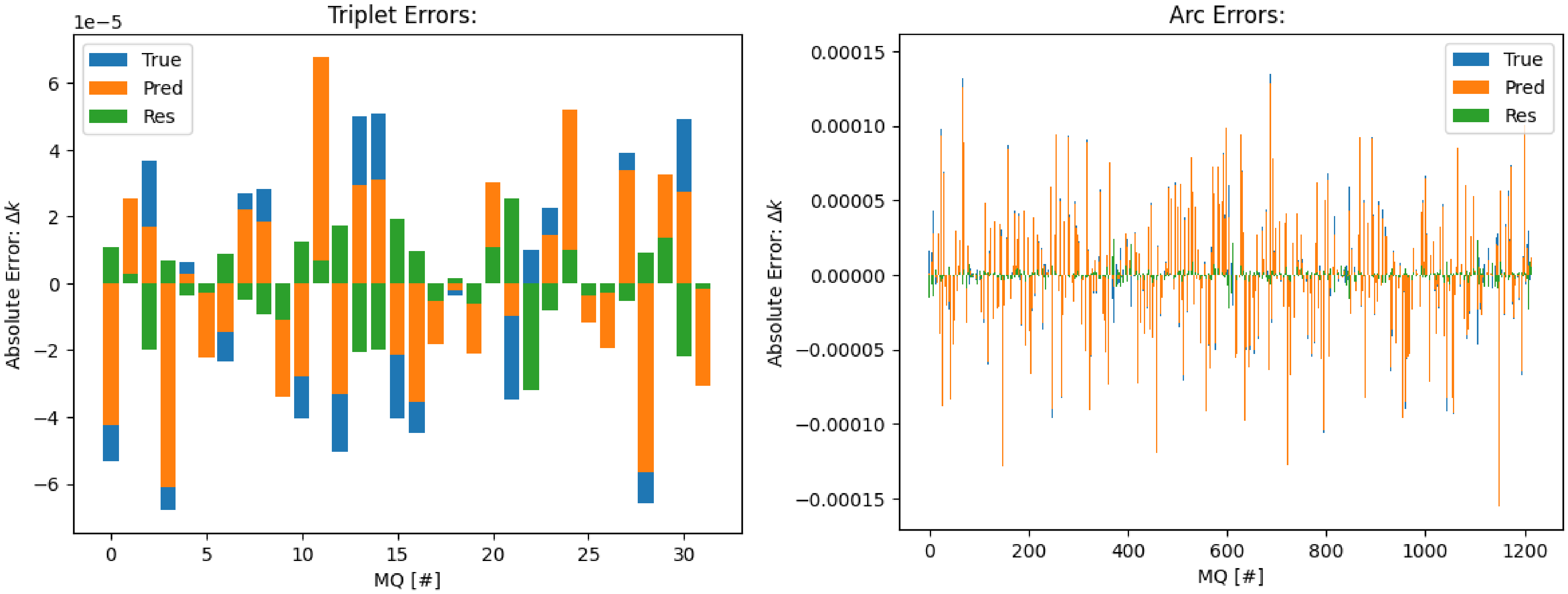
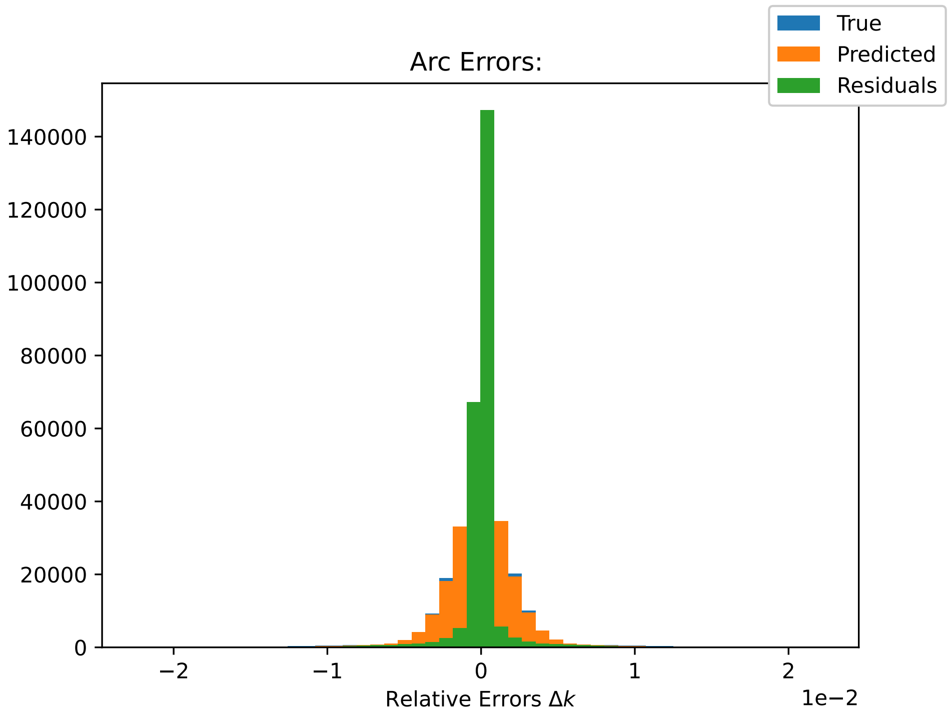


