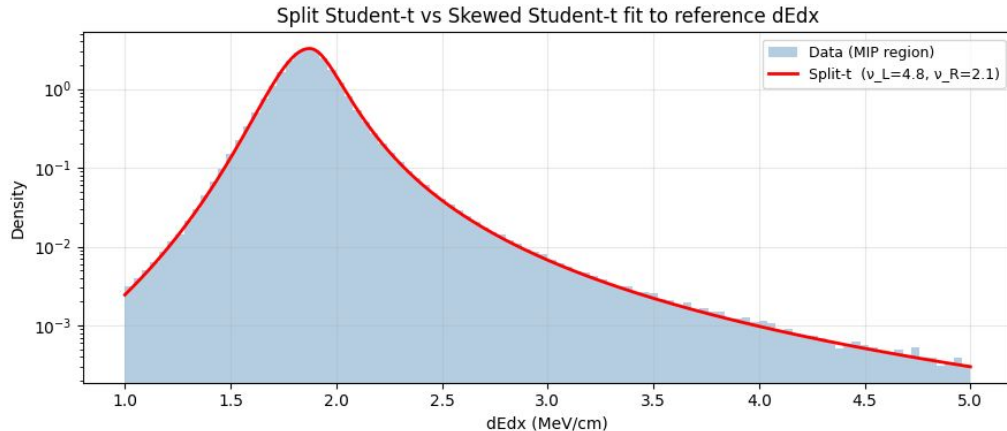


# LArTPC calibration with real-like fake-data

- How to do calibration when you don't know the underlying truth?
- Through-going cosmic muons will be MIPs. Their energy deposition rate in the detector stays in average constant
- Taking only the MPV is not enough, e.g. Ab/kb degeneracies
- Randomly drawing from the distribution is even worse



→ Treating the track parameters as nuisance parameters in the fit: they are co-optimized with the calibration parameters

# The setup

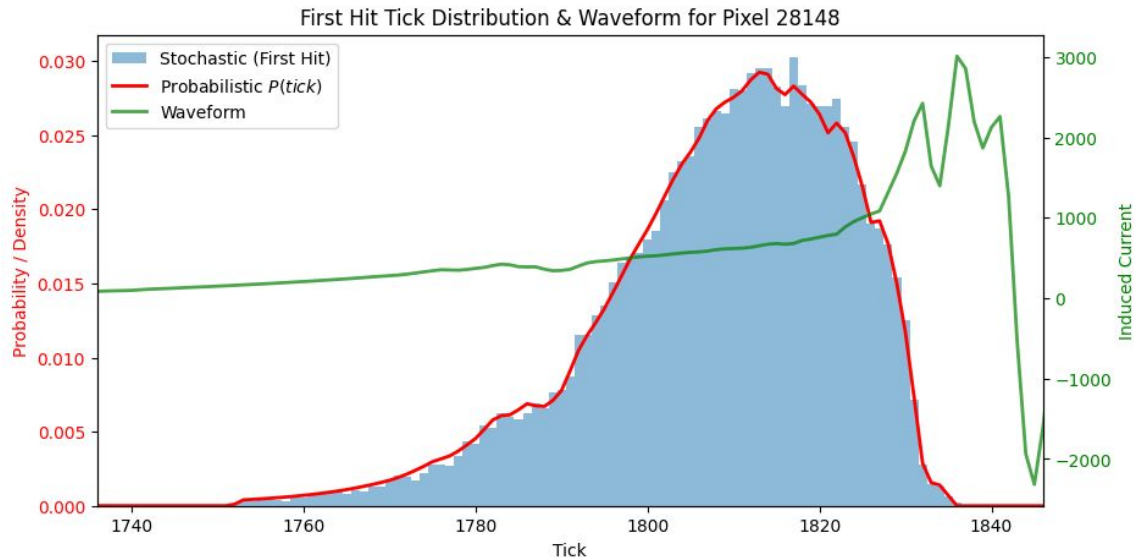
## Target:

- Target calib. params
- True  $dE dx$  depositions
- Stochastic draw of noise

## Fitted guess:

- Fitted calib. params
- Fitted  $dE dx$
- Probabilistic estimate of output given noise level

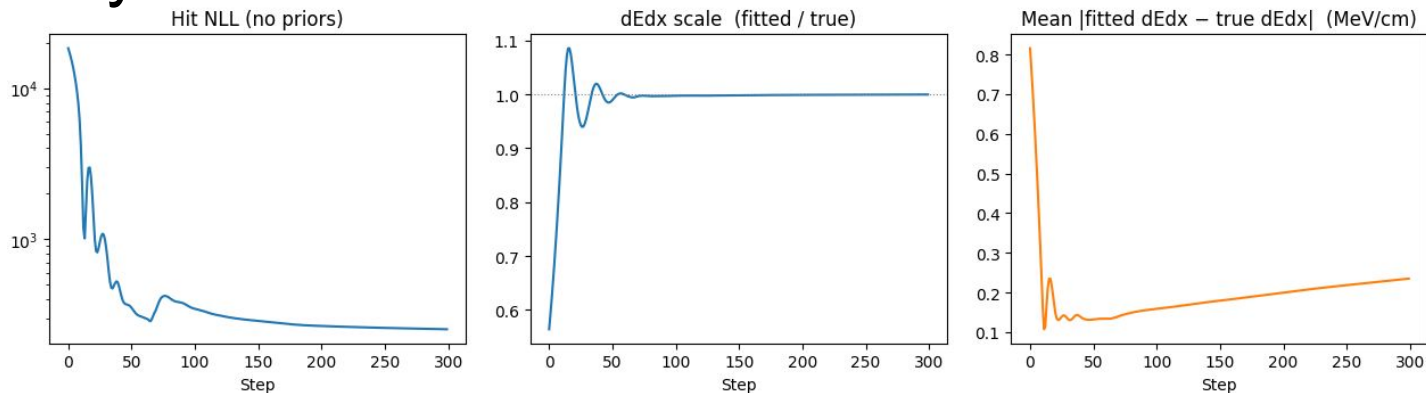
$$\mathcal{L}(\theta) = \sum_{p \in \text{pixels}} \int \lambda_p(t), dt - \sum_{i \in \text{hits}} \max \left[ \log \left( \lambda_{p_i}(t_i) \cdot \frac{1}{\sqrt{2\pi\sigma_q^2}} e^{-\frac{(q_i - \hat{q}_{p_i}(t_i))^2}{2\sigma_q^2}} \right), \log \epsilon \right]_2$$



