

# FastSim Parametrization of Beam Dump using Generative Adversarial Network (GAN)

Oleksander Borysov, Alon Levi, Arka Santra, Noam Tal Hod

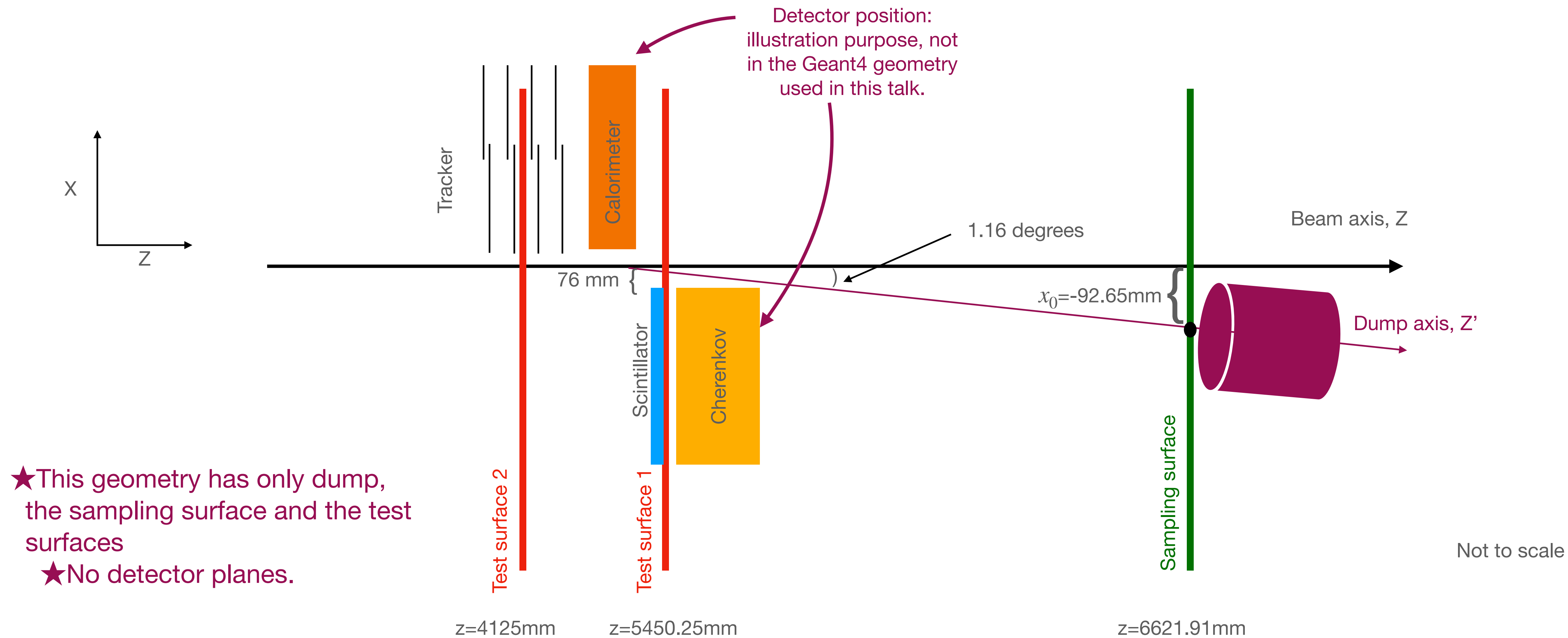
Feb 12, 2024

LUXE SAS meeting

# Overview

- Recap of [previous talk](#) given by Arka Santra (Oct 30)
- Updates and changes
- Summary

# Schematic diagram of the dump in the LUXE geometry



★ This geometry has only dump, the sampling surface and the test surfaces  
★ No detector planes.

# Approaches to background simulation

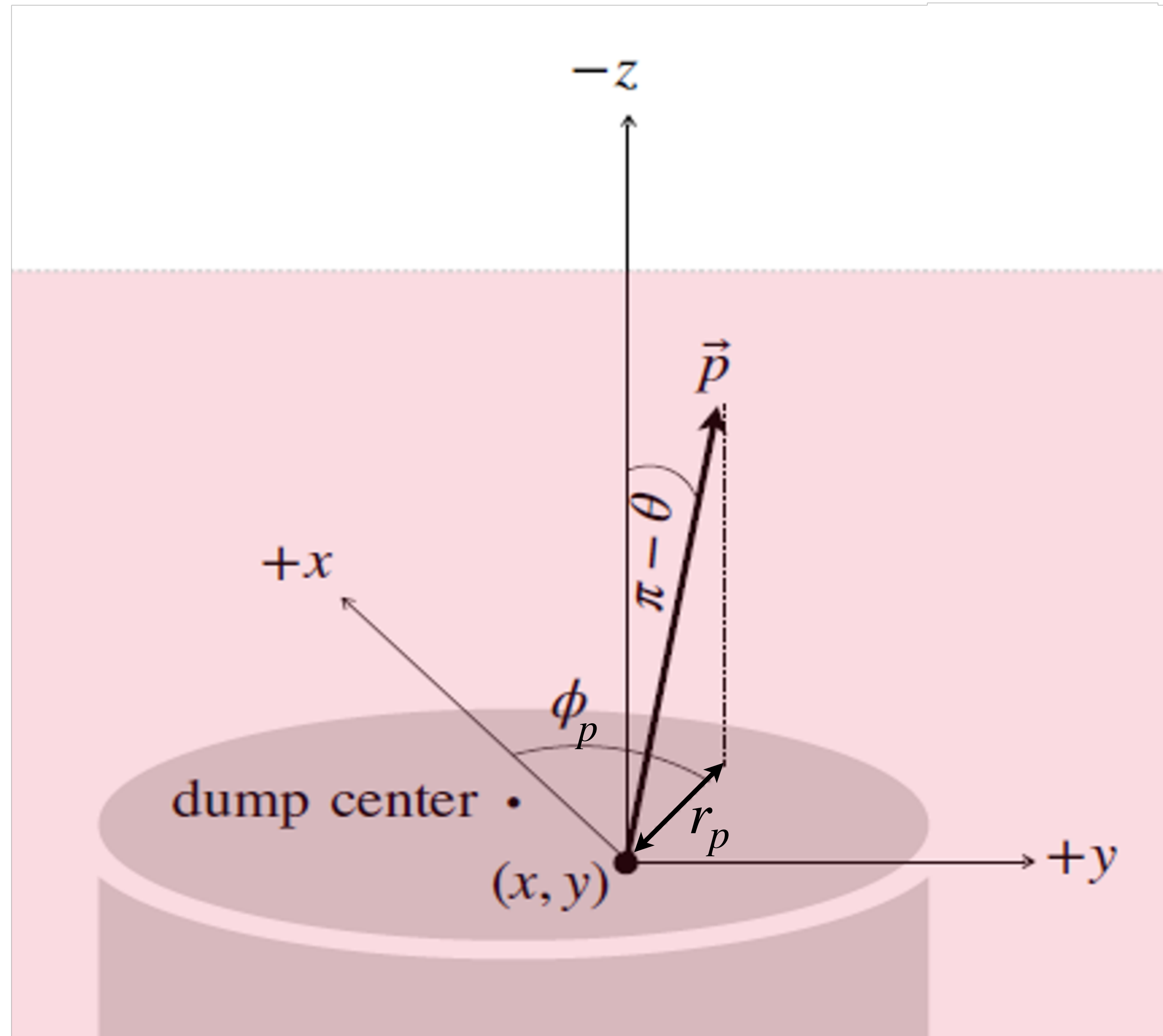
- FullSim - full Geant4 simulation, computationally heavy
- FastSim (correlation sampling) - lacks accuracy for backscattered particles
- FastSim using Wasserstein GAN

# Particle Features

$$\begin{bmatrix} x \\ y \\ r_p \\ \phi_p \\ p_z \\ t \end{bmatrix}$$

$$r_x = \sqrt{x^2 + y^2}$$

$$\phi_x = \arctan \frac{y}{x}$$

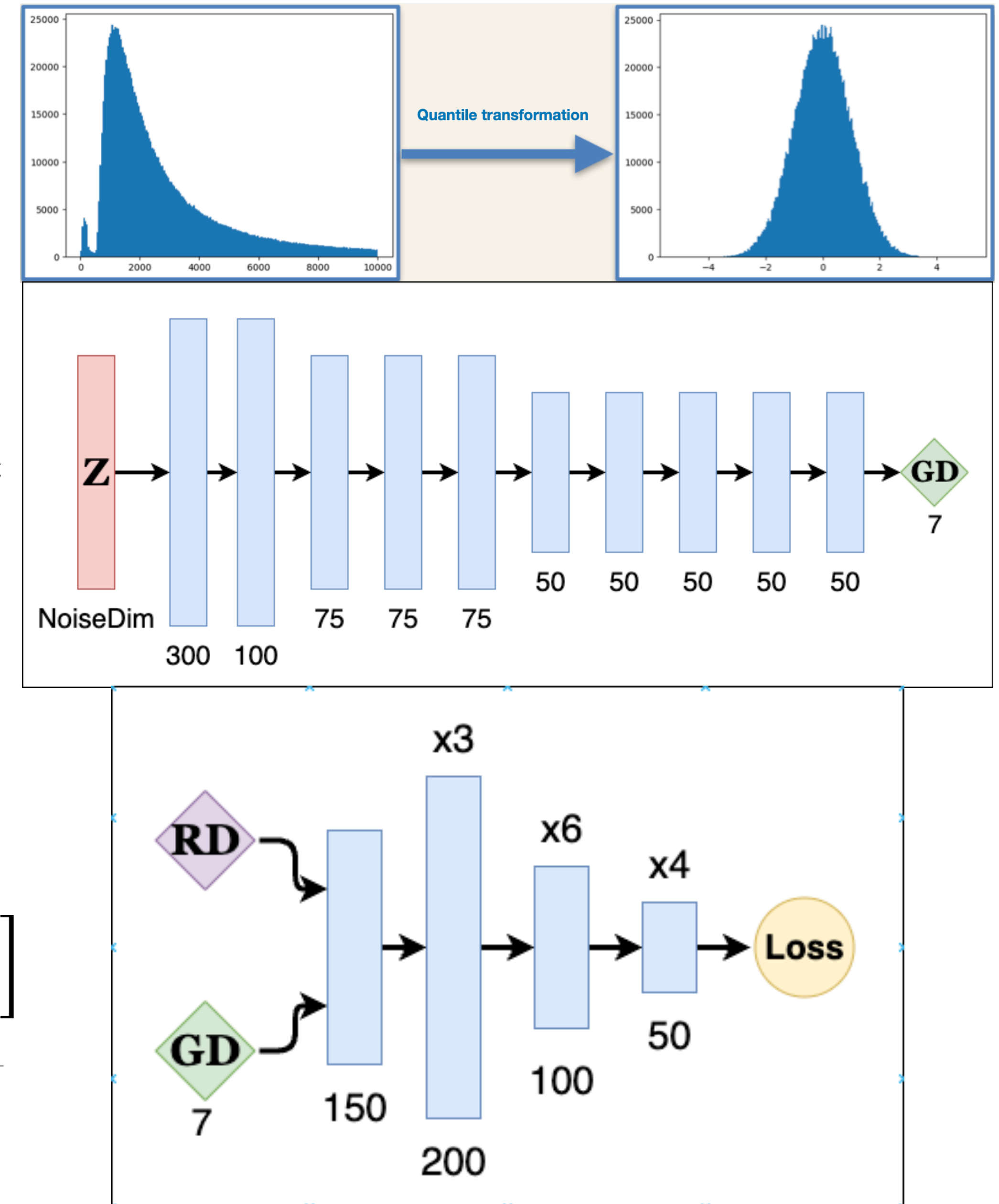


# WGAN method

1. Apply quantile transformation to the data
2. Generate data points from random noise
3. Pass real and generated data through critic
4. Determine loss via Wasserstein metric
5. Monitor Progress with KL divergence
6. Apply inverse quantile transformation

$$\mathcal{L}(p_r, p(z)) = \max_{w \in W, \theta \in \Theta} \left[ \underbrace{\mathbb{E}_{x \sim p_r}[f_w(x)]}_{\text{Expectation value from the original distribution}} - \underbrace{\mathbb{E}_{x \sim p(z)}[f_w(g_\theta(z))]}_{\text{Expectation value from the generated distribution}} \right]$$

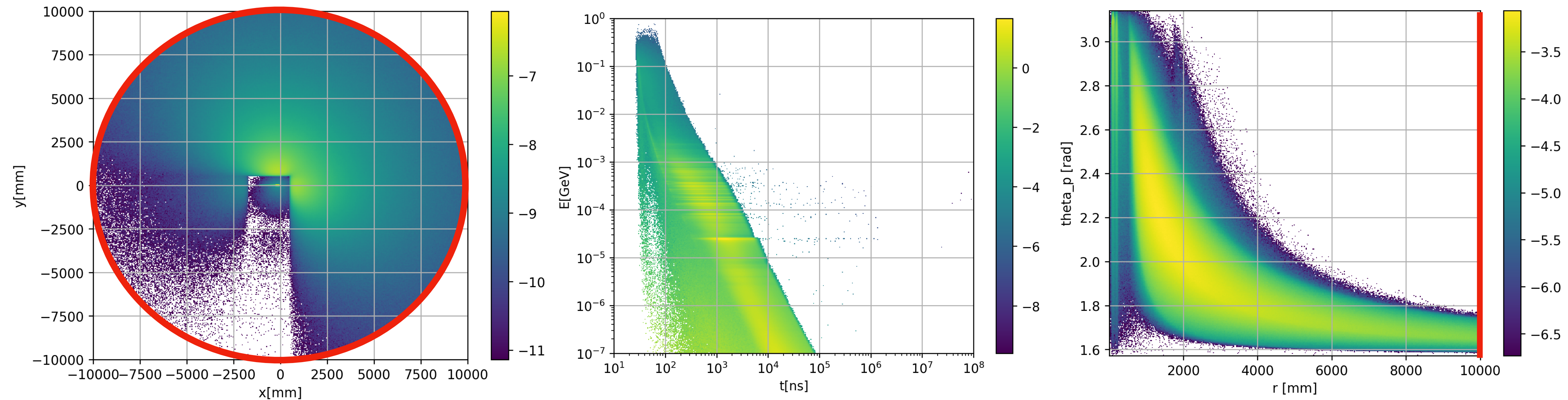
$$D_{\text{KL}}(P \parallel Q) = \sum_{x \in \mathcal{X}} P(x) \log \left( \frac{P(x)}{Q(x)} \right)$$





