

Building an ML-enhanced Optics Calibration Workflow for SHMS

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Introduction

Scope:

- Apply ML techniques to improve the optics calibration workflow

Workforce:

- Undergrad project by Xiaoyang Zheng



Beijing Normal University → Berkeley visiting student → University of Tokyo

- Monthly-ish discussion and SLACK channel (R-SIDIS/optics)



Eric Fuchey  Eric Fuchey



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Provakar Datta  Provakar Datta



Shujie Li (you)  Shujie Li



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Zeke Wertz  Zeke Wertz

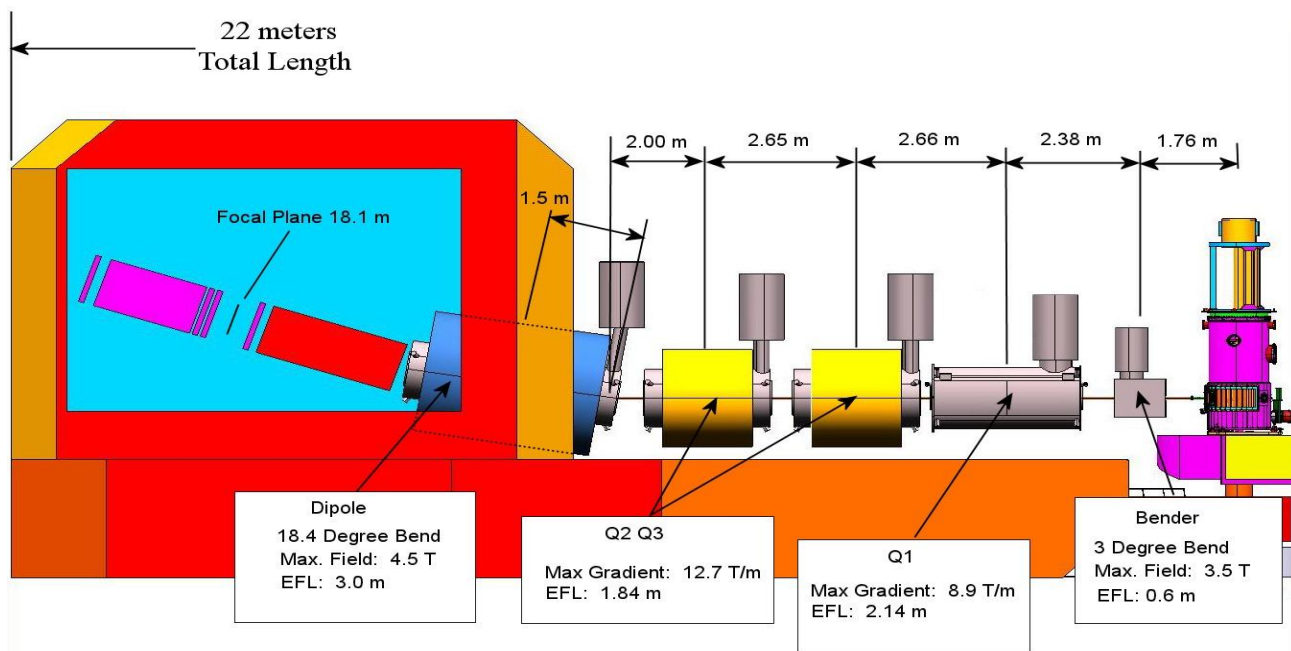
- Special thanks



Copilot

Define the Question

Particle path: Focal Plane ← QQQD ← (sieve) ← HB ← Target plane



Optics reconstruction: learning the inverse transport map from focal-plane tracks and spectrometer settings to target-plane kinematics;

Existing Knowledge

- **Simulation:** COSY transport and inverse matrices
- **Calibration data:**
 - geometric constraints on y_{tar} (foil) and y_{ptar} , x_{ptar} (sieve)
 - **Delta scan:** hydrogen elastic data to fix delta
- **Optics Matrix:** up to 5th order polynomial to connect 5 target plane observables \rightarrow 4 focal plane observables (+ the 5th variable from vertical beam position).

First order:

$$\begin{pmatrix} x_{fp} \\ x'_{fp} \\ y_{fp} \\ y'_{fp} \end{pmatrix} = \begin{pmatrix} -1.5 & 0.0 & 0.0 & 0.0 & 1.65 \\ -0.5 & -0.7 & 0.0 & 0.0 & 3.2 \\ 0.0 & 0.0 & -1.9 & -0.2 & -0.1 \\ 0.0 & 0.0 & -3.0 & -0.8 & 0.1 \end{pmatrix} \begin{pmatrix} x_{tar} \\ x'_{tar} \\ y_{tar} \\ y'_{tar} \\ \delta \end{pmatrix}$$

5th order polynomial:

$$x'_{tar} = \sum_{ijklm} X'_{ijklm} x_{fp}^i x'_{fp}{}^j y_{fp}^k y'_{fp}{}^l x_{tar}^m$$

$$y_{tar} = \sum_{ijklm} Y_{ijklm} x_{fp}^i x'_{fp}{}^j y_{fp}^k y'_{fp}{}^l x_{tar}^m$$