## Loss: Poisson Point Process (PPP)

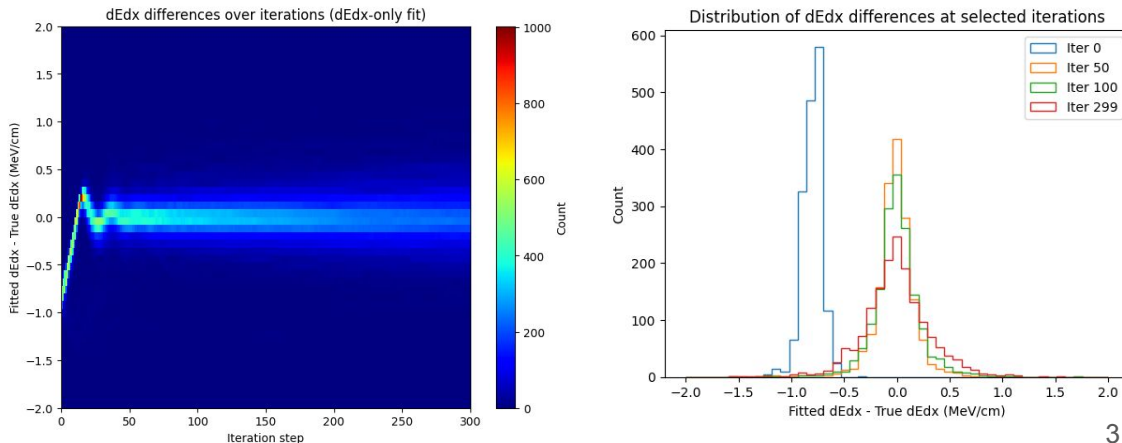
# Fitting $dEdx$ only

$dEdx$ -only fit — physics params fixed at nominal, no priors

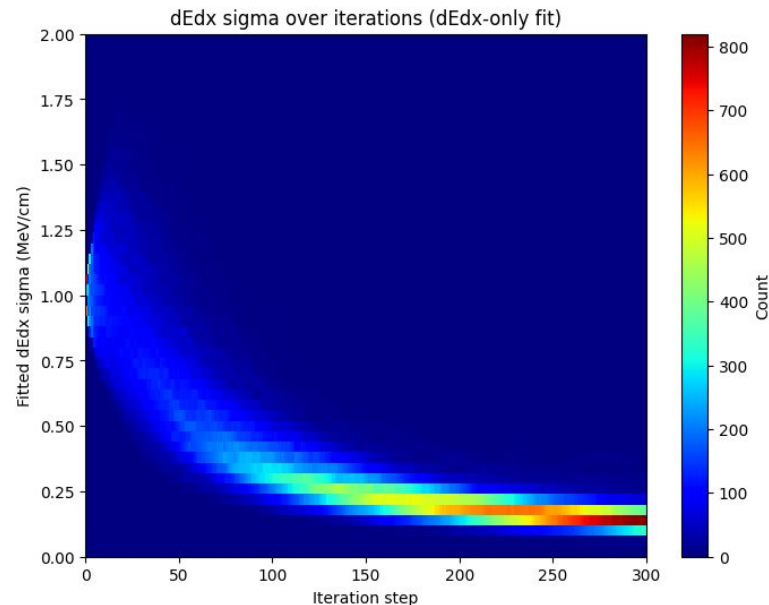
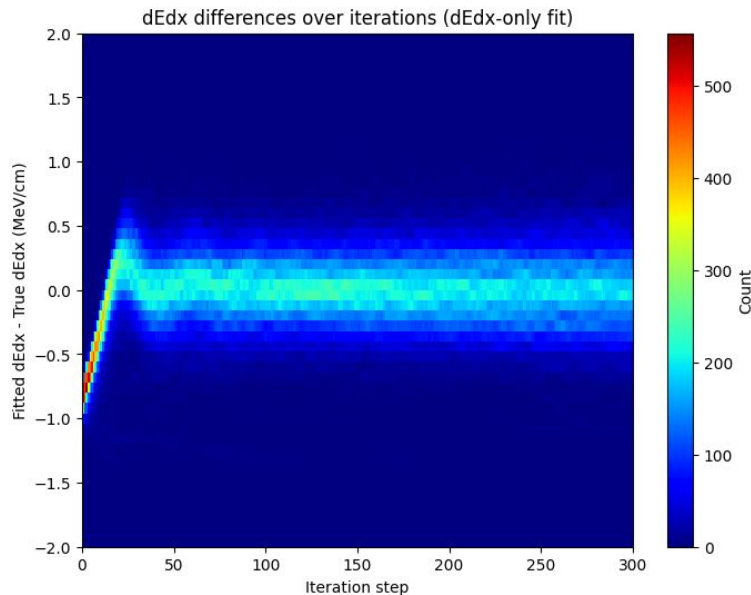


Fitting the chopped segments  $dEdx$ : works well but overfitting to fit noise as we continue the fit.