# Improvements

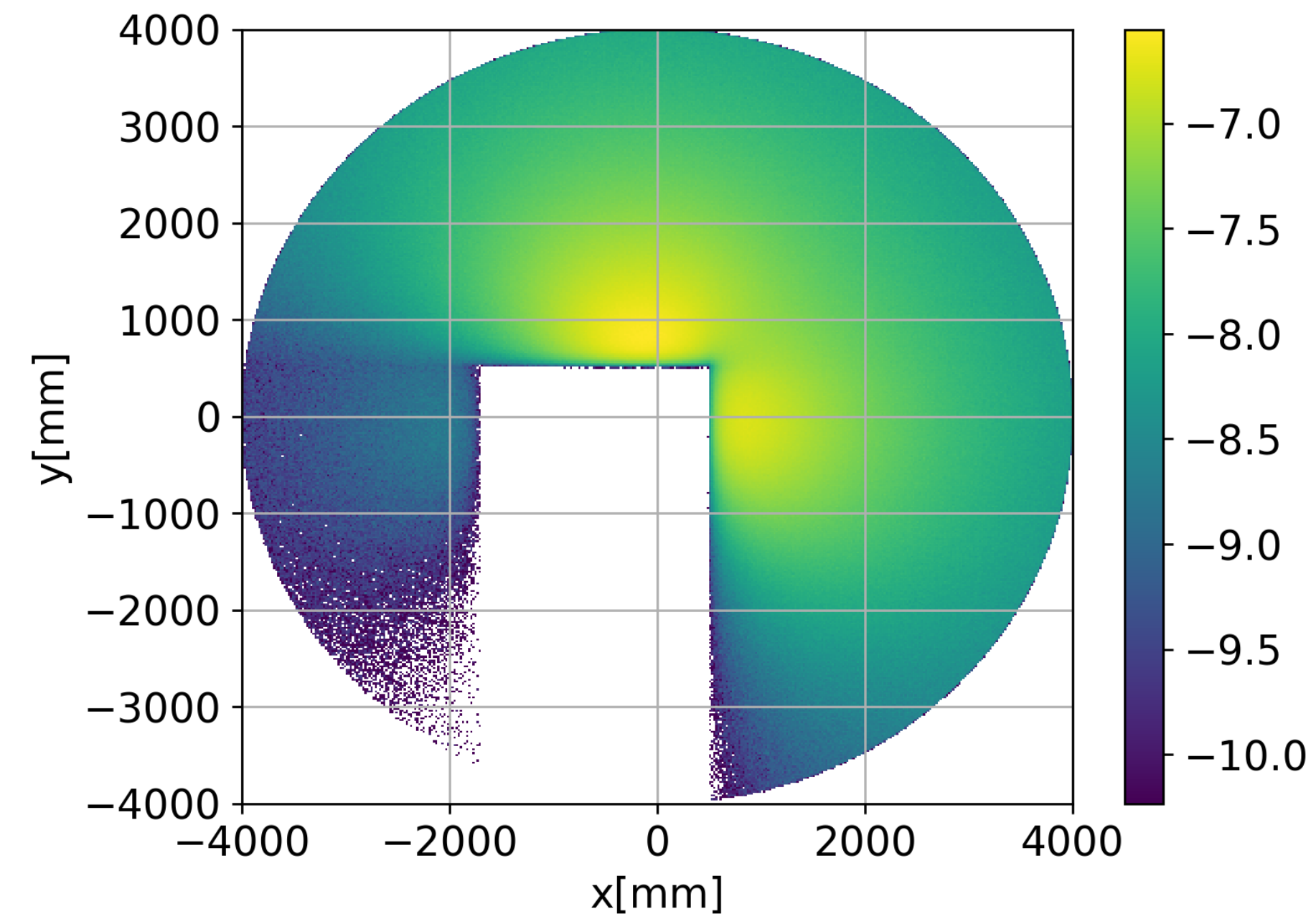
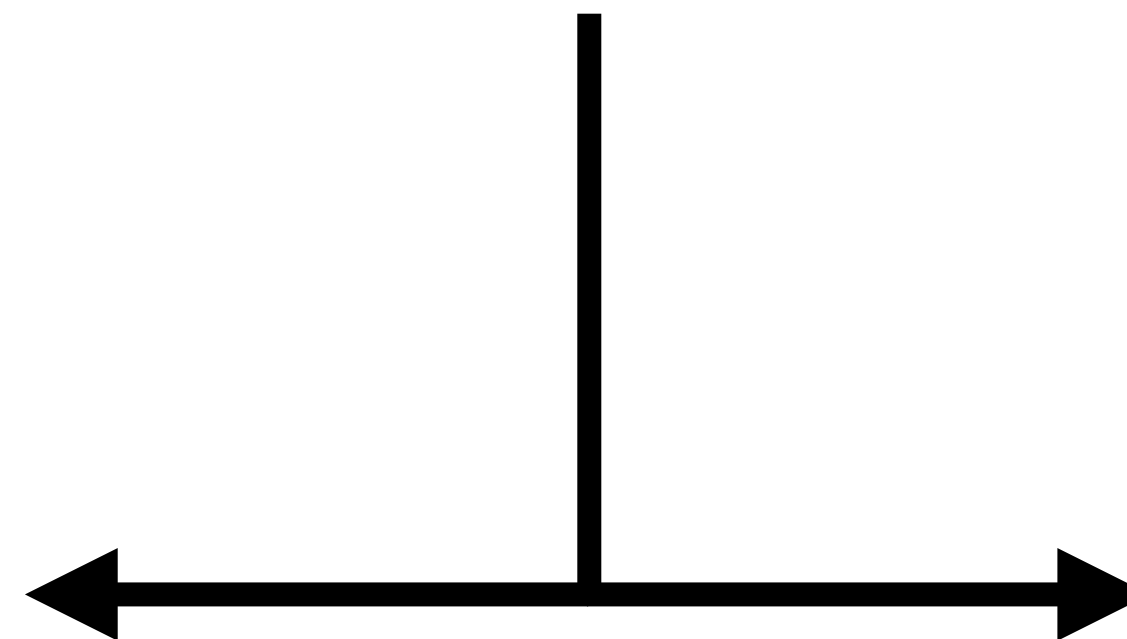
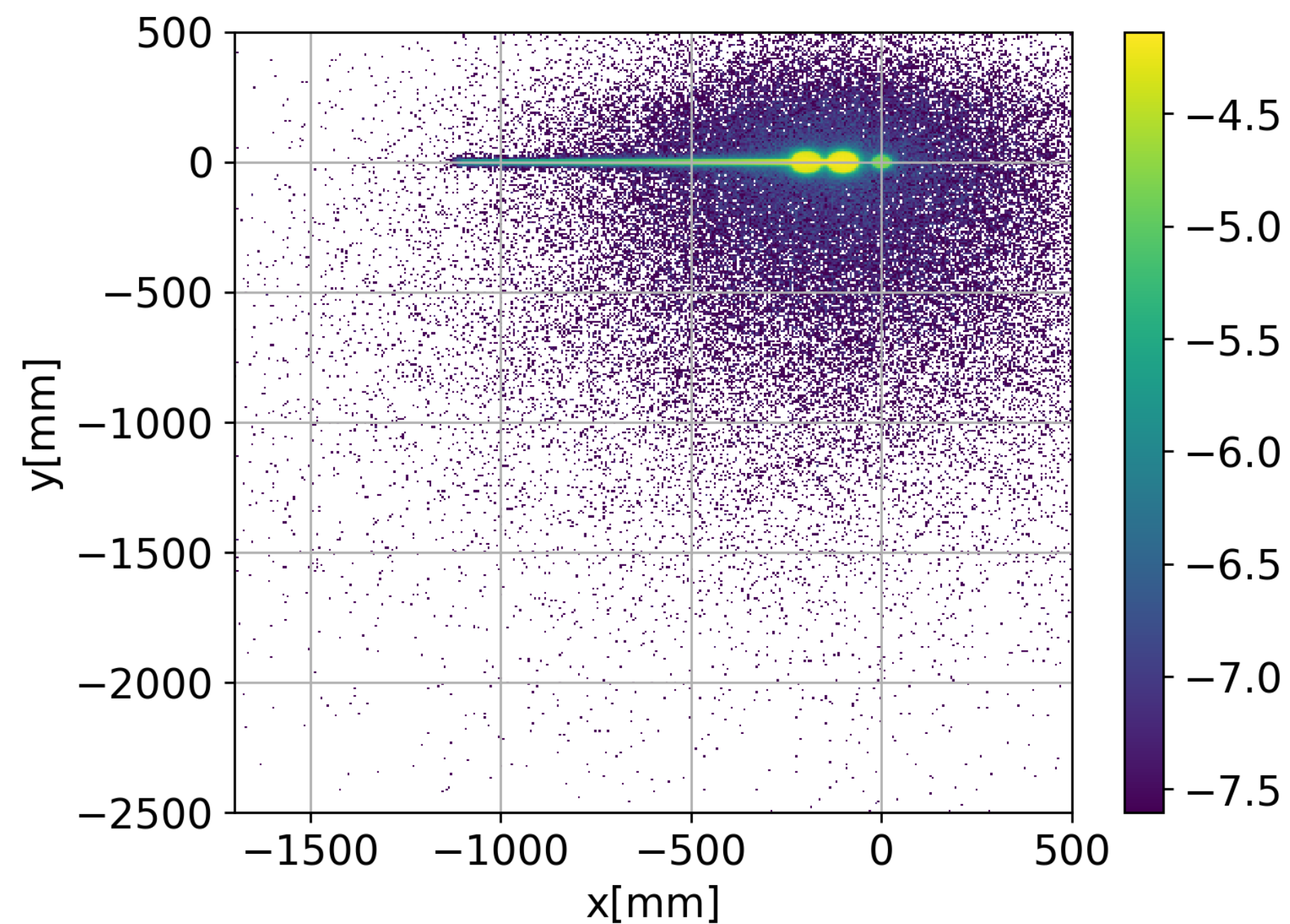
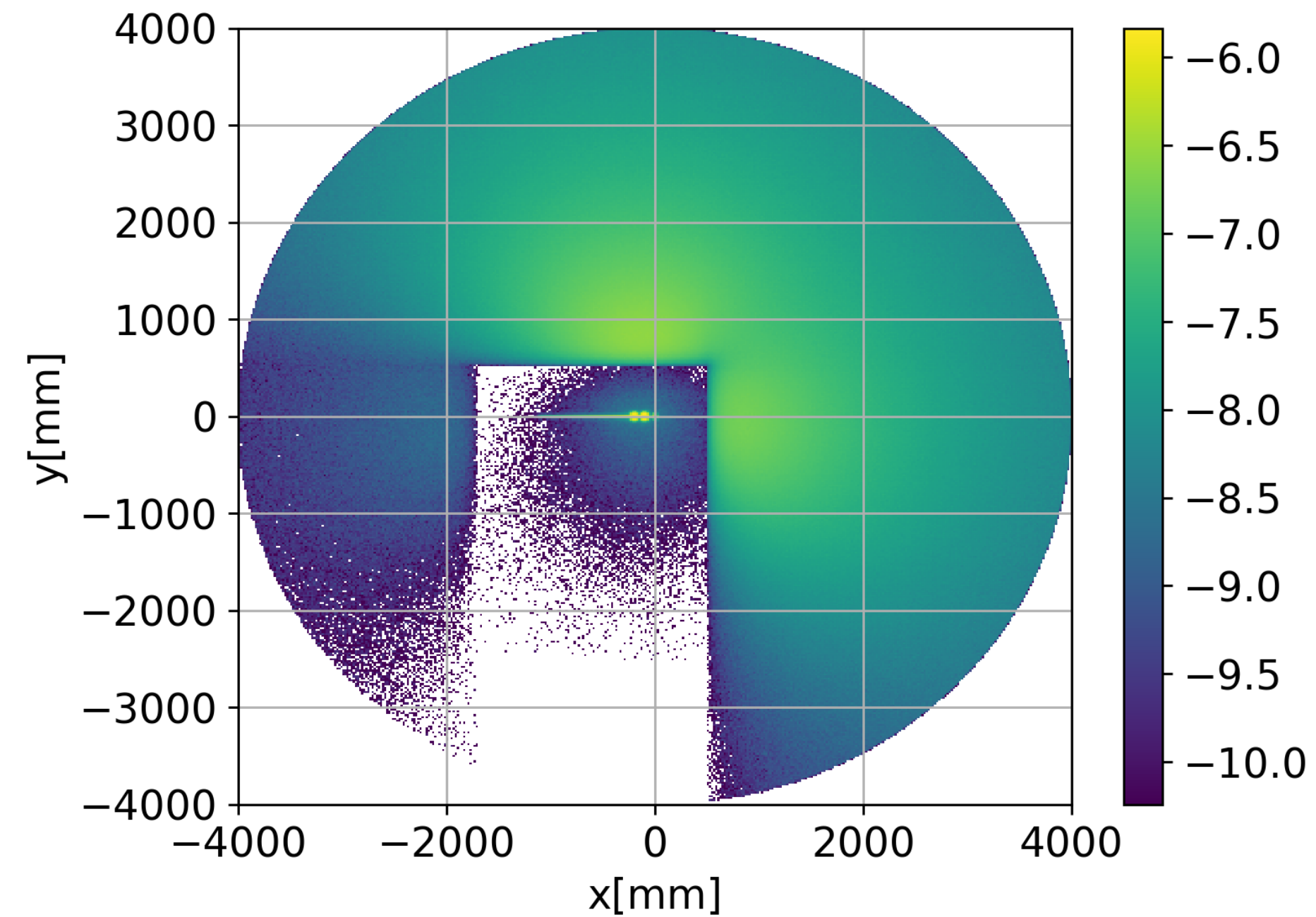
- GAN struggles to learn sharp features
  - Larger networks
  - Decrease radius - focused learning
  - Split learning