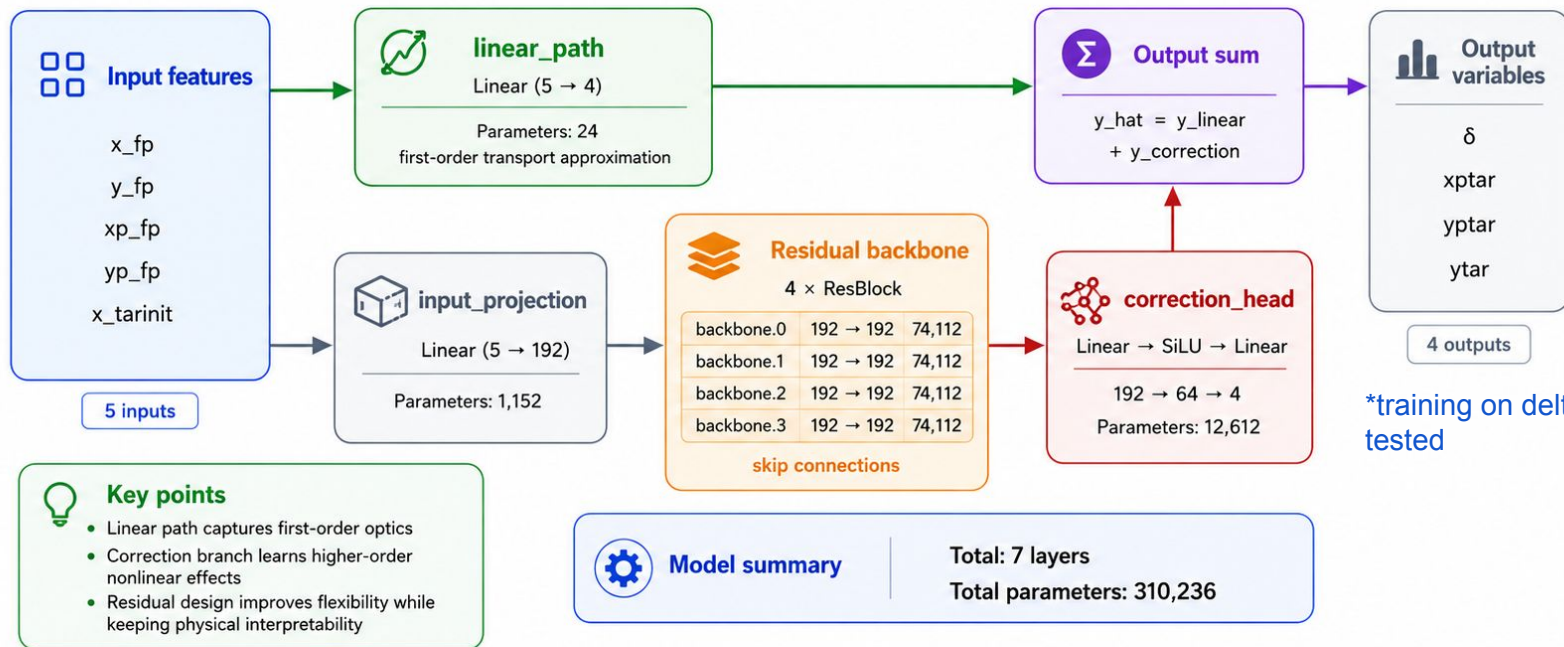
$$y'_{tar} = \sum_{ijklm} Y'_{ijklm} x_{fp}^i x'_{fp}{}^j y_{fp}^k y'_{fp}{}^l x_{tar}^m$$

$$\delta_{tar} = \sum_{ijklm} D_{ijklm} x_{fp}^i x'_{fp}{}^j y_{fp}^k y'_{fp}{}^l x_{tar}^m$$

ML-enhanced Workflow

- **Simulation** → use MC data for pre-training
- **Calibration data** → weak labels to provide geometric constraints for fine-tuning
- **Optics Matrix** → use as a benchmark, introduce an alternative **residual MLP** (Multilayer Perceptron) model

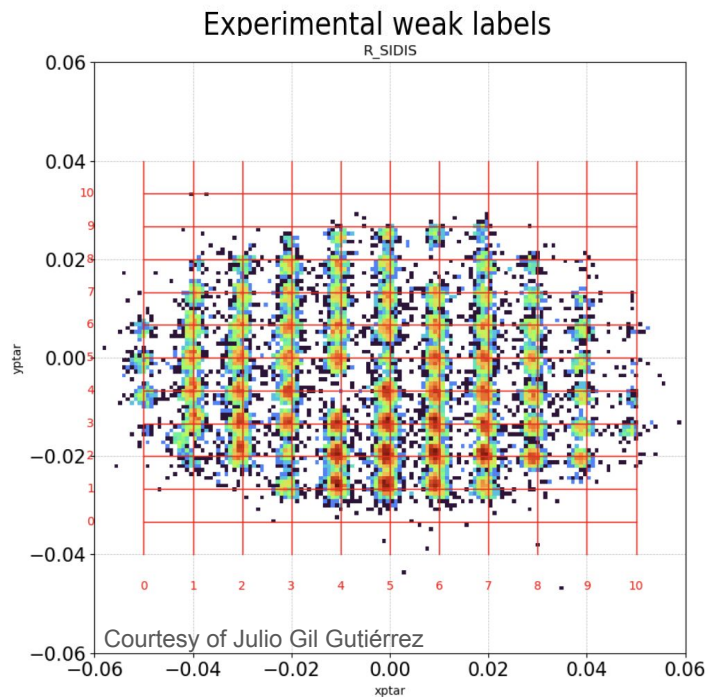
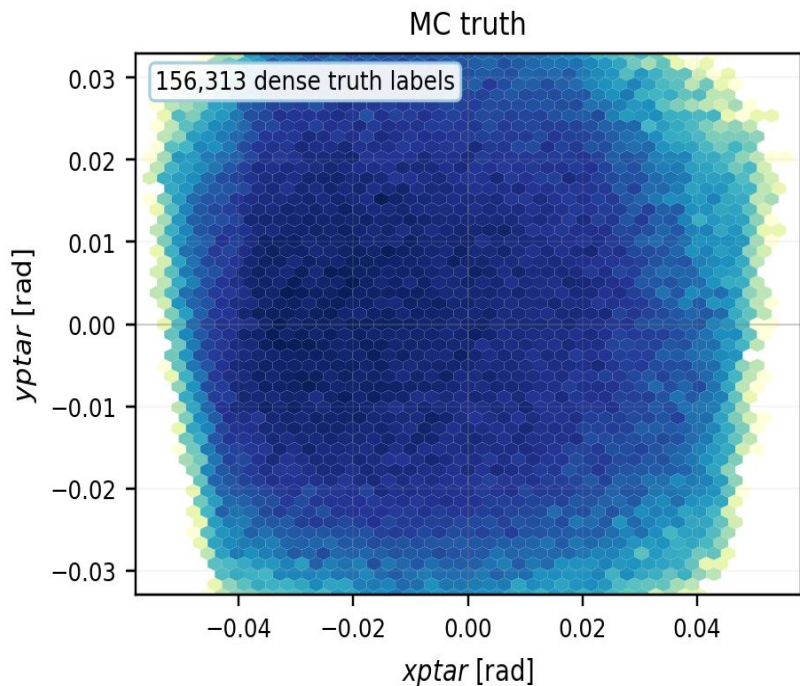
Linear transport path + nonlinear correction branch