In practice cheating with lo-hi compensations on neighboring segments



# Fitting $dE dx$ only: adding some noise to prevent over-fitting



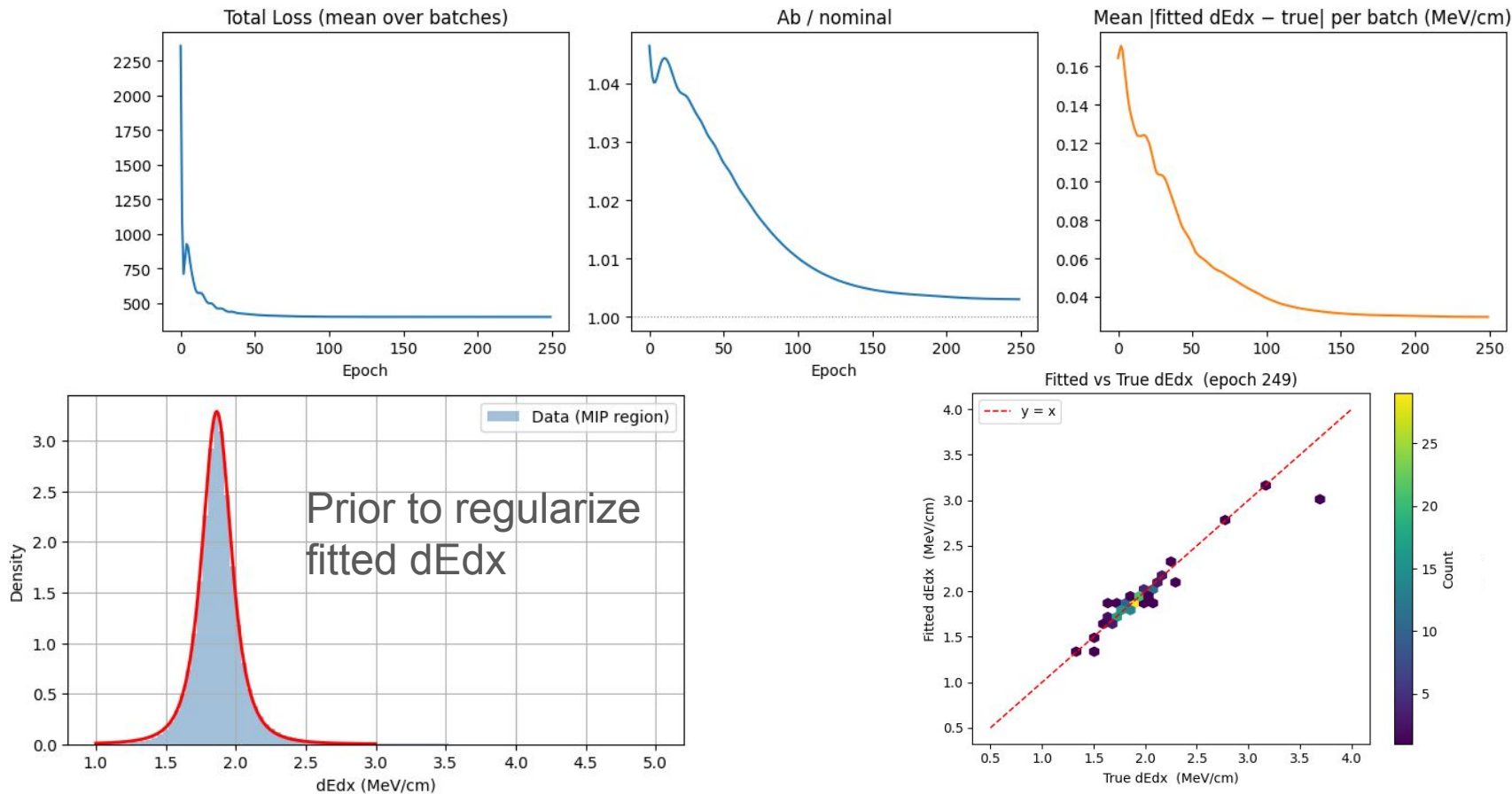
Adding random noise along the fit to prevent overfitting:

$$\frac{dE}{dx} \rightarrow \mu + \sigma \mathcal{N}(0, 1)$$
$$\mathcal{L} \rightarrow \mathcal{L} - \sum \log \sigma$$

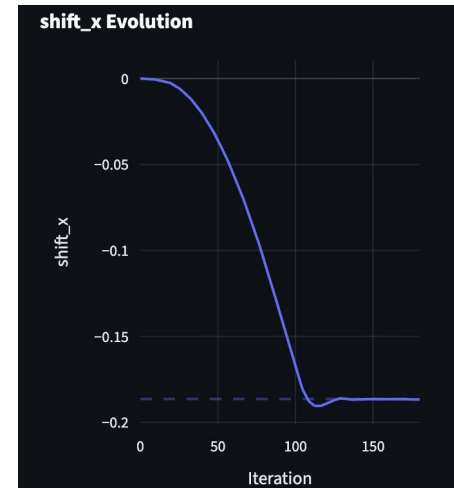
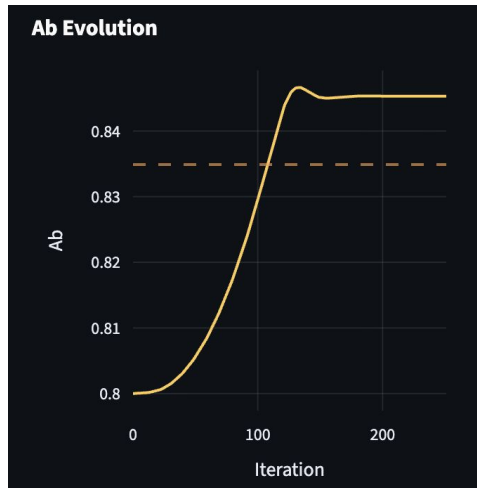
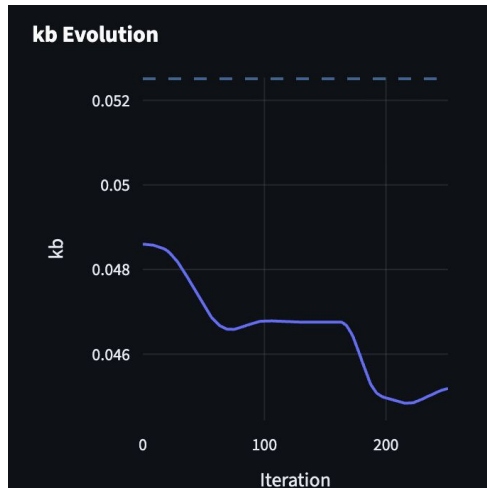
*Actually, only fitting the original bigger segments also solves the issue and is easier...*

# Joint calibration/dEdx fit

Multi-batch joint fit: Ab + per-batch dEdx (sigmoid param)