# Split learning

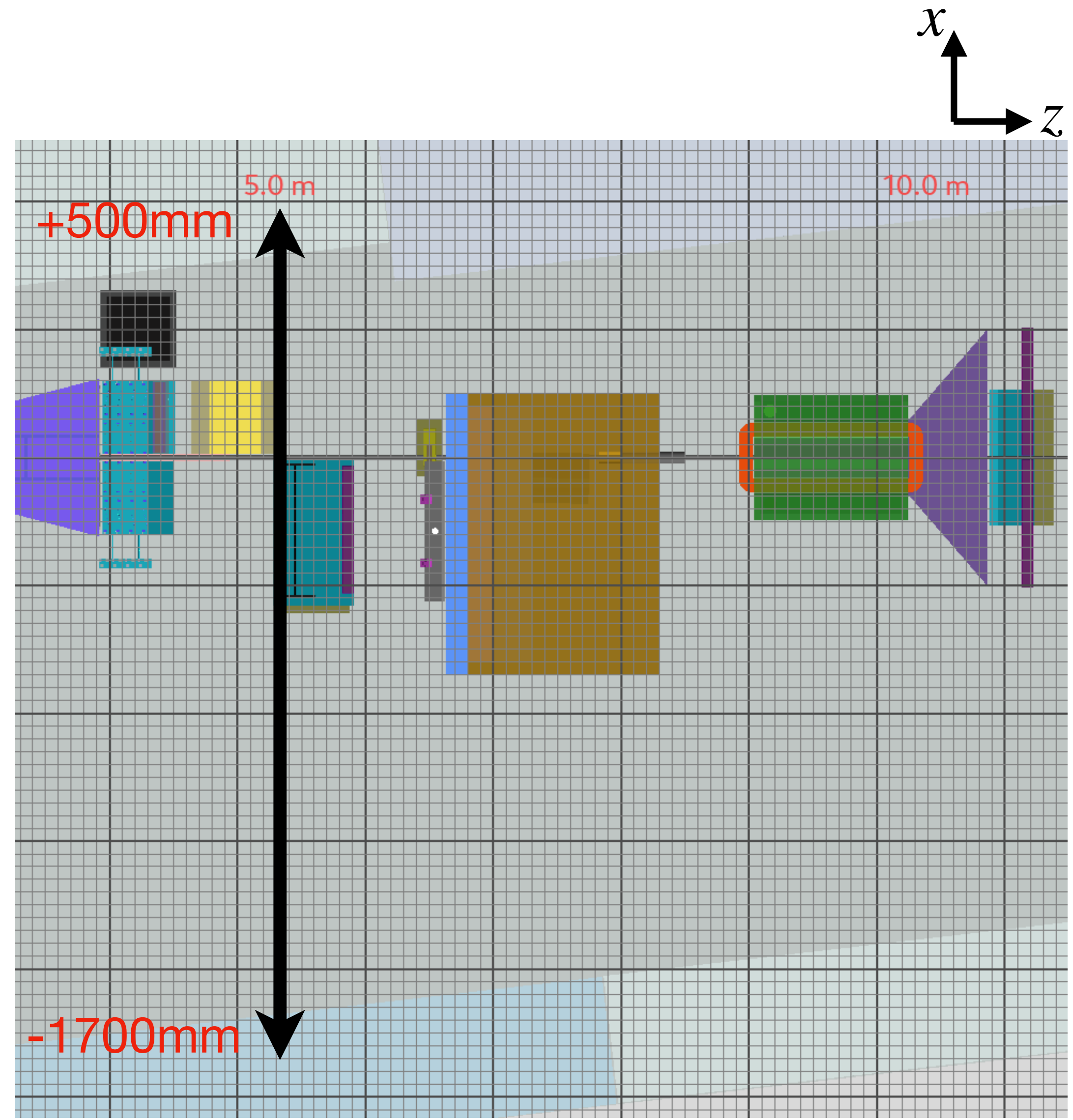
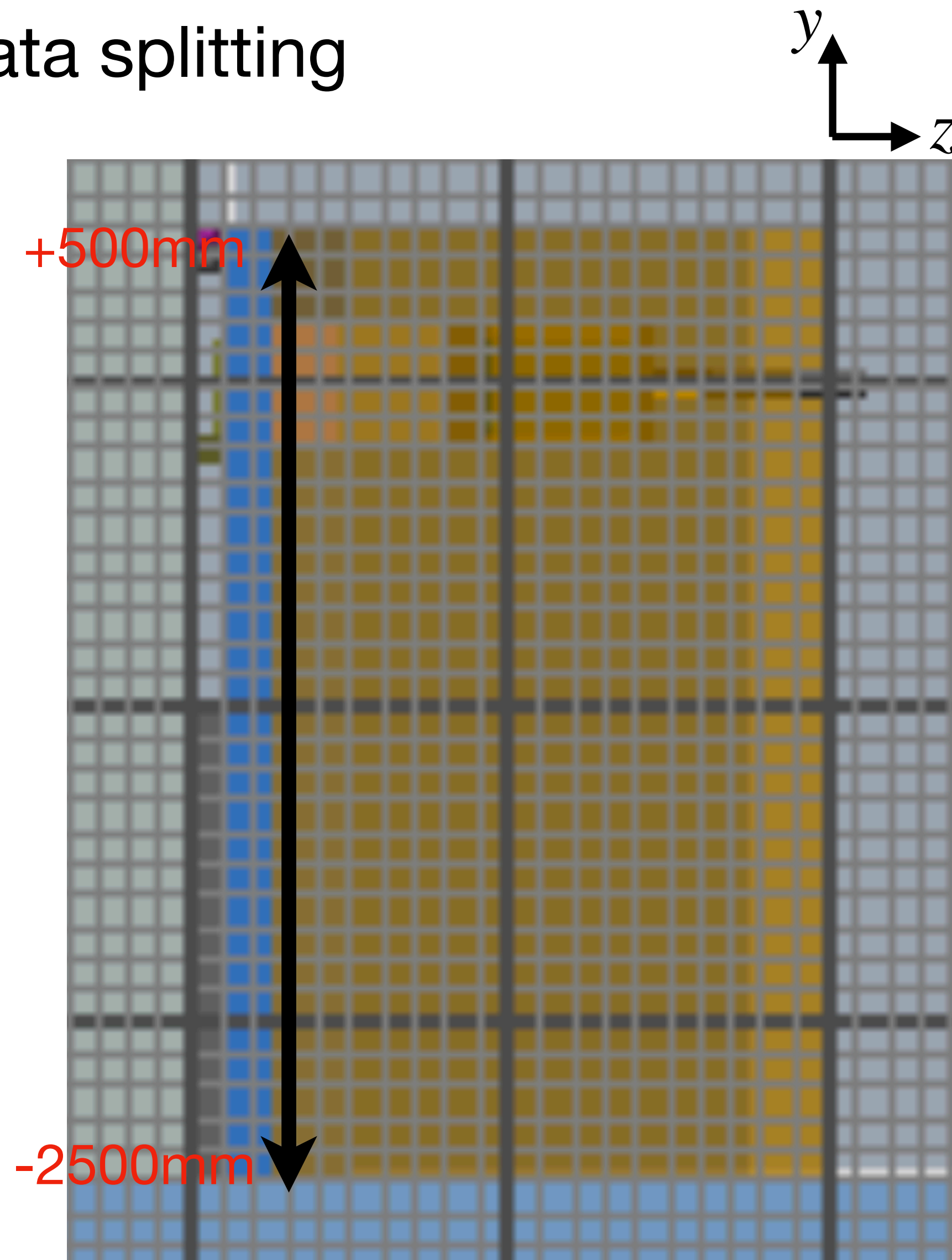
- Data splitting