Two-stage Training

Stage 1: pre-train model with MC data:

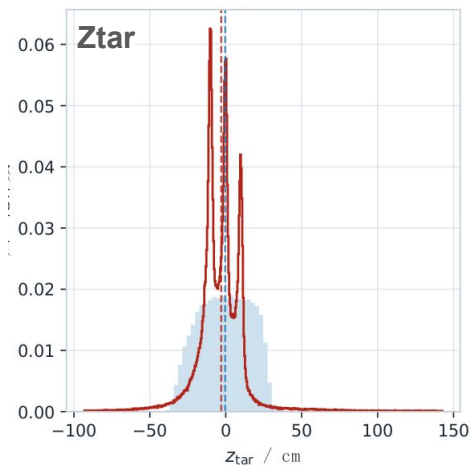
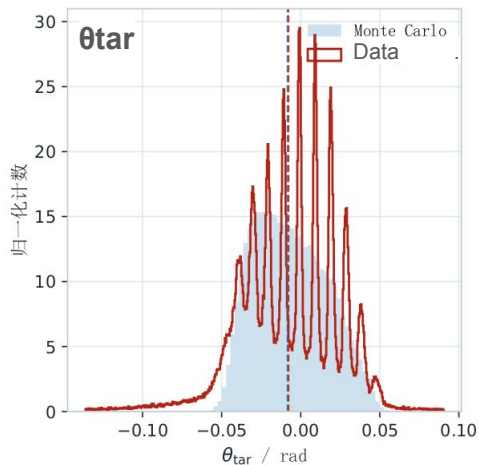
- 4 focal + 1 beam variables \rightarrow 4 target variables
- Continuous coverage of phase space, dense label of truth info but imperfect reality (v.s. sieve data) \rightarrow smooth global optics map to be **transferred** to real data.



Two-stage Training

Stage 2: weak-label tuning with optics foil + sieve data

- Real but discrete, geometric constraints (sieve hole position) not truth value at target plane



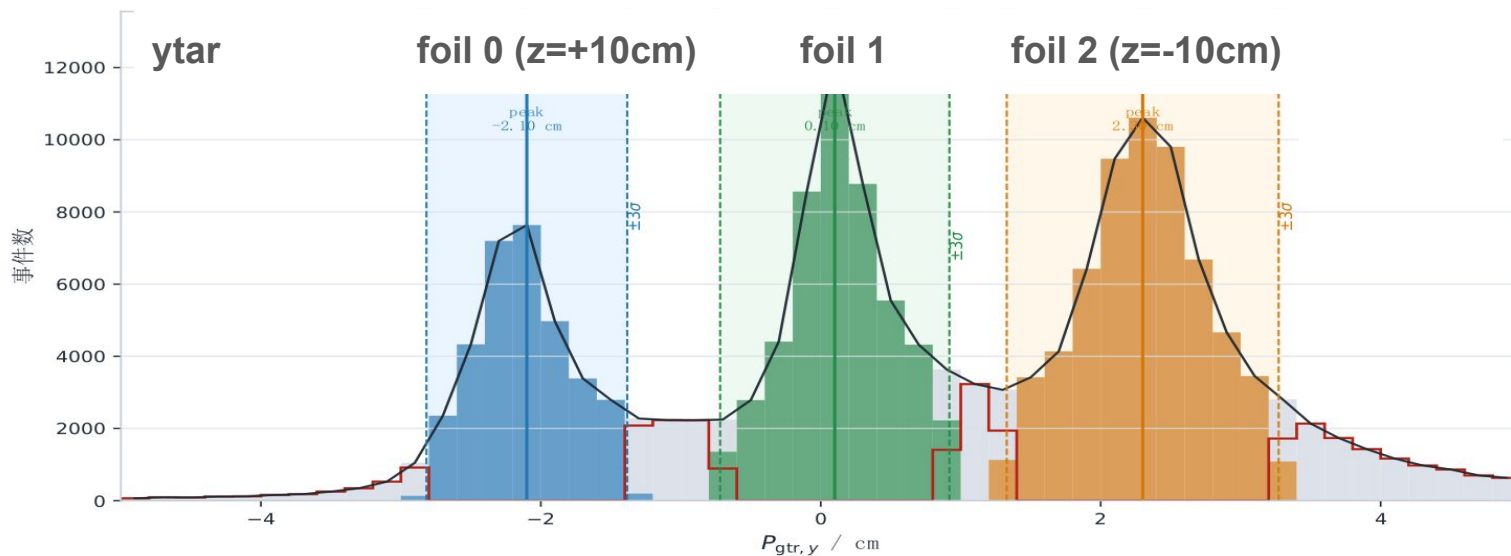
- Deadzone Huber Loss to provide robust penalty considering the finite the sieve hole size