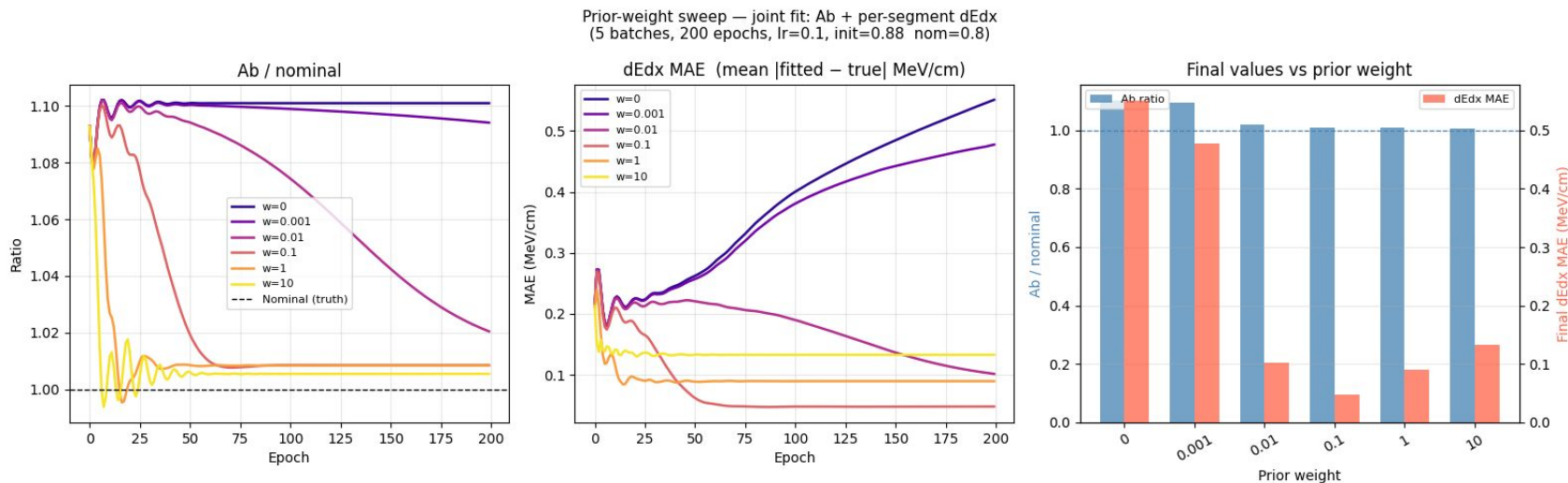


# In practice fits are not that good



Getting some  $\sim 10\%$  error on some parameters, which is not really great (especially that currently I still assume the true segment positions)

# The relative weights of the loss terms matter



- Depending on the choice of  $w$  we either give more importance to:
  - penalizing differences in the hit output
  - penalizing differences in the **dEdx** distribution
- High- $w$  ~ fixing **dEdx** to MPV ; Low- $w$  ~ no physics prior on **dEdx**

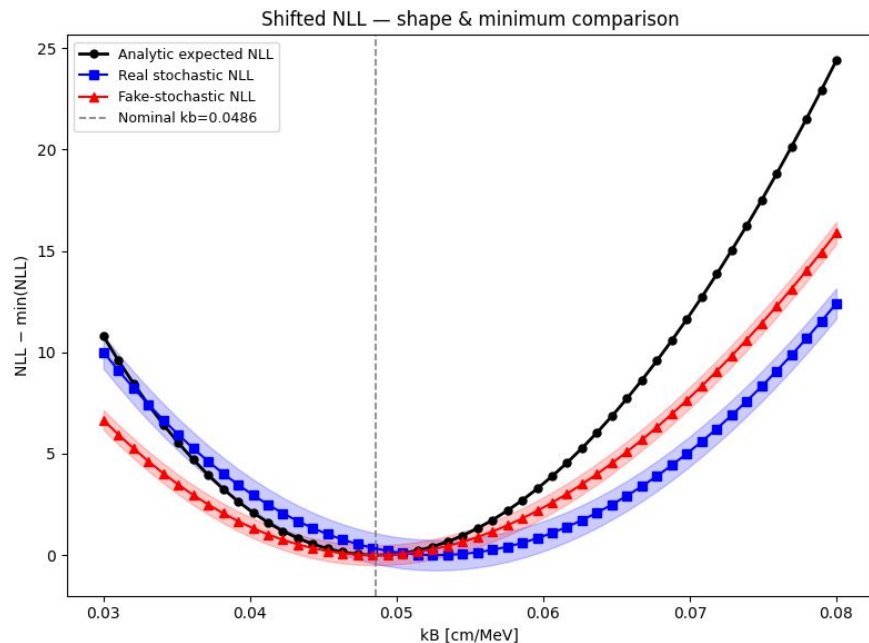
# Back to basics

Studying whether the loss bias comes from:

- improper loss formulation
- lack of accuracy of the probabilistic estimate

Using a “Fake-stochastic” sample:

- Stochastic draws from the probabilistic estimate

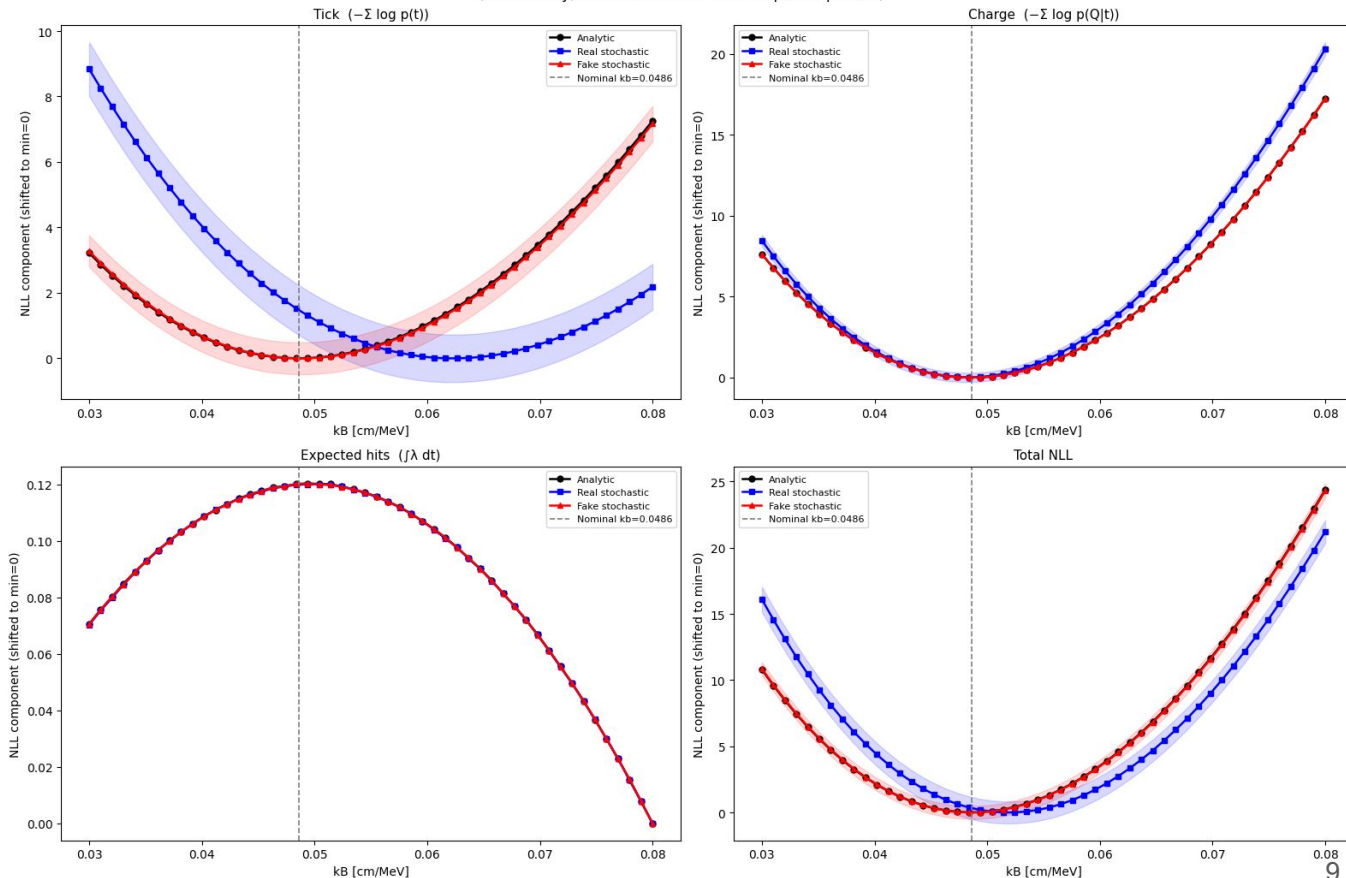


**By drawing directly from the guessed distribution, we fix the bias**

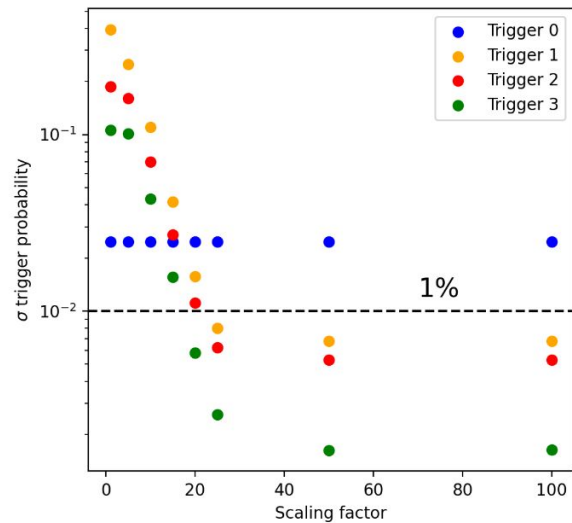
# Back to basics

The tick probability estimate seems to be the issue in the loss  
→ went back to reintroduce a fix in the probabilistic estimate that got lost on some function refactor...

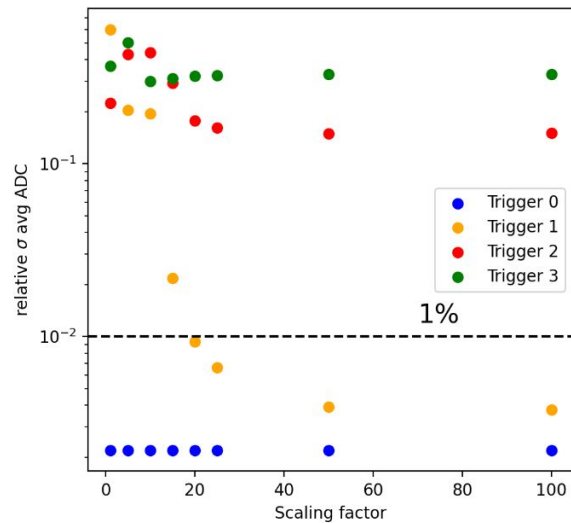
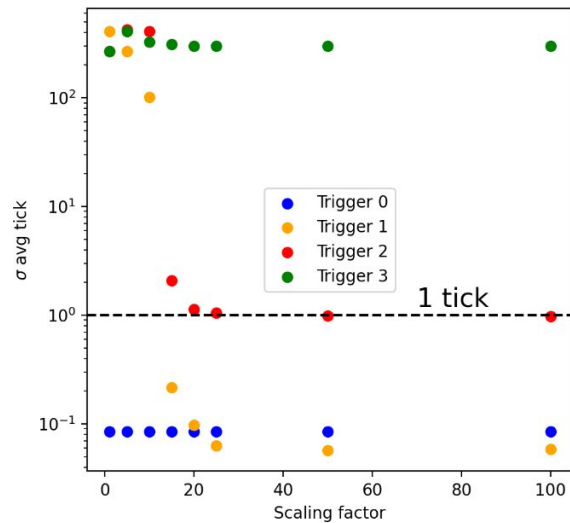
Decomposed NLL vs  $kB$  — Analytic / Real stochastic / Fake stochastic  
(first-hit only, all shifted to  $\min=0$  for shape comparison)