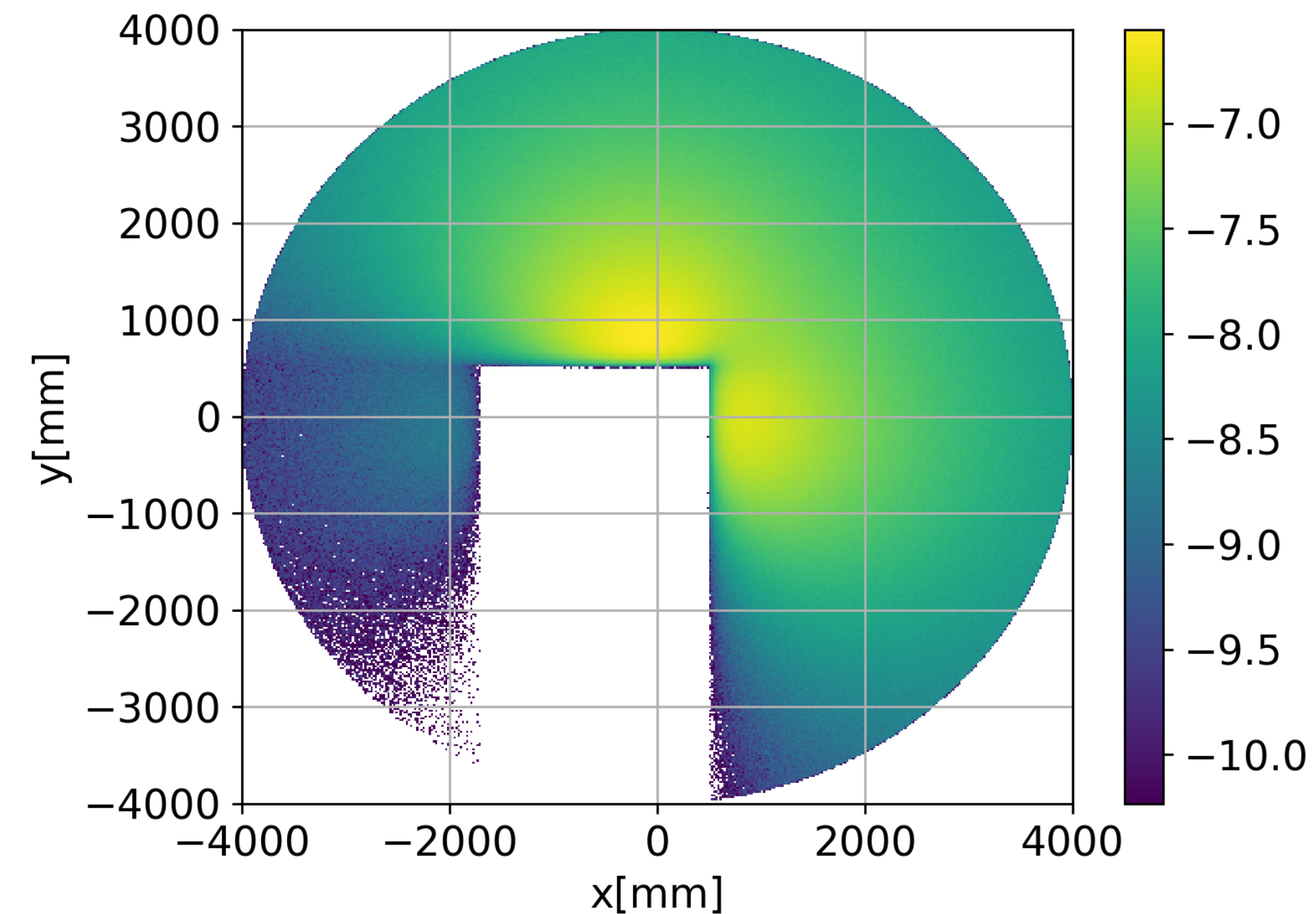
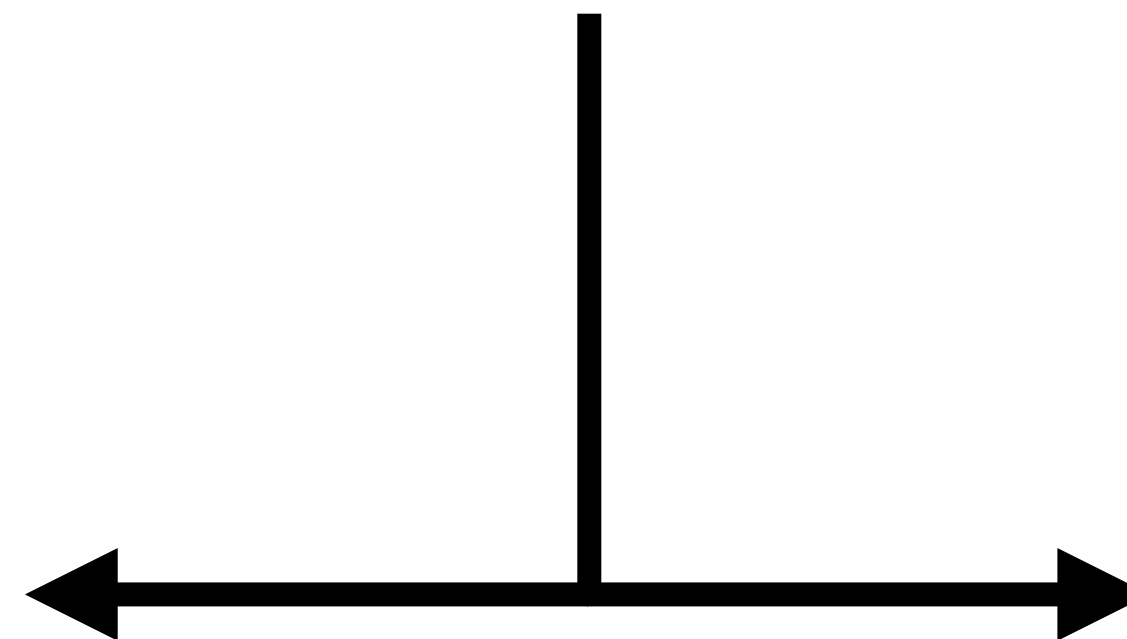
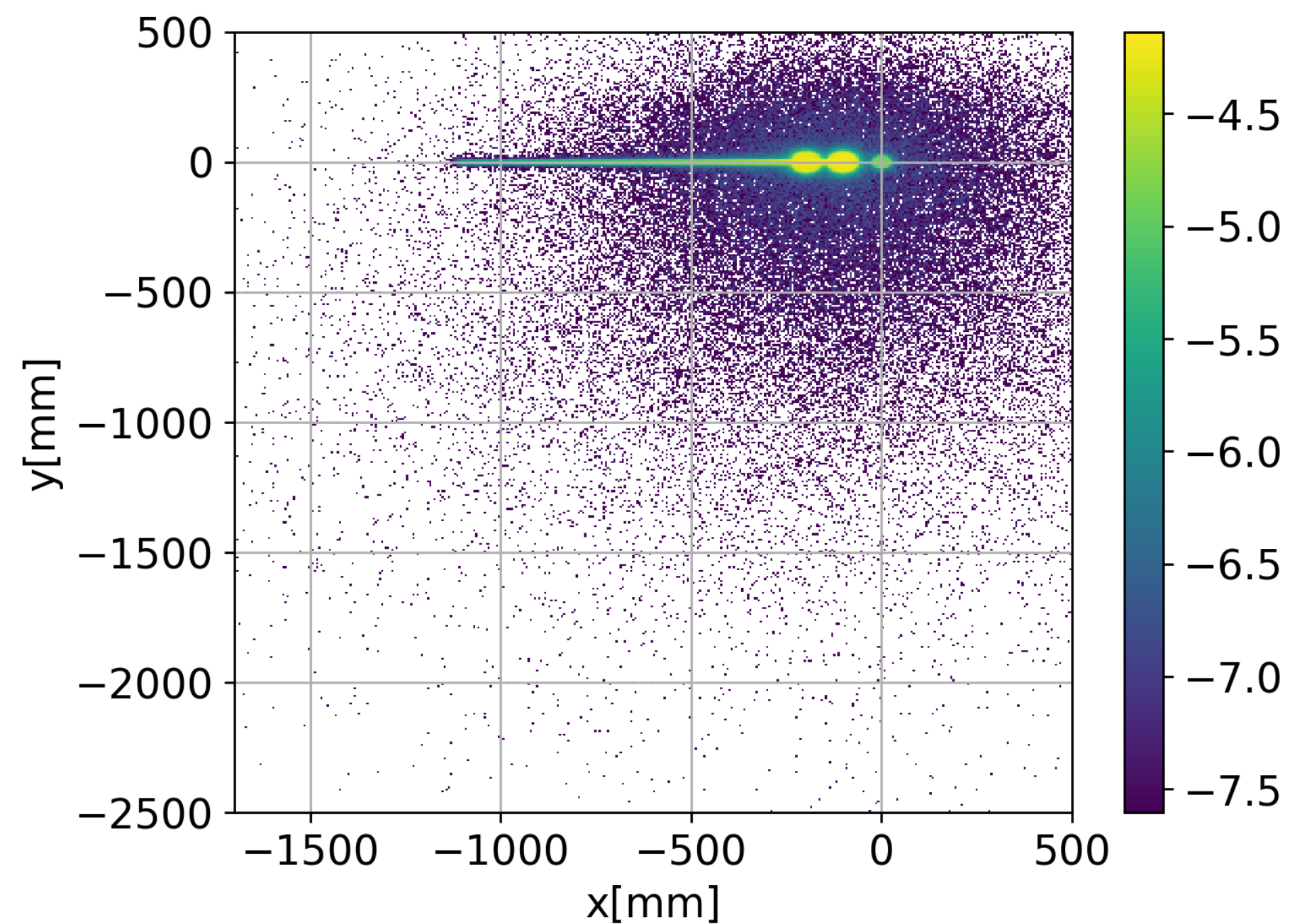
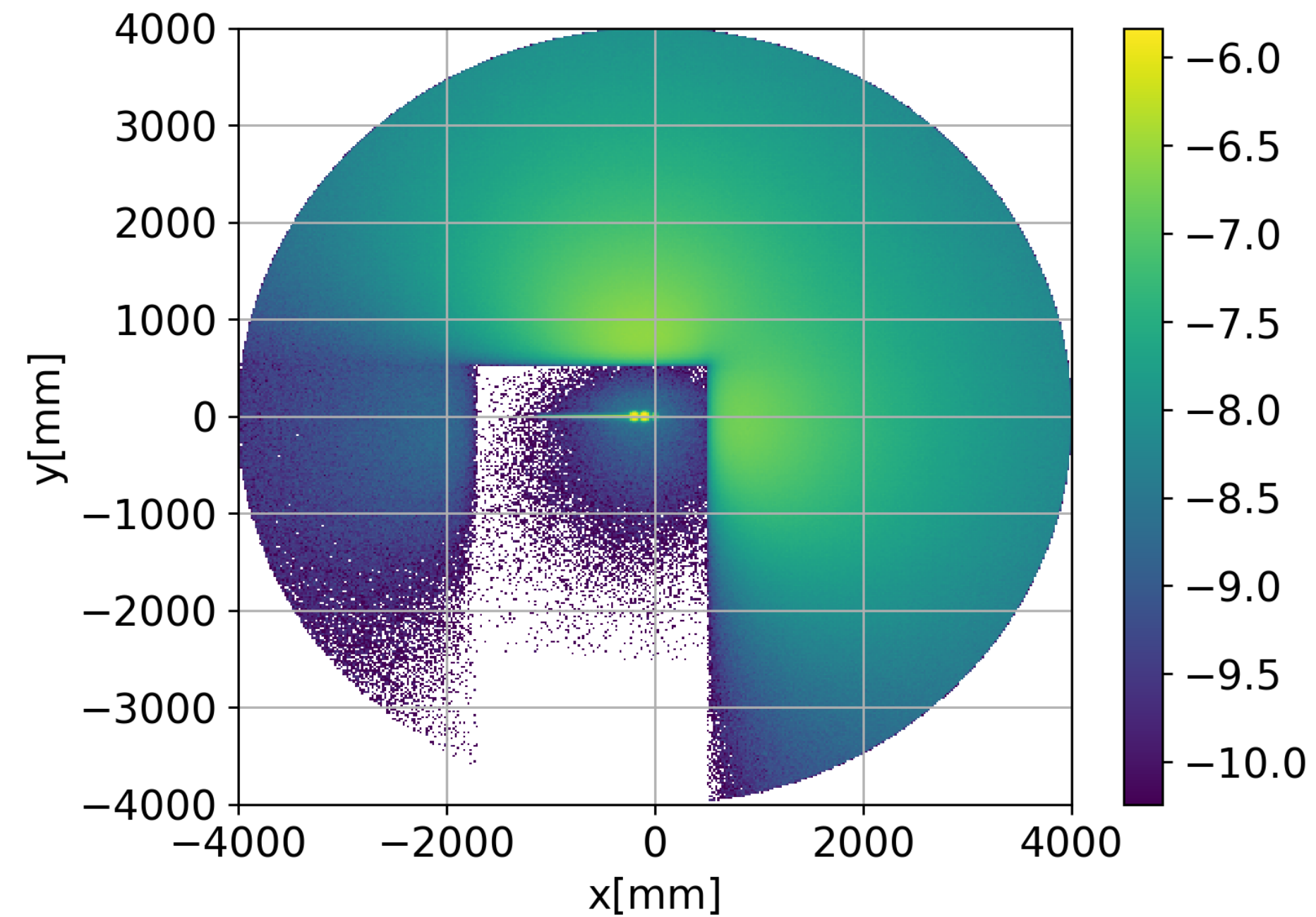
# Split learning

- Data splitting



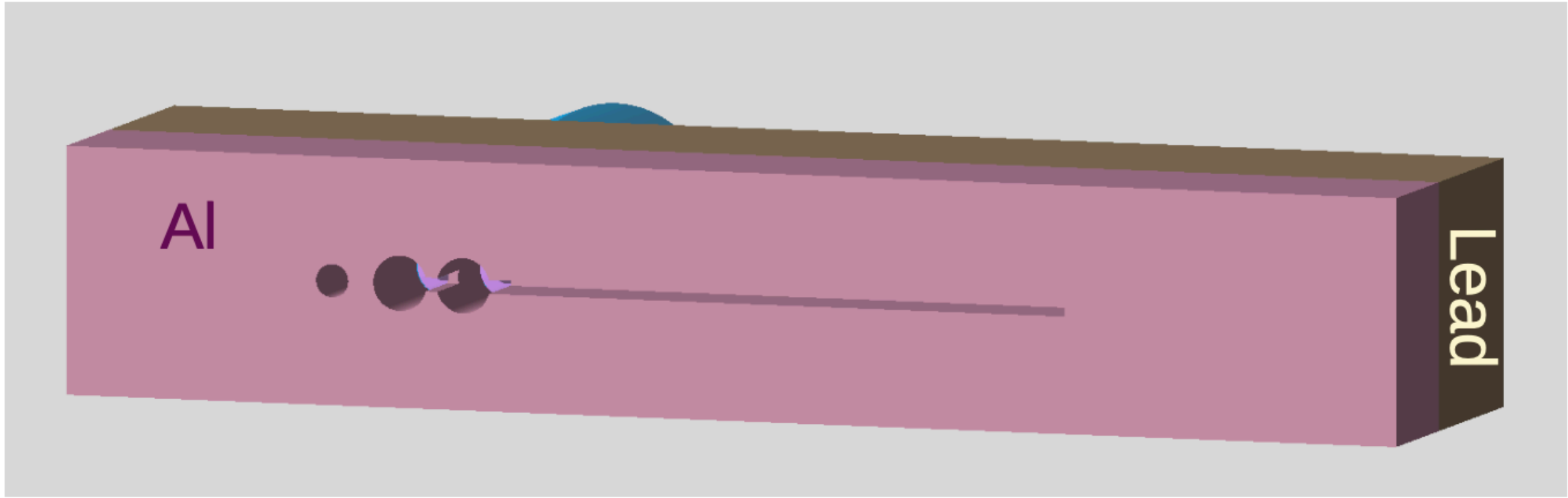
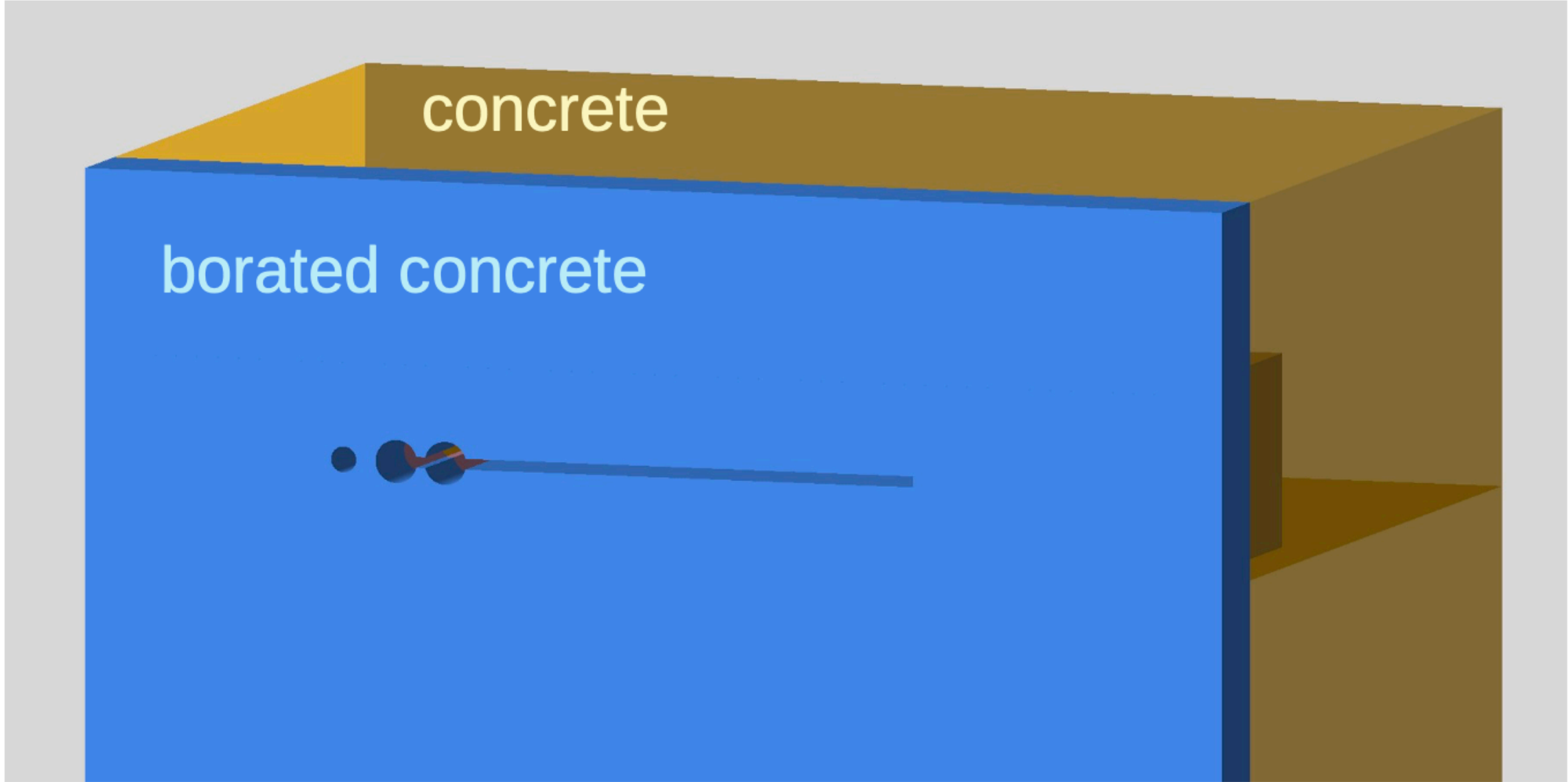
# Split learning