$$L_{\delta}(r) = \begin{cases} \frac{1}{2}r^2 & \text{当 } |r| \leq \delta \\ \delta \cdot (|r| - \frac{1}{2}\delta) & \text{当 } |r| > \delta \end{cases}$$

Automated Data Labeling

1. Peak search and foil separation

- **Cuts:** $\text{etracknorm} > .8$ && $\text{sumnpe} > 6$ && $\text{delta} > -15$ && $\text{delta} < 24$



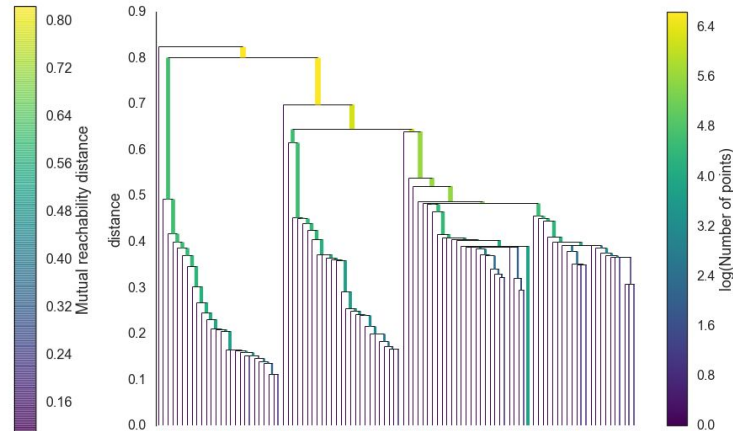
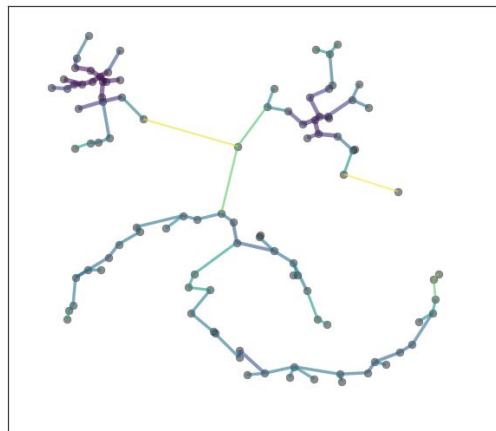
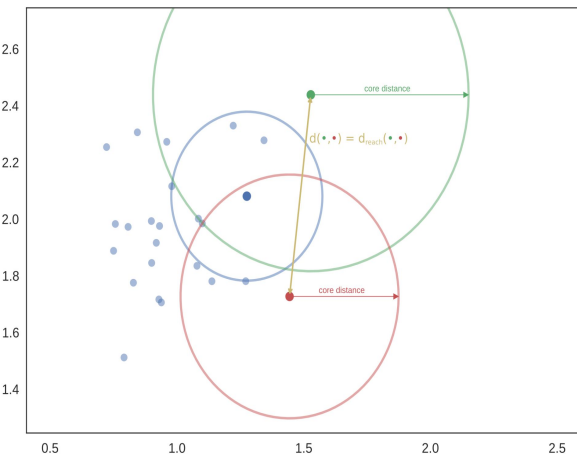
Automated Data Labeling

2. Sieve data clustering with [HDBSCAN](#):

Hierarchical Density-Based Spatial Clustering of Applications with Noise, Campello, R.J.G.B., Moulavi, D., Sander, J. (2013)

- Handle both central and edge clusters well despite big change in density

Calculate core distance → build minimum spanning tree → form the cluster hierarchy