Fig 5. Quadrupole error prediction using linear reg. (random sample)

Results: Error Histogram Prediction



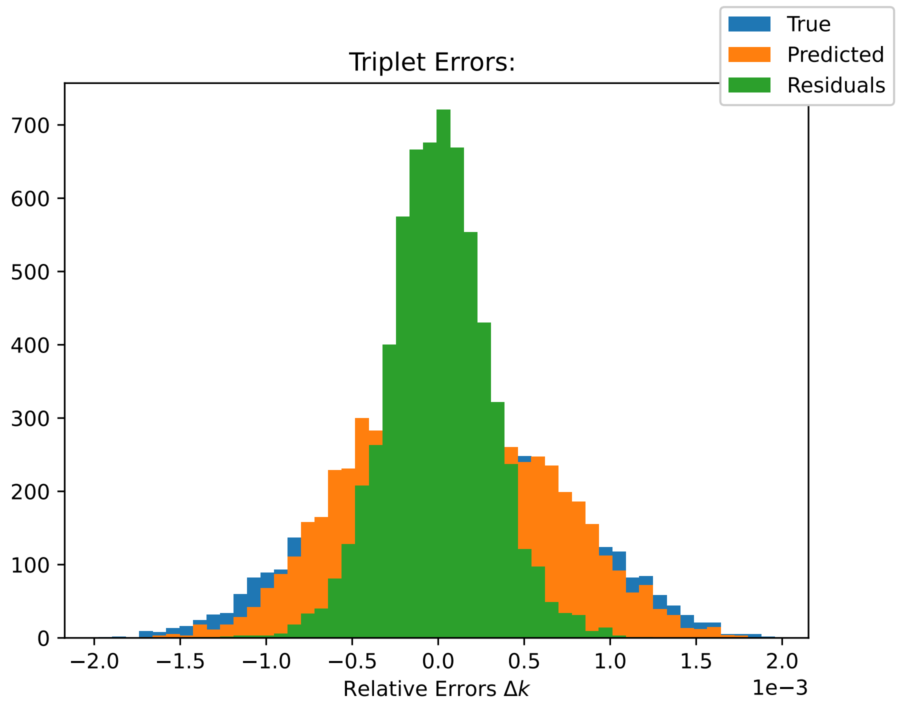
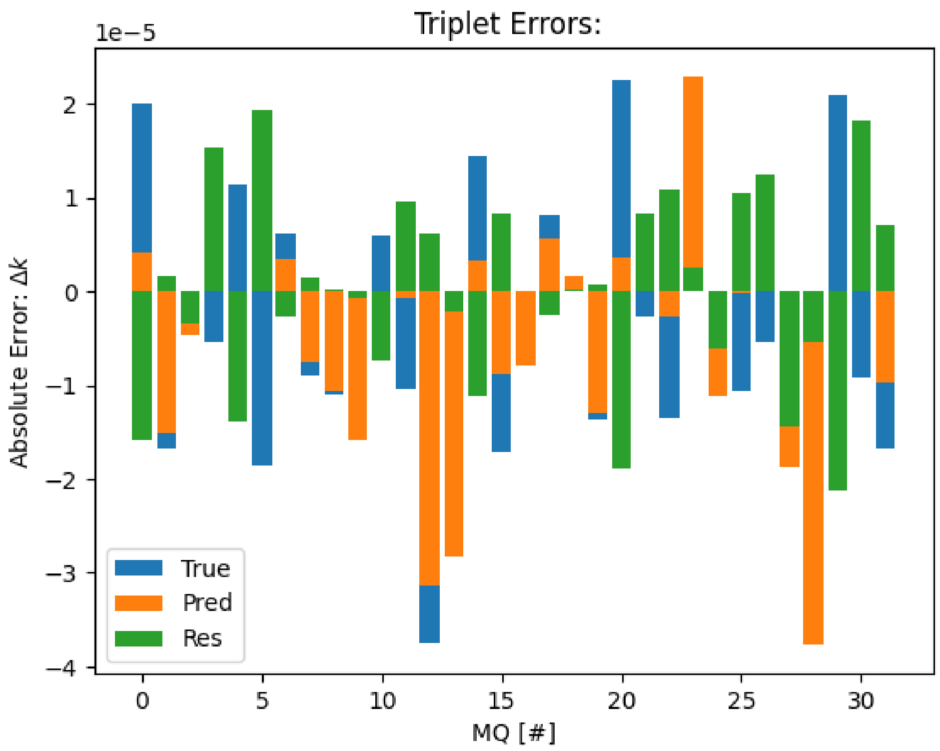