- Data splitting





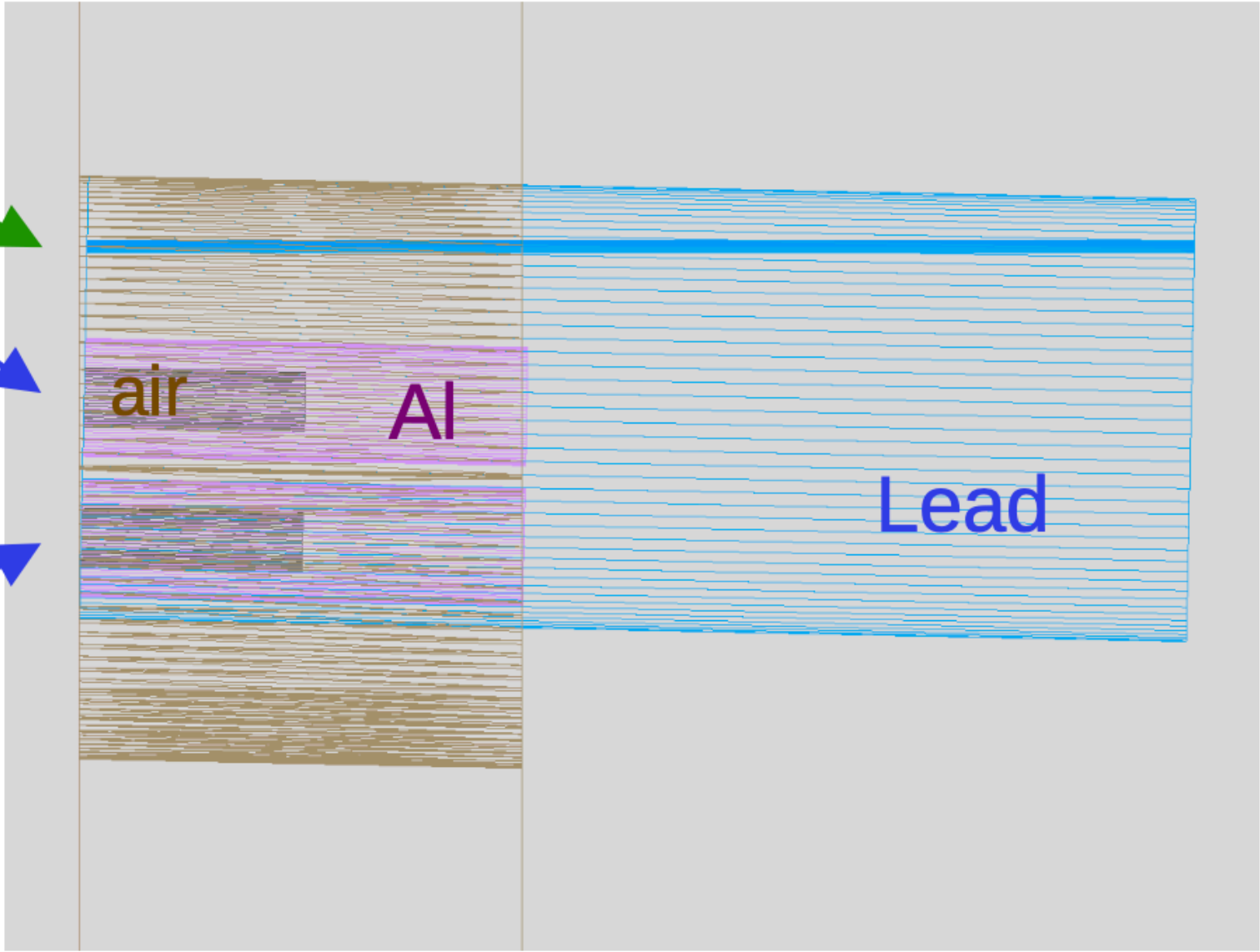
# Beam dump and shielding



## Top wire-frame view

e- dump at 0.95T field

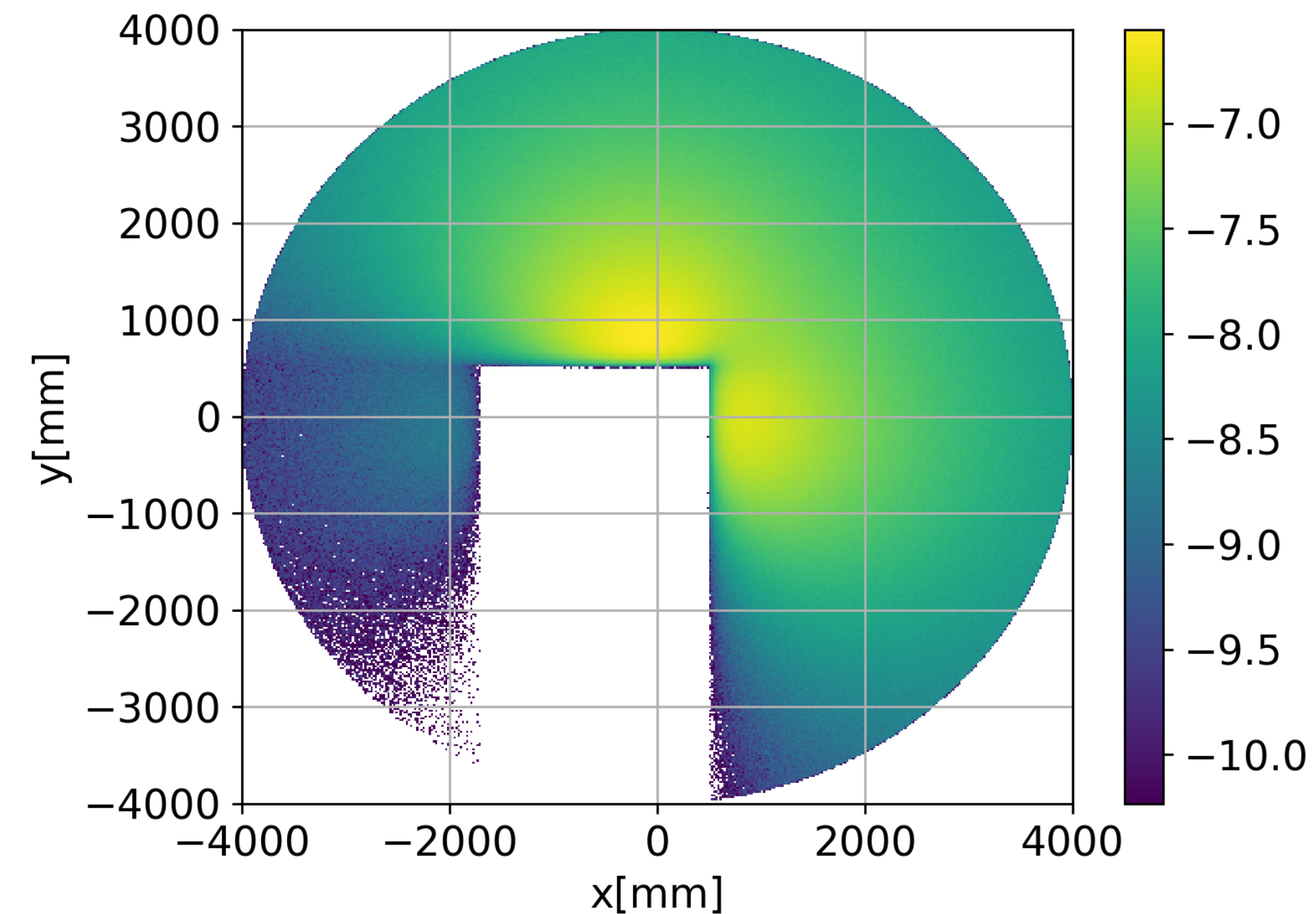
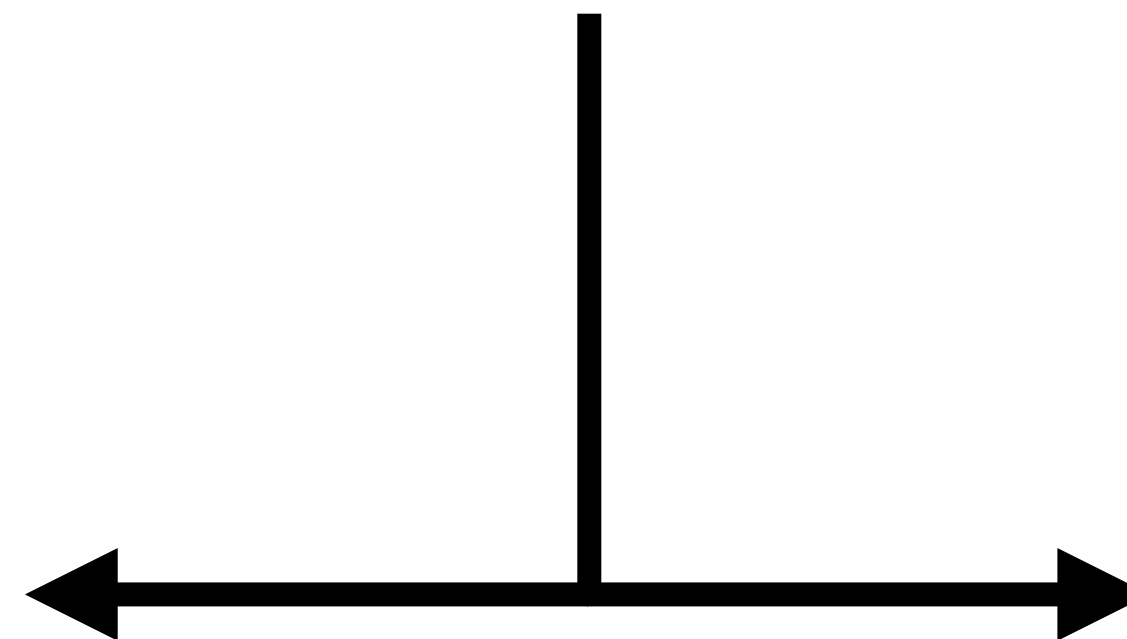
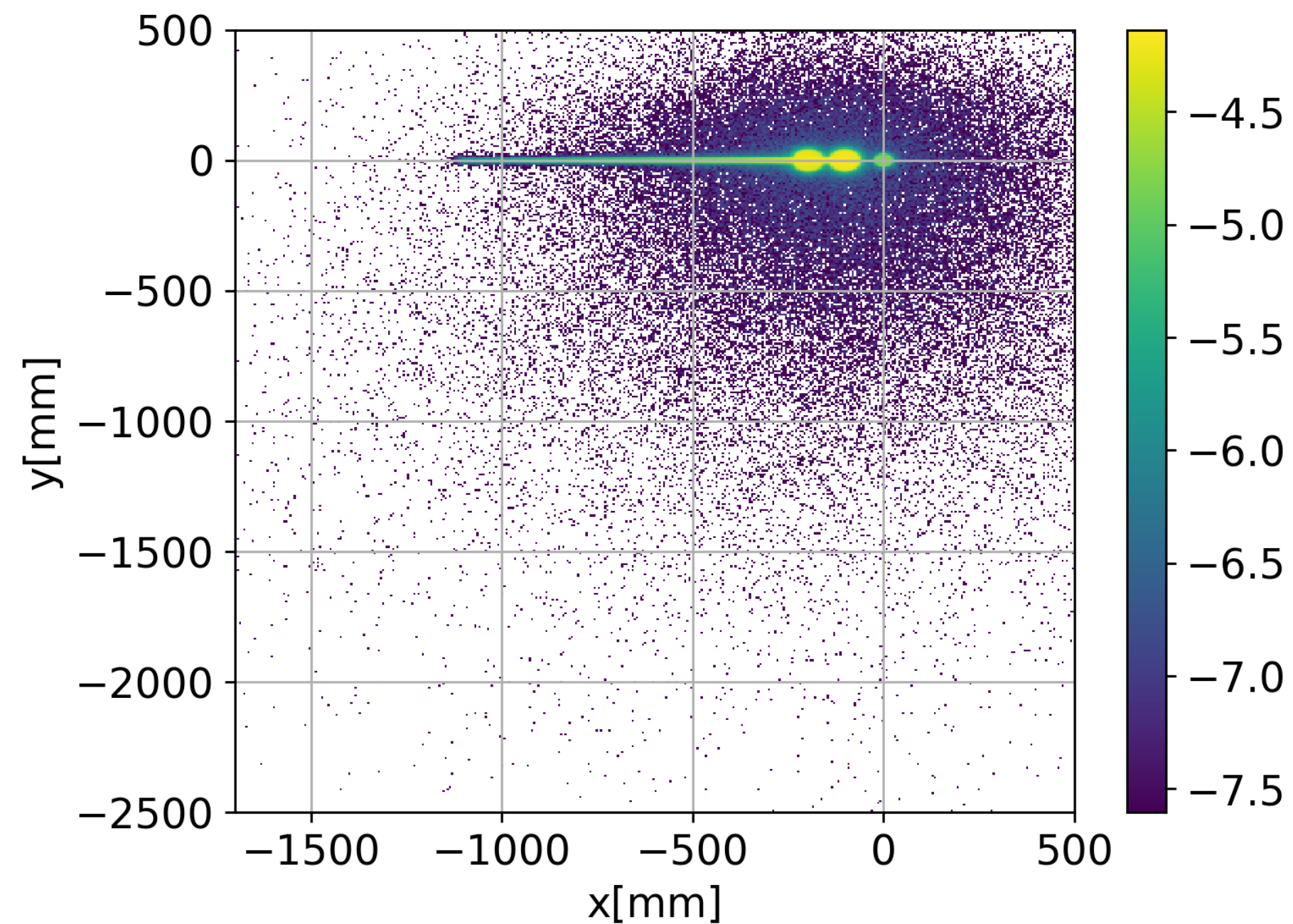
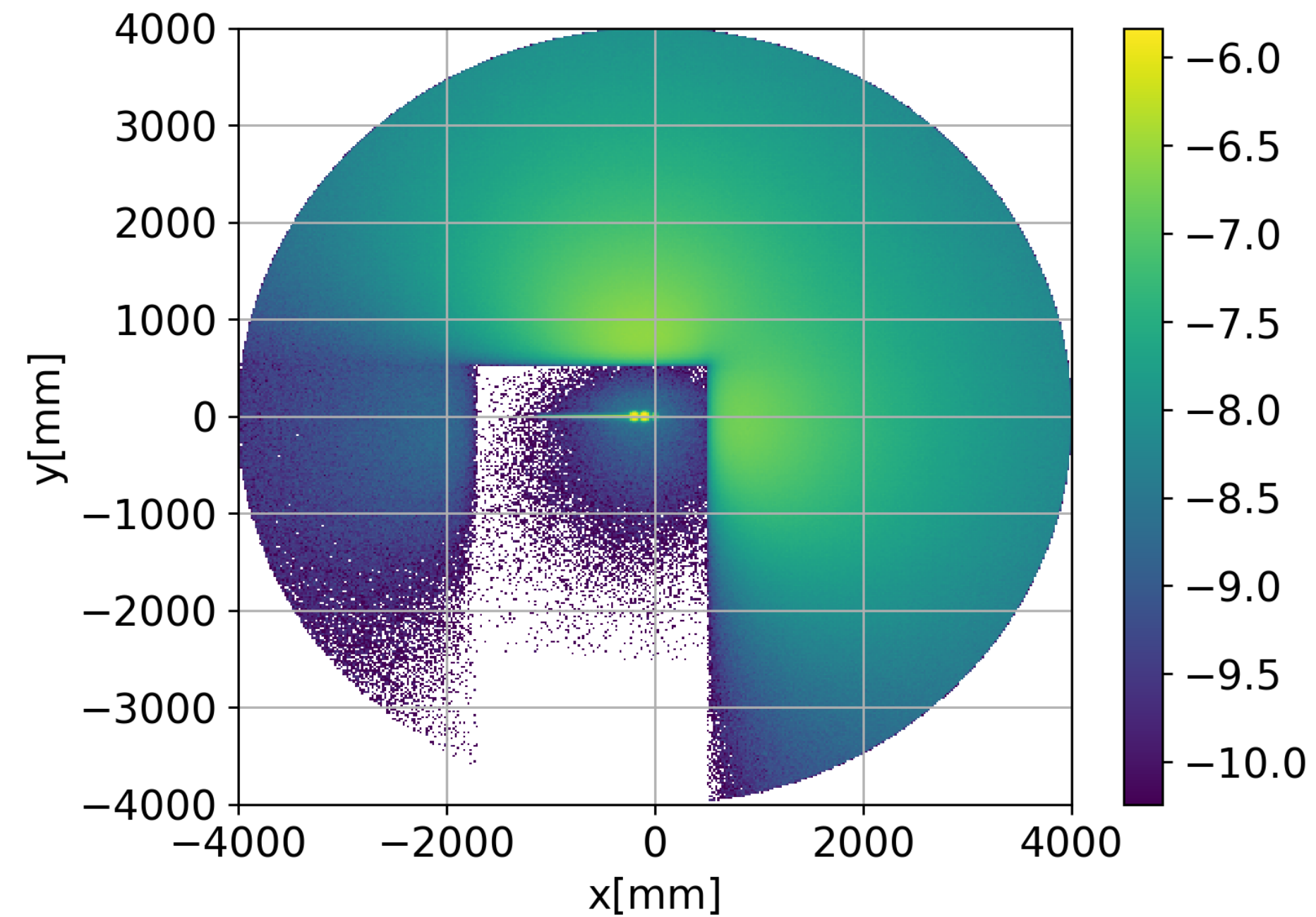
photon beam