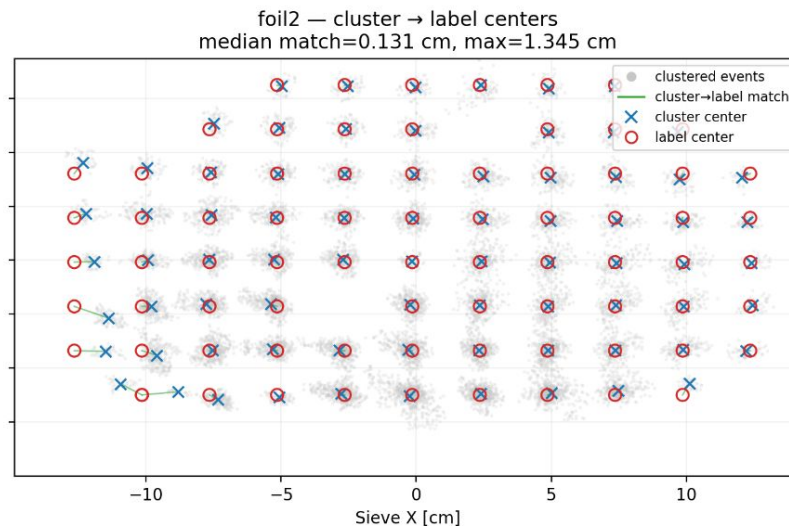
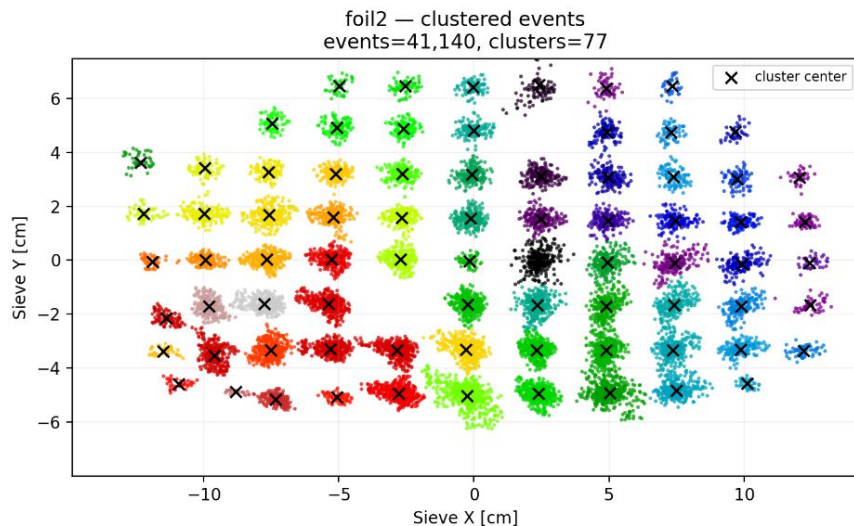


Automated Data Labeling

Package is available on [github](#) (work in progress)

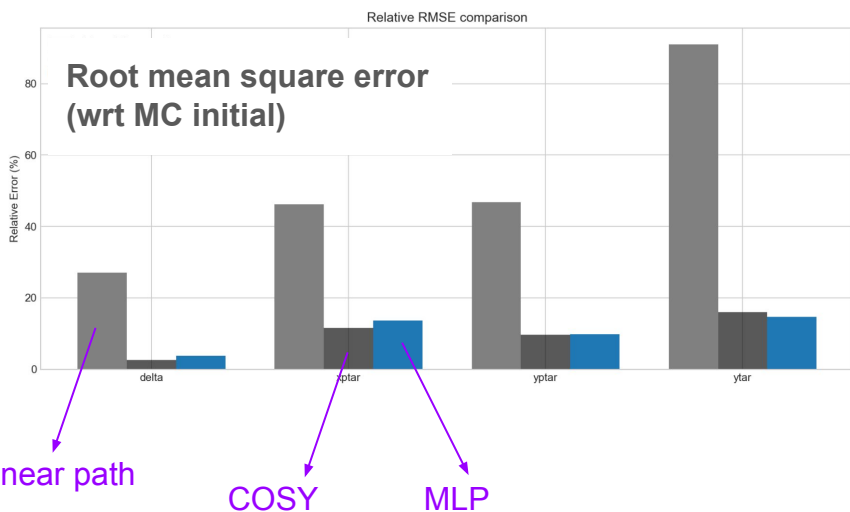
2. Label the data

- Compute center point of each cluster
- Align cluster center with sieve hole center
- Support optional manual QA/corrections
- Weighting with cluster size

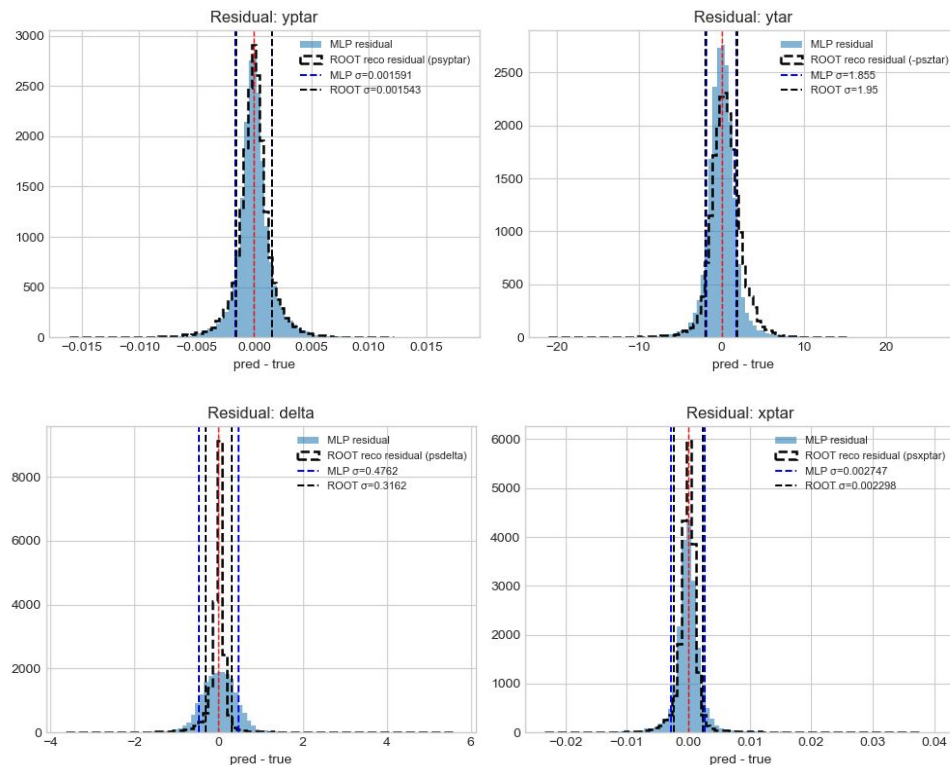


Performance

- Pre-training:
 - 156k MC events, 32 epoch
 - 8:2 training/validation
 - MLP result comparable to COSY