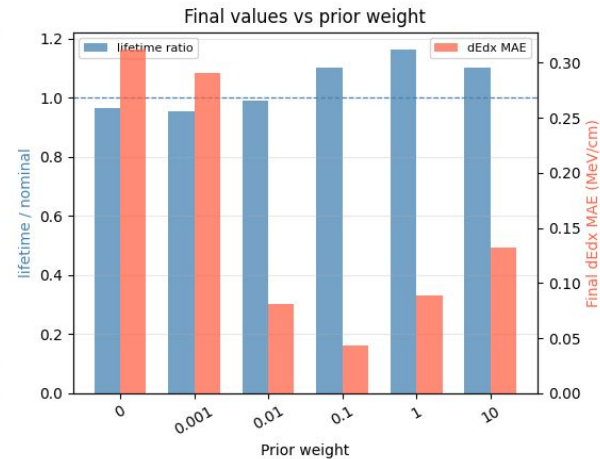
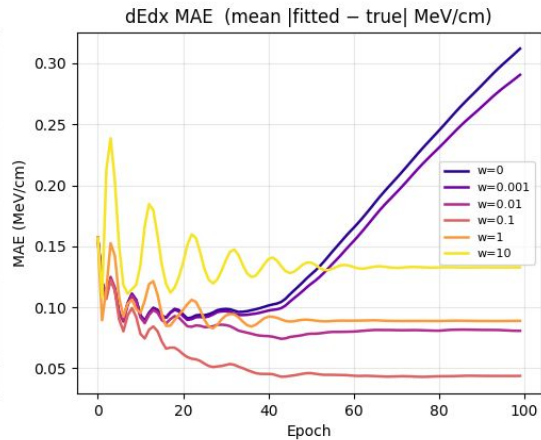
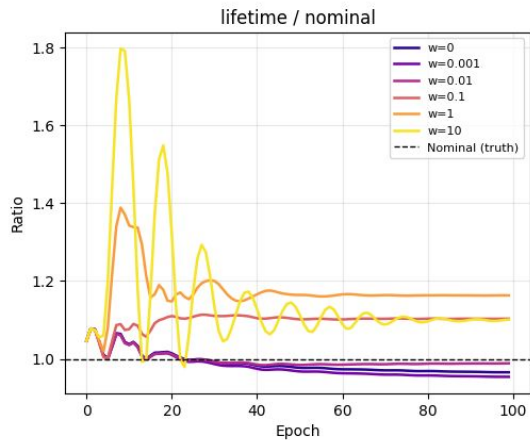
# Backup



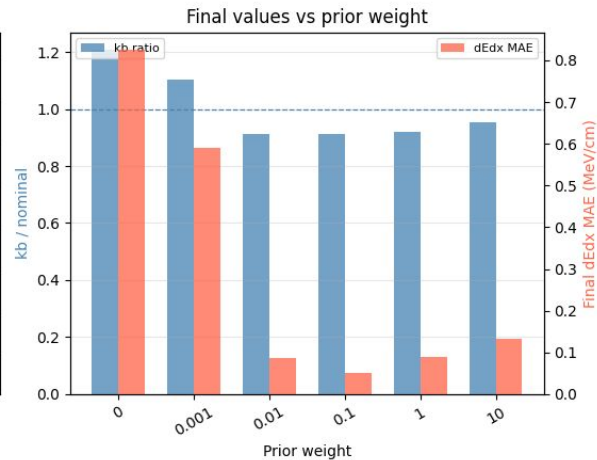
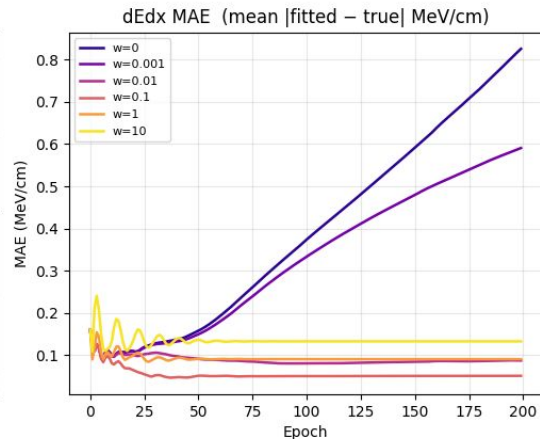
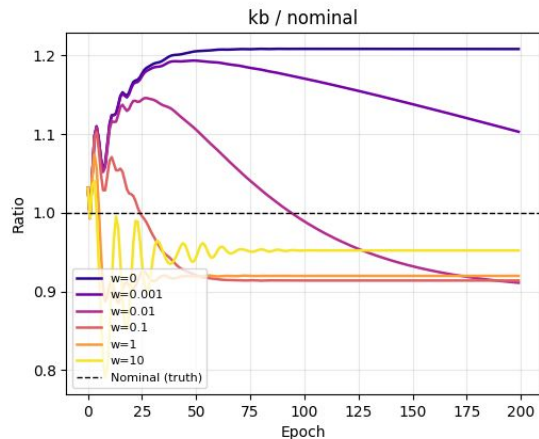
Threshold: 5000



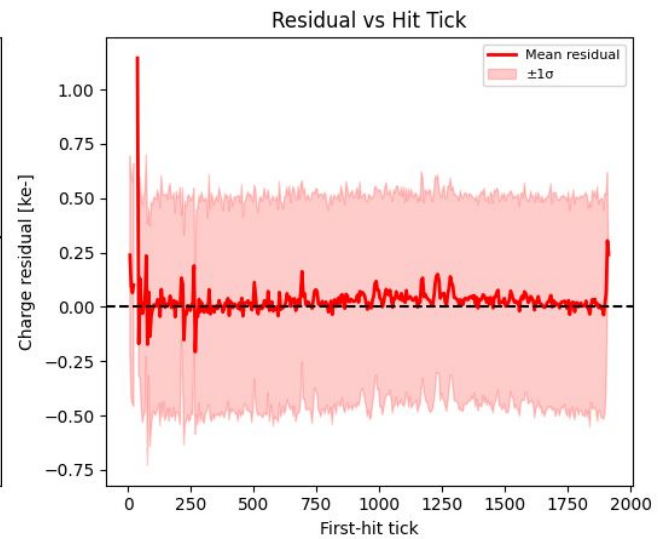
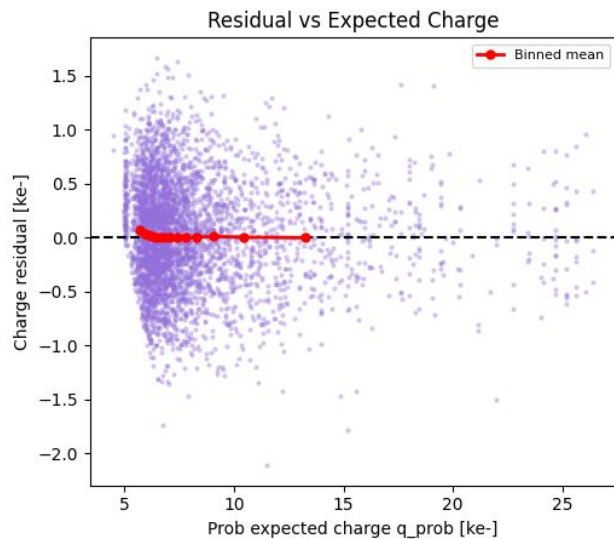
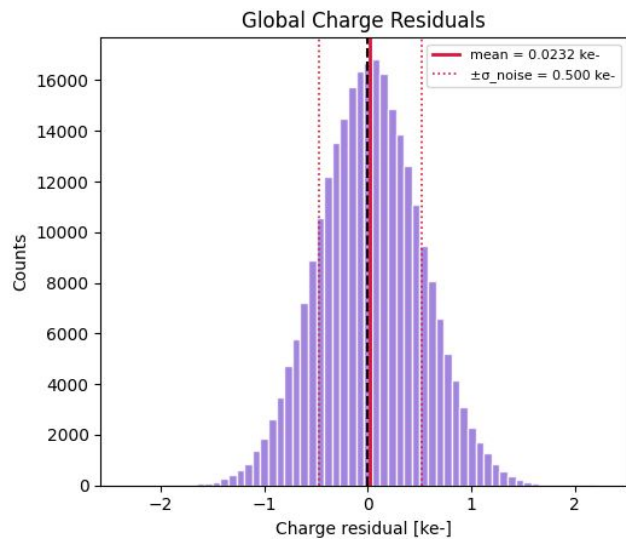
Prior-weight sweep — joint fit: lifetime + per-segment dEdx  
(5 batches, 100 epochs, lr=0.1, init=2420 nom=2200)