e- dump at 2T field

# Split learning

- Data splitting
- Treat each region separately



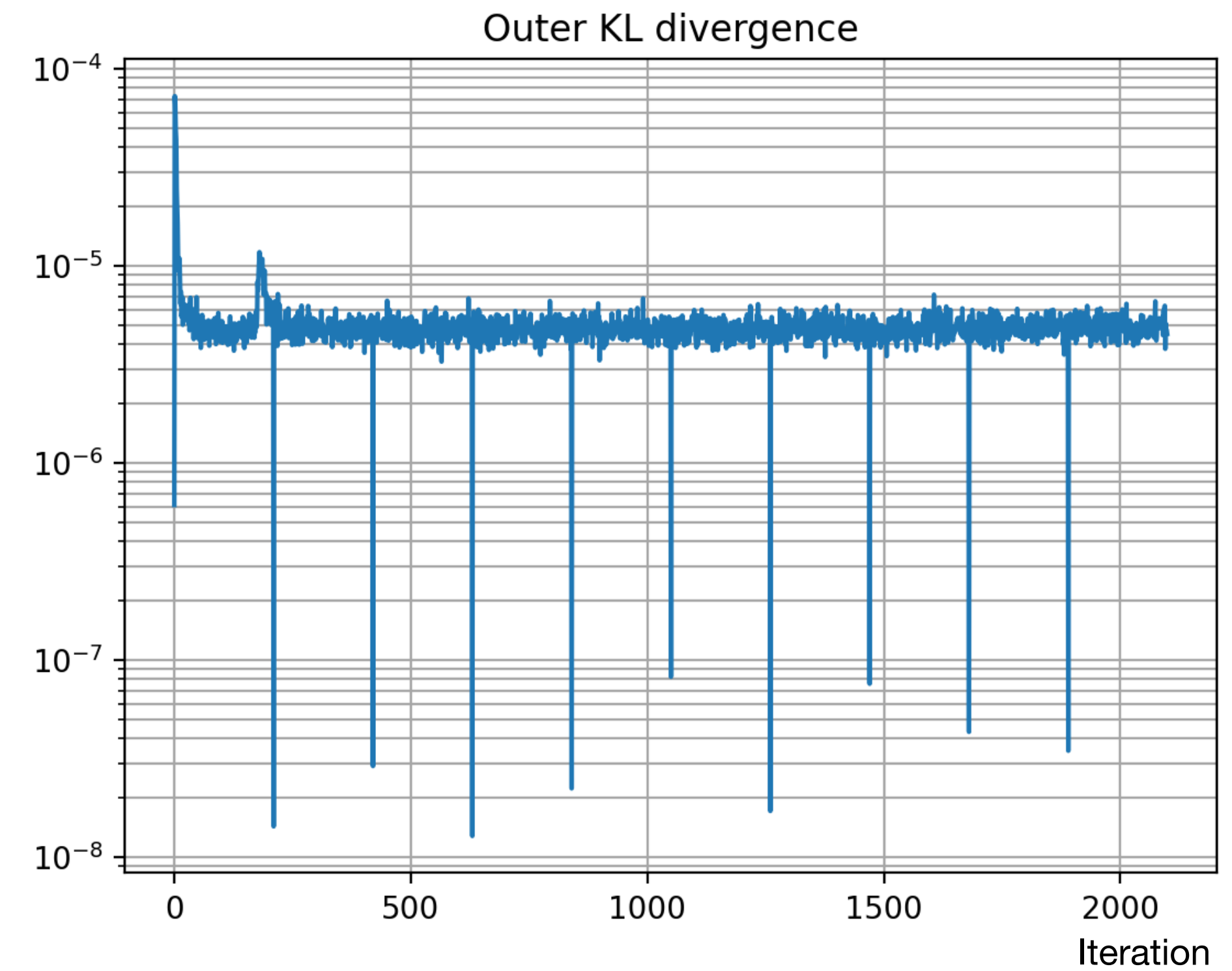
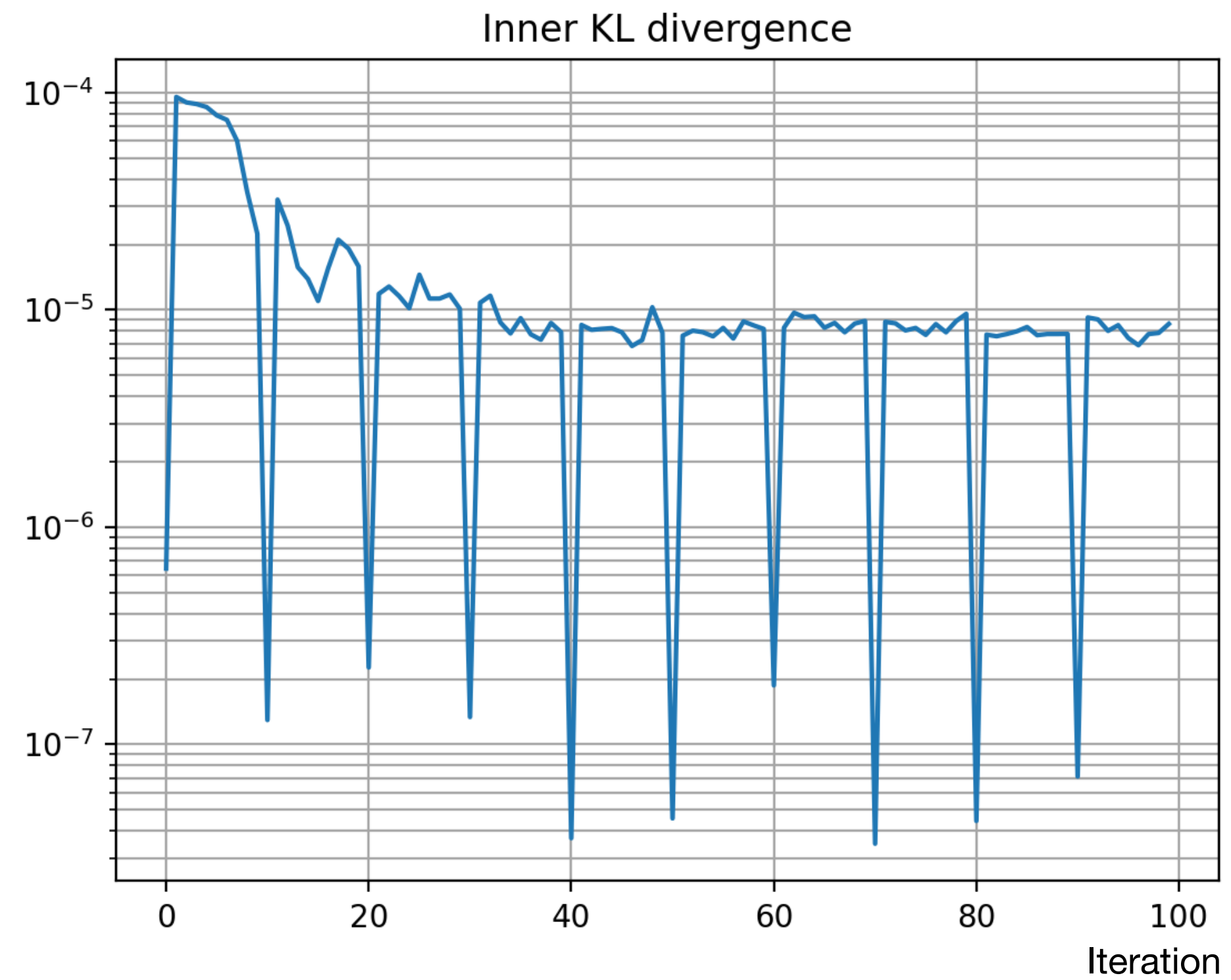