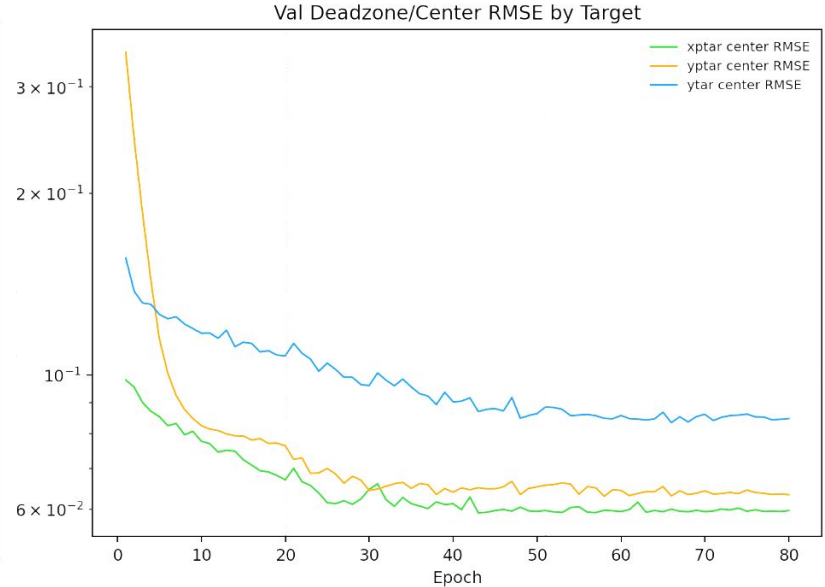
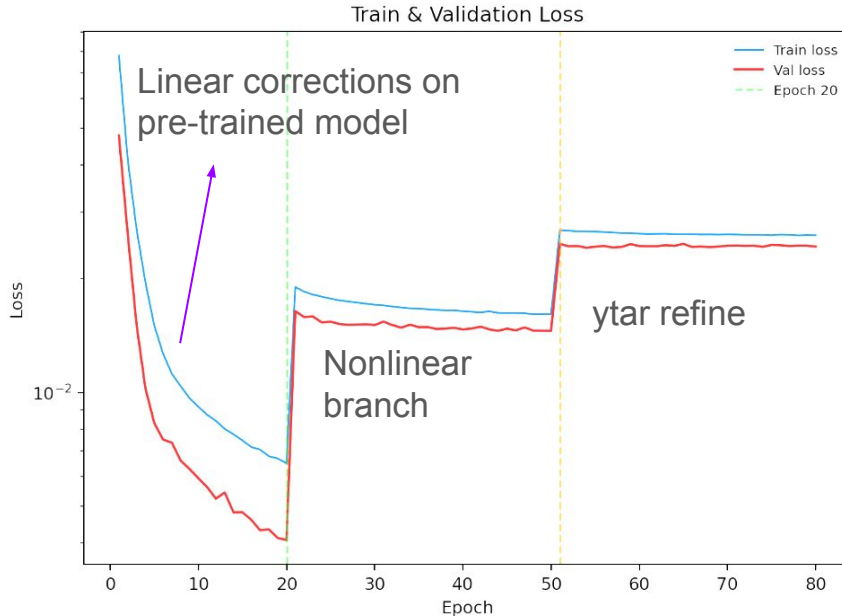
Residuals on target variables



Performance

- Stage 2:

- R-SIDIS run 25521 SHMS with optics target, 100k events, holdout 5 holes for validation. No data for **delta** training
- RTX 4060 Ti (16 GB)
- Cost per epoch: 1.1s (head) / 1.3s (corr) / 2.4s (refine)
- Loss function jumps at different phase, while validation performance steadily improving



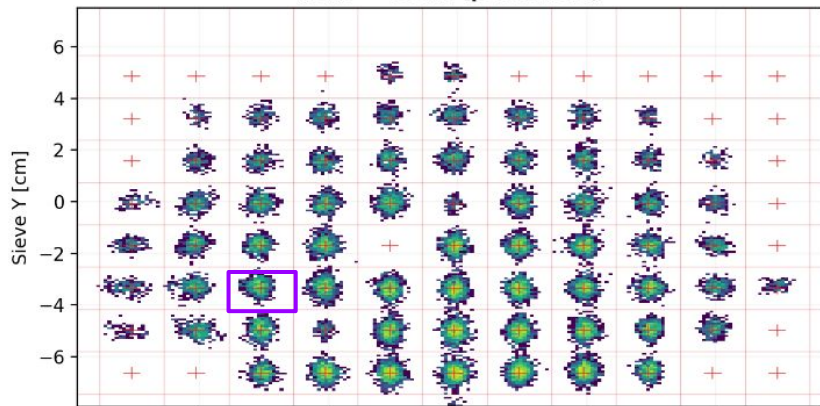
Performance

Left: MLP results.