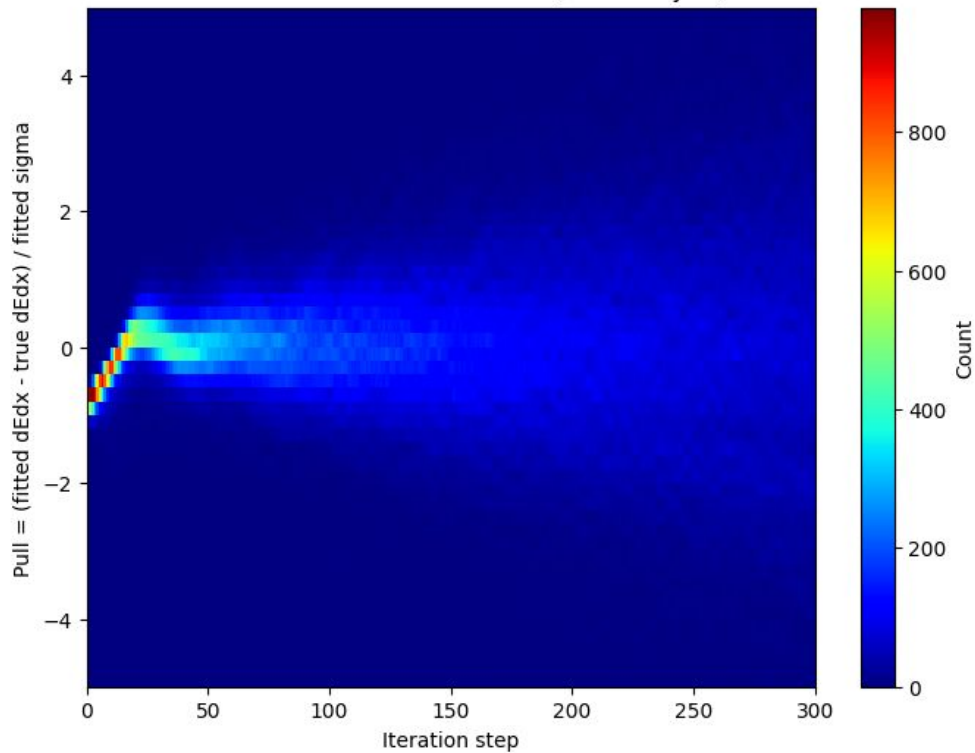
Prior-weight sweep — joint fit: kb + per-segment dEdx  
(5 batches, 200 epochs, lr=0.1, init=0.05346 nom=0.0486)



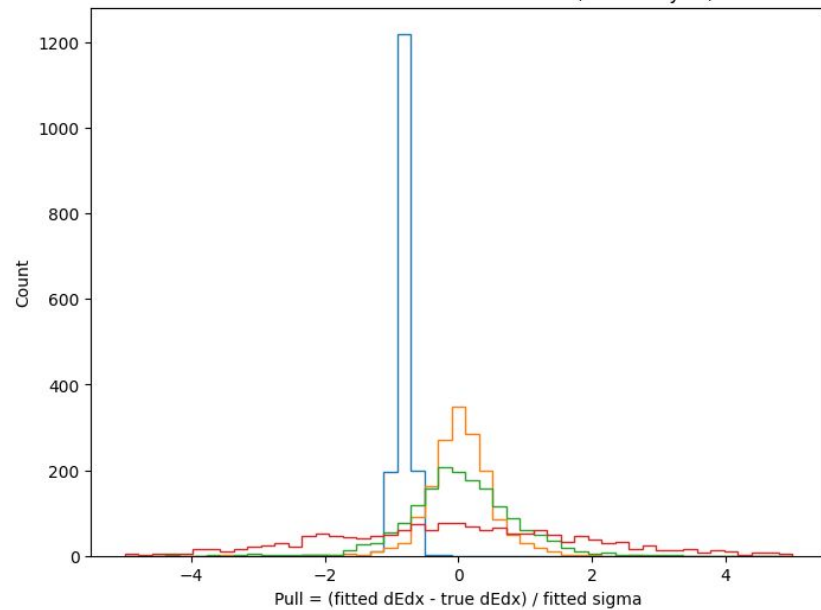
## Charge Residuals: $q_{\text{stoch}} - q_{\text{prob}}(t_{\text{drawn}})$