Fig 6. Relative error histograms for 200 test samples

Results: Error Histogram Prediction



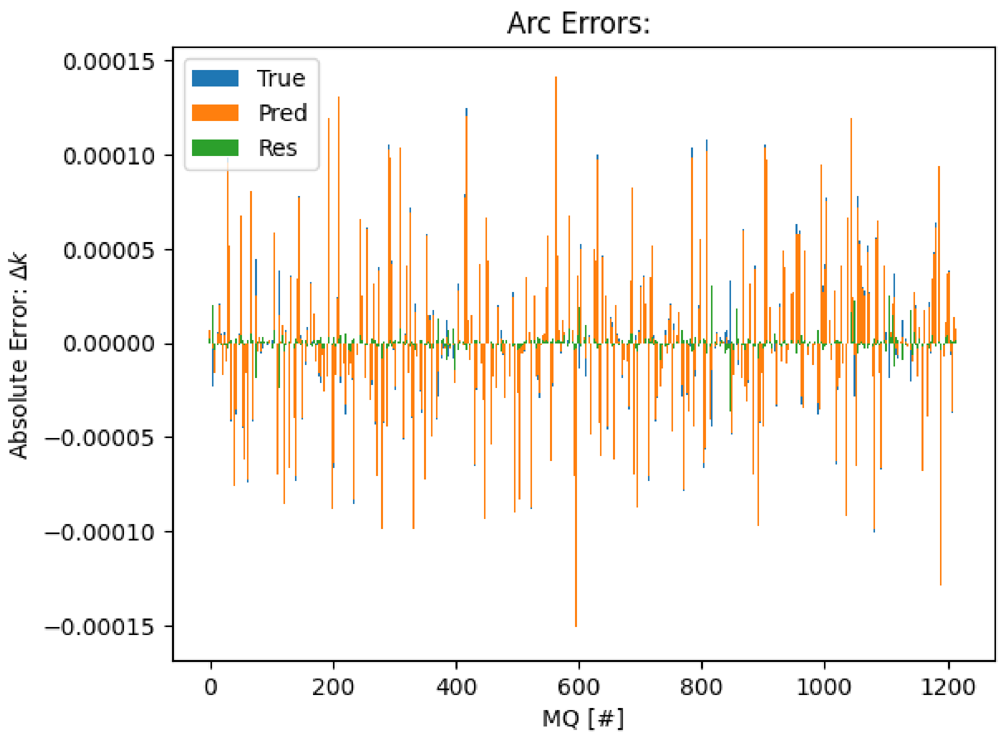


Fig 7. Example of worse performing sample (Triplets!)