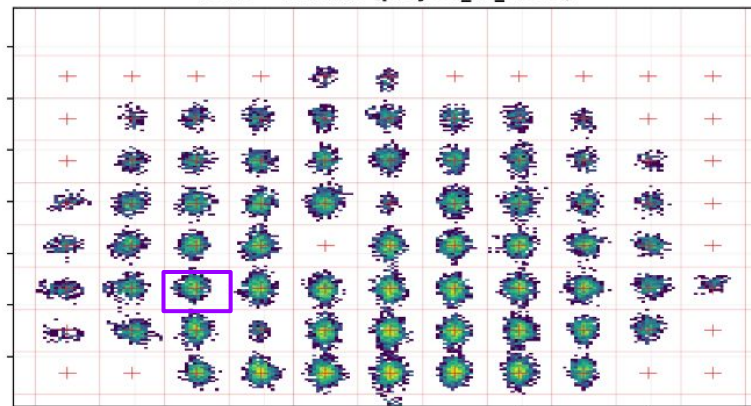
Right: optics matrix.

 : holdout holes

foil0 — v3 NN (per-foil tol)



foil0 — HCANA (project_to_sieve)



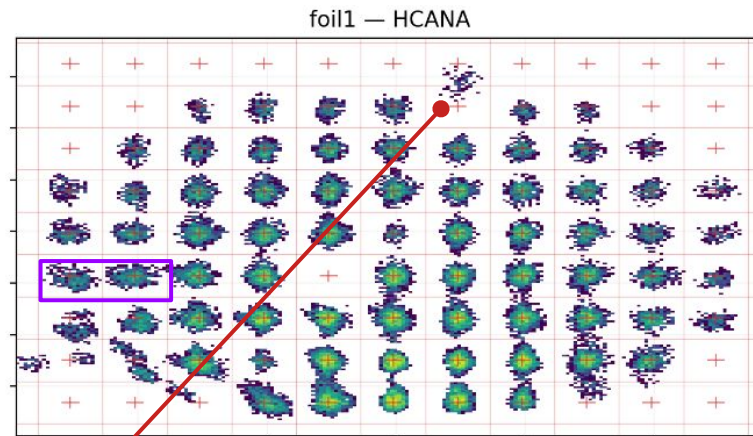
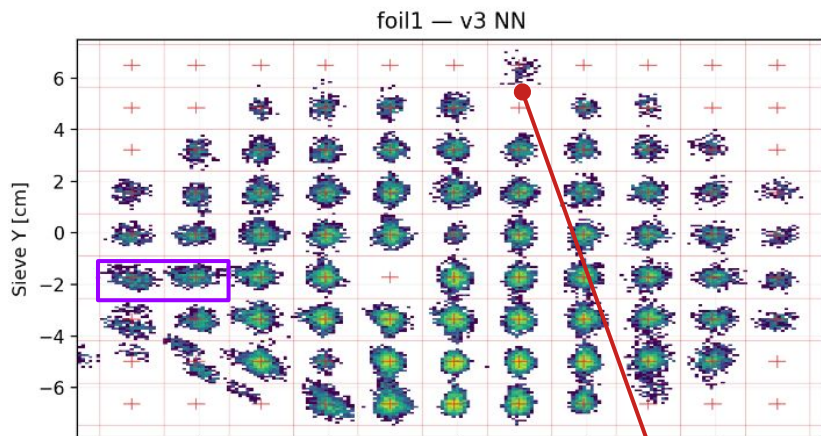
Foil 0 ($z=10\text{cm}$): very consistent performance

Performance

Left: MLP results.

Right: optics matrix.

 : holdout holes



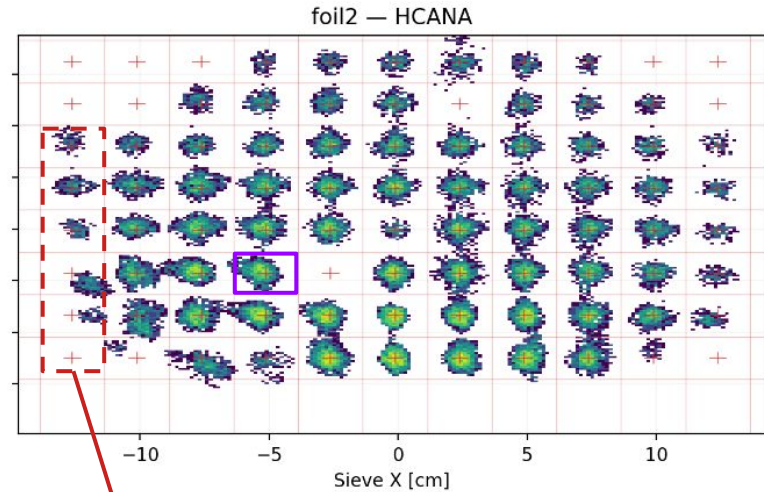
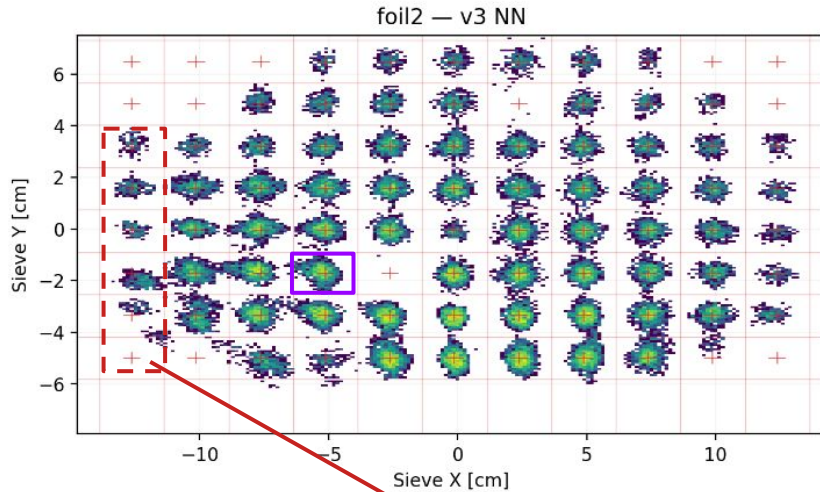
Foil 1 ($z=0$ cm): slightly improved y-span

Performance

Left: MLP results.