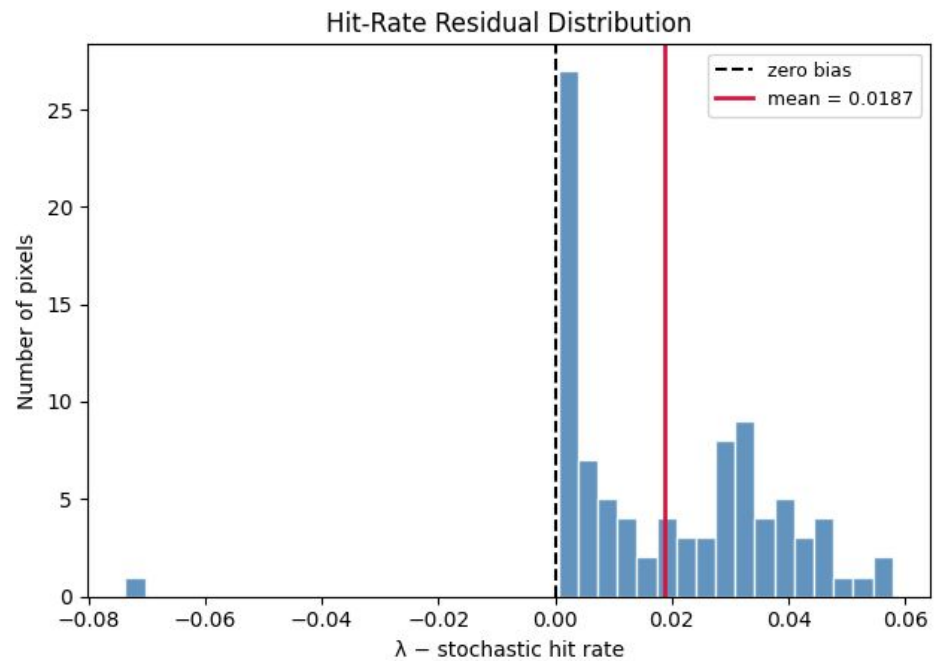
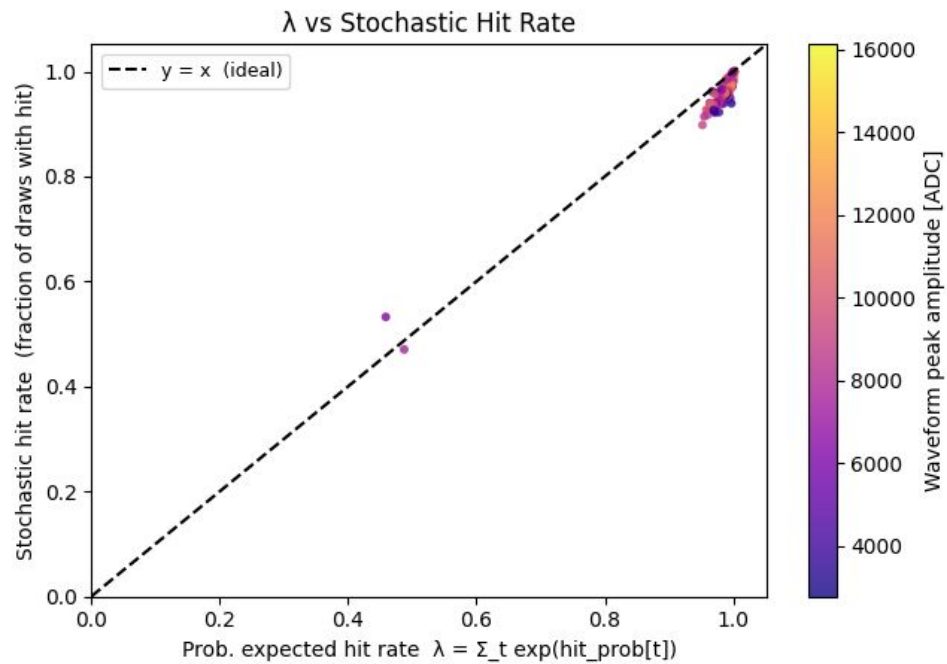
Pull distribution over iterations (dEdx-only fit)



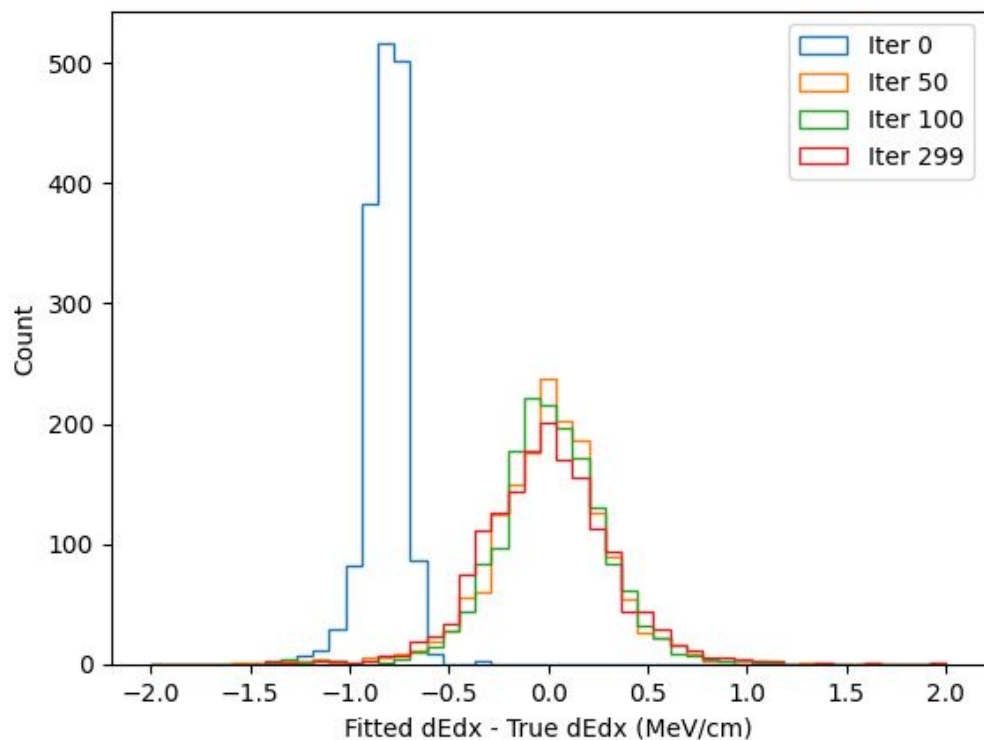
Pull distribution at selected iterations (dEdx-only fit)



## Probabilistic $\lambda$ Calibration (first-hit slot)



Distribution of dEdx differences at selected iterations



Distribution of dEdx sigma at selected iterations