# Hyperparameters and testing

- Larger batch sizes
- Different coordinate systems
- Training redundancy

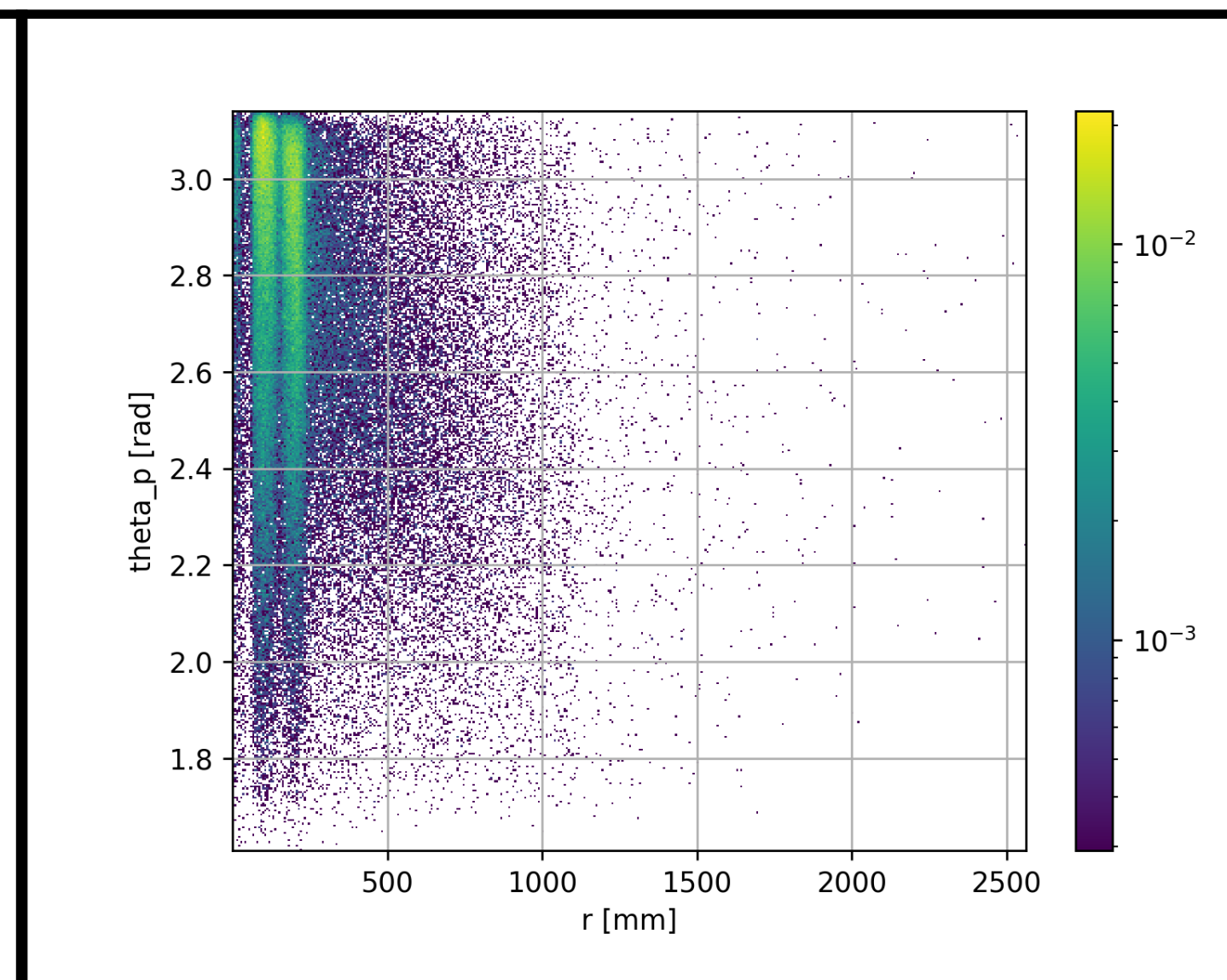
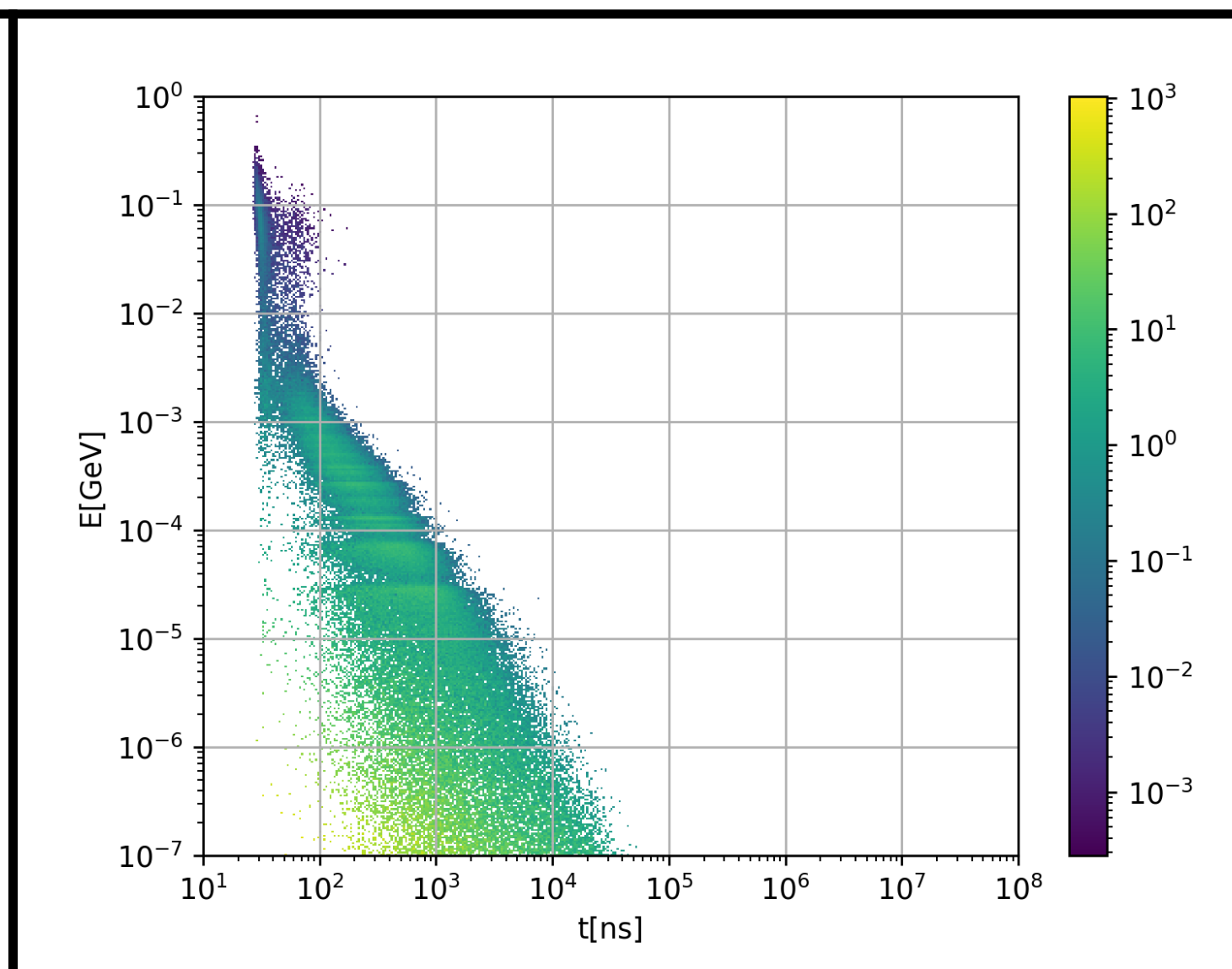
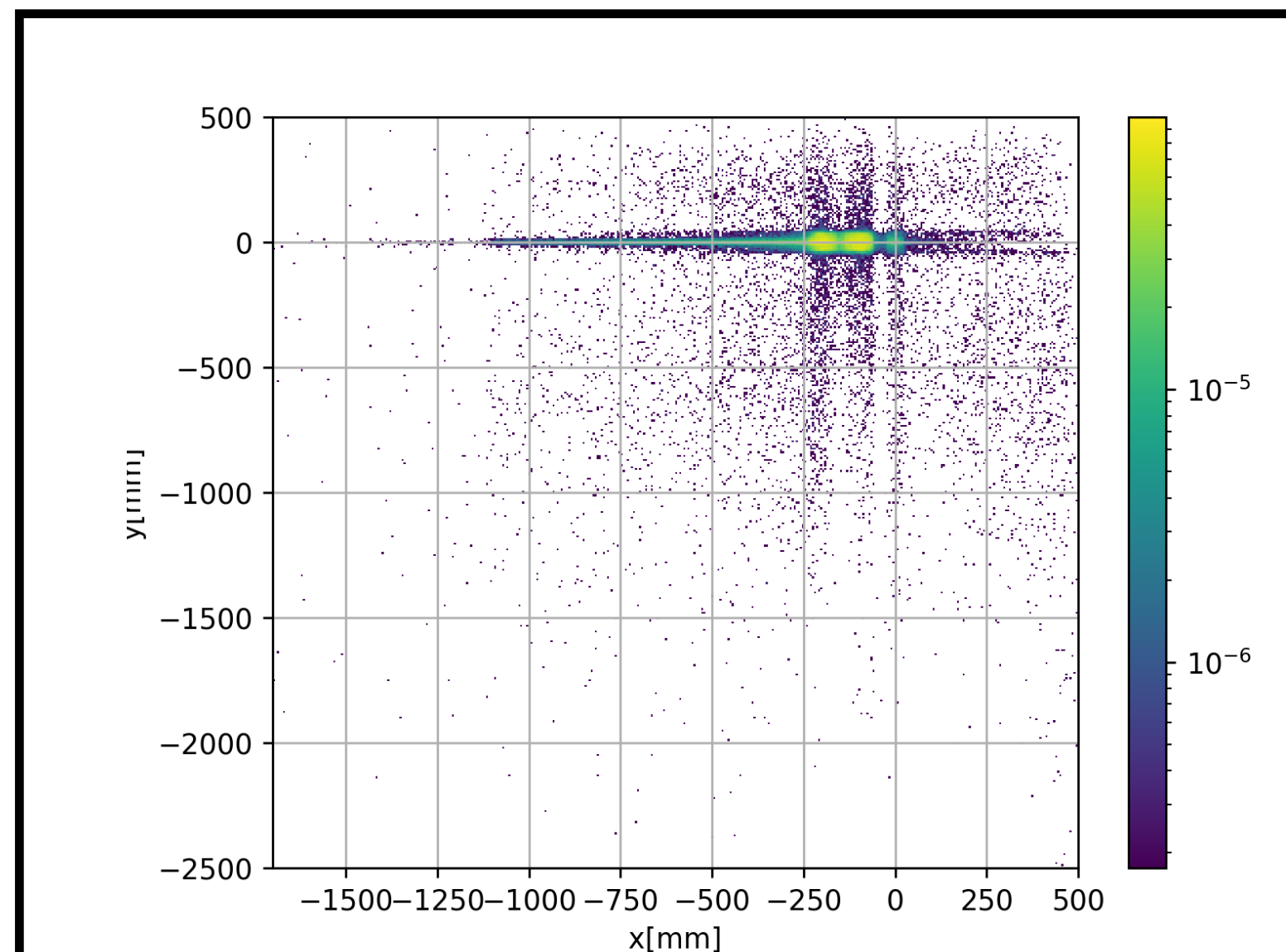
Train with:  $\begin{bmatrix} r_x = \sqrt{x^2 + y^2} \\ x \\ y \end{bmatrix}$ , Generate only:  $\begin{bmatrix} x \\ y \end{bmatrix}$