Right: optics matrix.

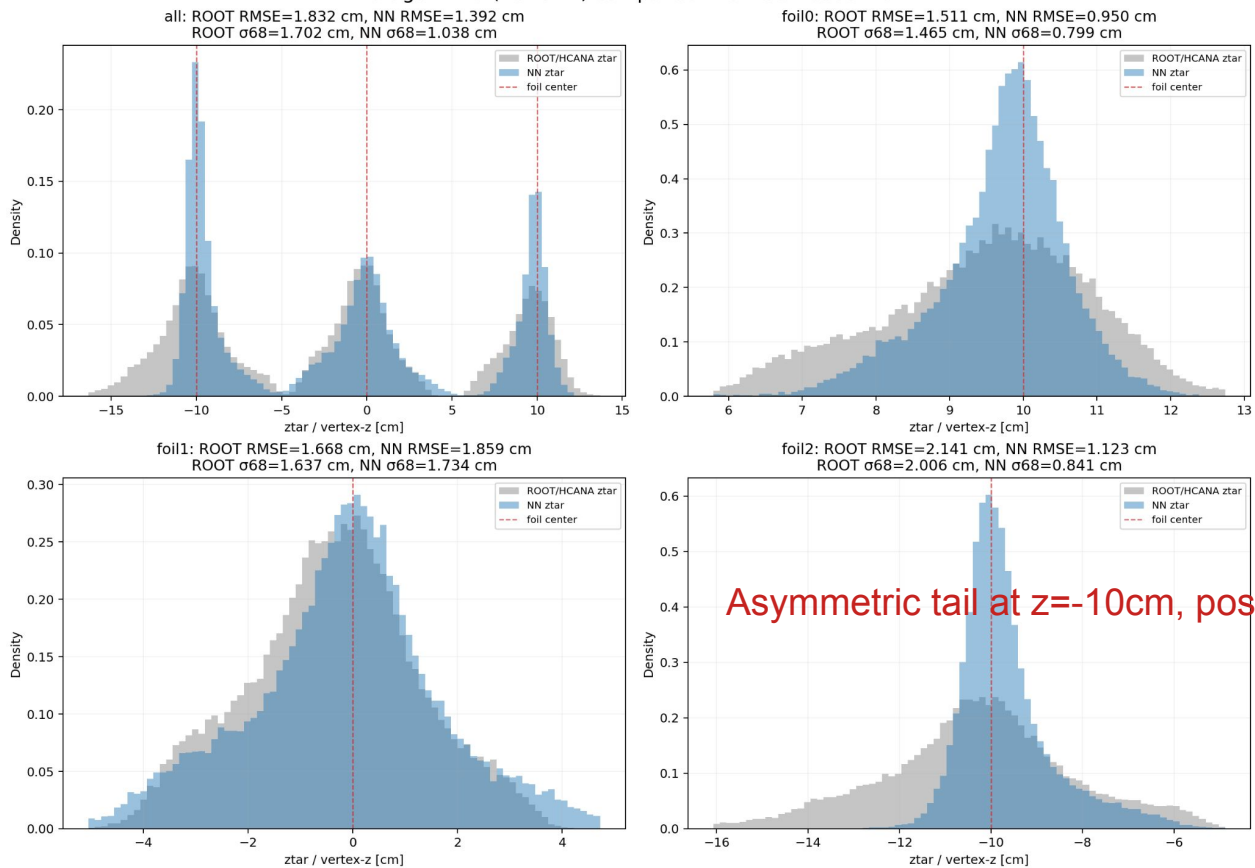
 : holdout holes



Foil 2 ($z=-10$ cm): noticeable better distortion correction at lower left corner, but clusters still have tails.

Performance

Stage-2 ztar(vertex-z) comparison vs ROOT baseline



Summary

- We demonstrated an **ML-enhanced optics reconstruction workflow** that:
 - Follows the logic of established procedure, while providing
 - Automated sieve data labeling tool
 - Two-stage transfer-learning framework with Residual MLP for focal \rightarrow target plane mapping instead of 5th order polynomial fit
 - Shows promising performance on sieve and foil reconstruction.
- **Next step:**
 - Rigorous validation/stability test, and understand ztar behaviors.
 - Add delta scan data
 - Benchmark with popular models from HEP community, before considering larger models
 - Consider approaches that deviates from traditional optics workflow e.g. clustering on focal plane?
- **Long term goal:**
 - A largely-automated optics reconstruction package for (SHMS, HMS, HRS...) that can provide reliable performance at **extended phase space** coverage and **extreme kinematics**.

Thanks!

```
sieve y=-0.019*psdelta+0.00019*psdelta*psdelta+(138.0+75.0)*psyptar+psytar +  
40.0*(-0.00052*psdelta+0.000052*psdelta**2+psyptar) ## horizontal
```

```
Sieve x=fry+psxptar*253.0 #vertical, along target x
```