Results: Performance for different magnets

Magnets	Correlation Coefficient: R2	Mean Absolute Error: MAE
Triplet	Train: 0.853 Test: 0.843	Train: 4.67e-06 Test: 4.83e-06
Arc + Triplet	Train: 0.888 **Test: 0.872**	Train: 3.45e-06 **Test: 3.69e-06**

Unexpected! R2 slightly worse or similar for triplet errors, expected better R2

MAE Is not a great indicator since error generation is different for triplet and arc

Conclusion

- Improvement in simulation with respect to 2016, maybe because of the decrease in degeneracy in the arc magnets.
- Linear regression shows better results than ridge
- Triplet errors prediction is more challenging than arc magnet error prediction in our case obtaining worse samples and worse R2
- Testing the model on real world data is the next step and most important!

Backup slides: Results for 45CM

Triplet quadrupole performance is worse than in arc. Maybe the errors generated for 40CM in 2016 are too big for 30CM. Testing for 45 CM optics.

Train: R2 = 0.895 MAE = 3.118e-06
Test: R2 = 0.884 MAE = 3.292e-06

R2 Test 0.872 for 30CM

Similar results, hypothesis is wrong.

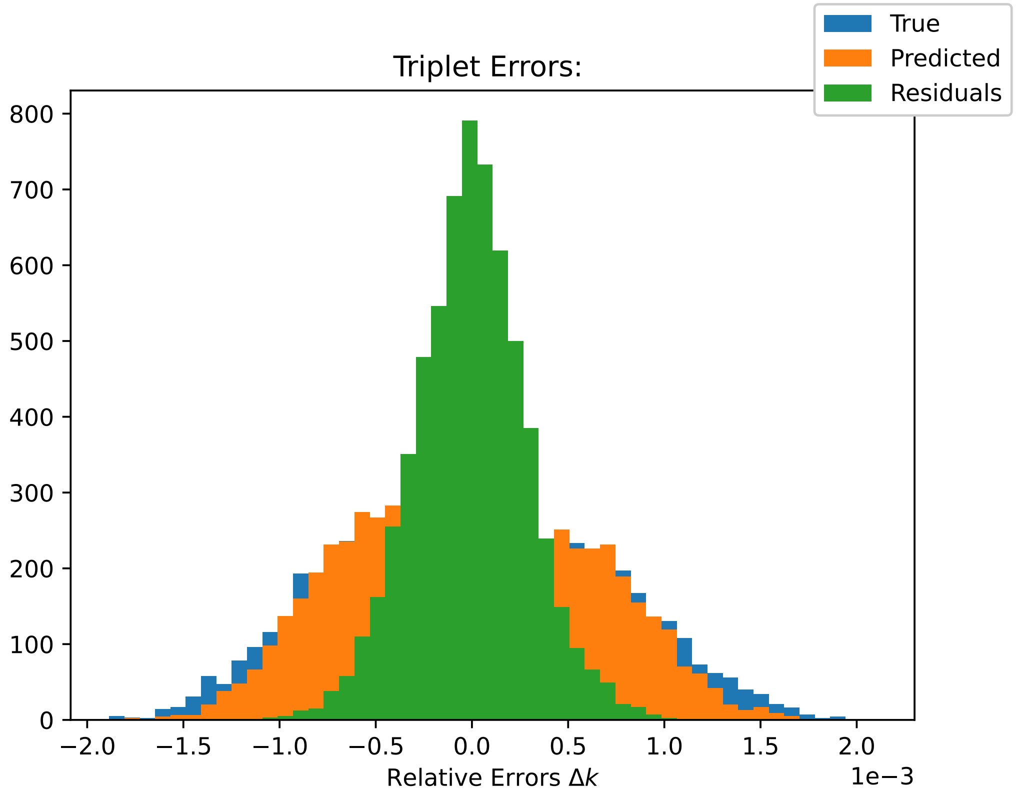


Fig 8. Quadrupole error histograms for 200 test samples

References

- *Fig 1. Data pipeline.* **"Supervised learning-based reconstruction of magnet errors in circular accelerators"** ***by E. Fol***, *2021*, *https://doi.org/10.1140/epjp/s13360-021-01348-5*
- *Fig 2. Example Ridge regression.* **"Regularization Part 1: Ridge (L2) Regression"** ***by J. Stamer***, *2018*, *https://www.youtube.com/watch?v=Q81RR3yKn30*

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