# Learning process

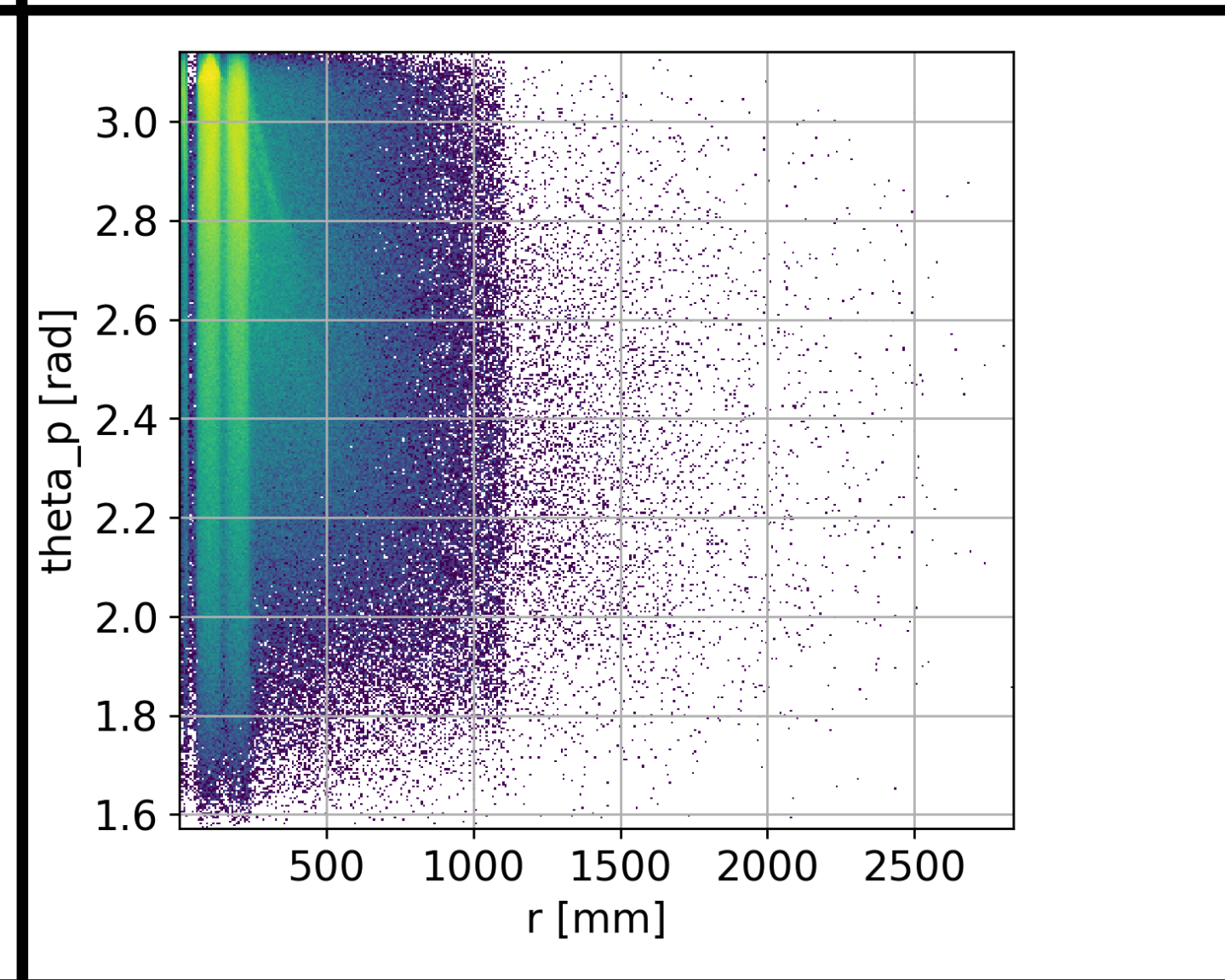
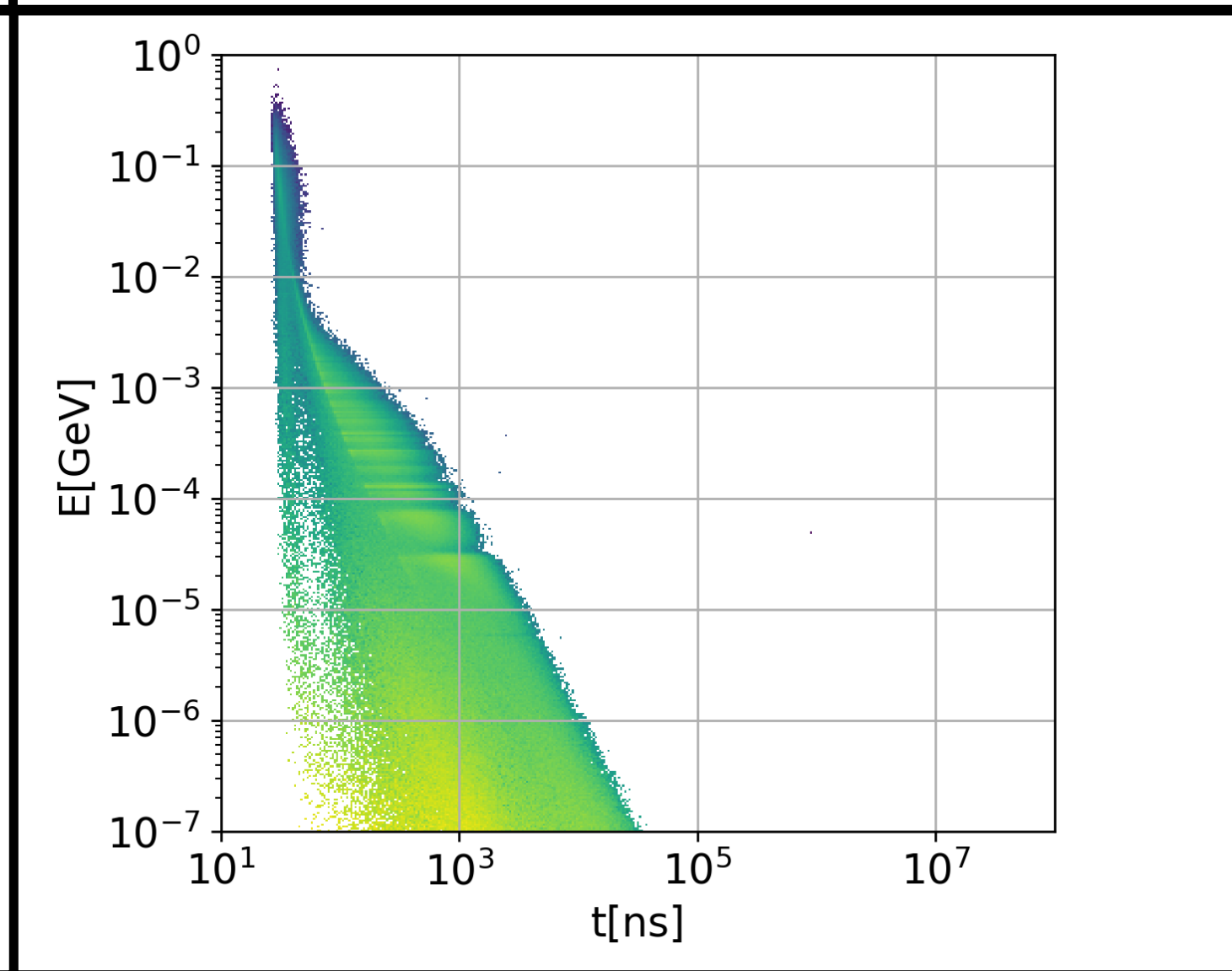
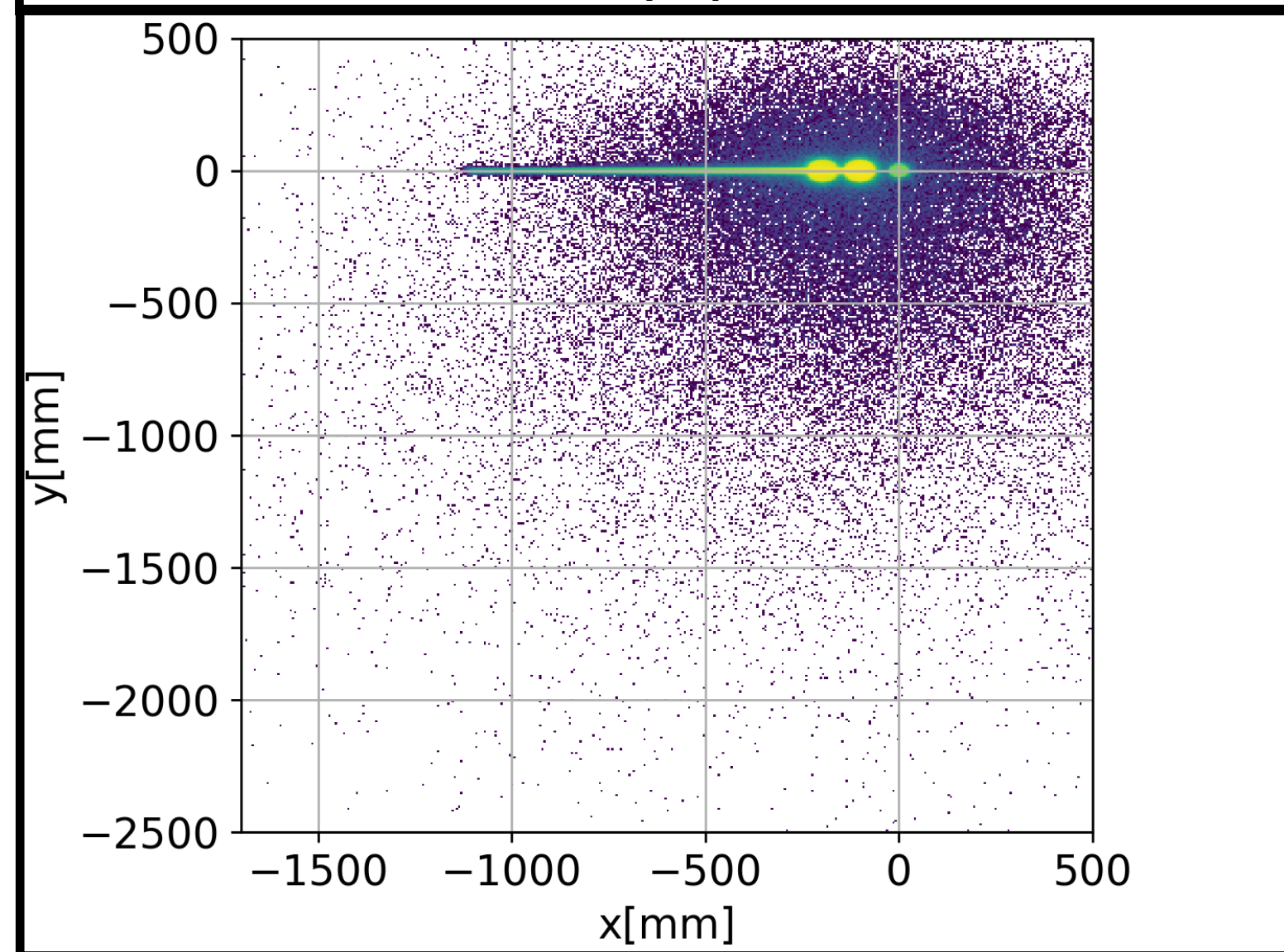


# “Inner” points

Generated  
Data



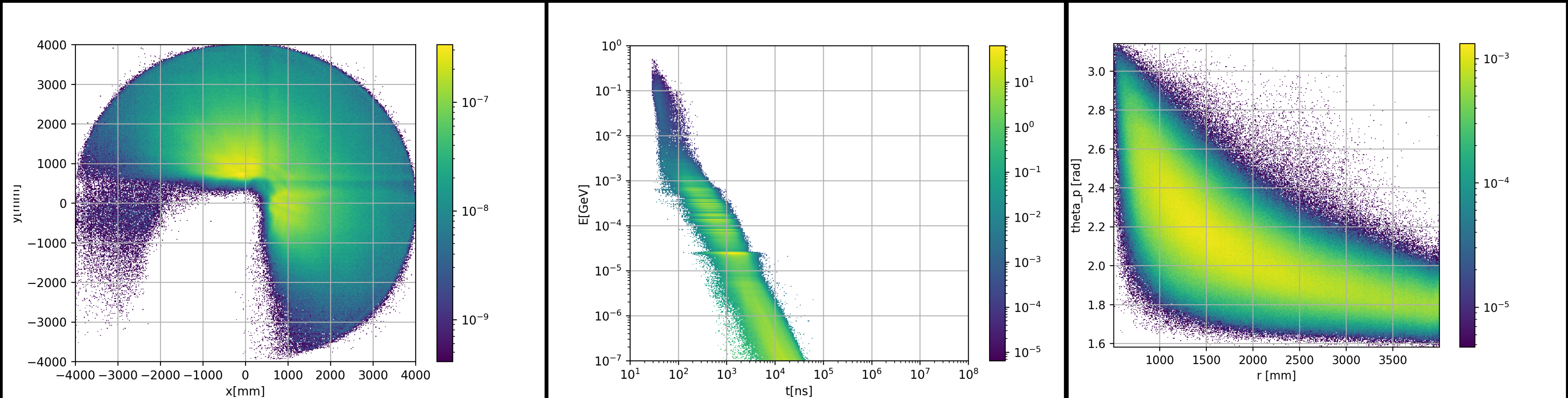
FullSim



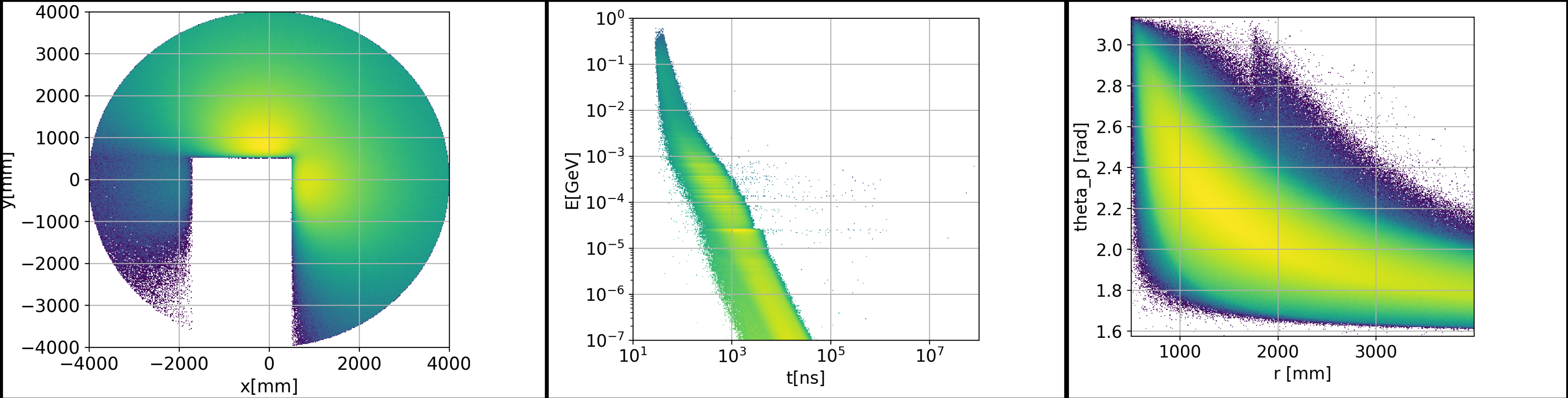


# “Outer” points

Generated  
Data

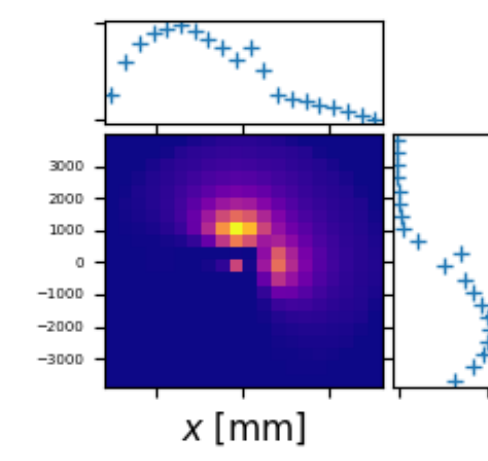


FullSim

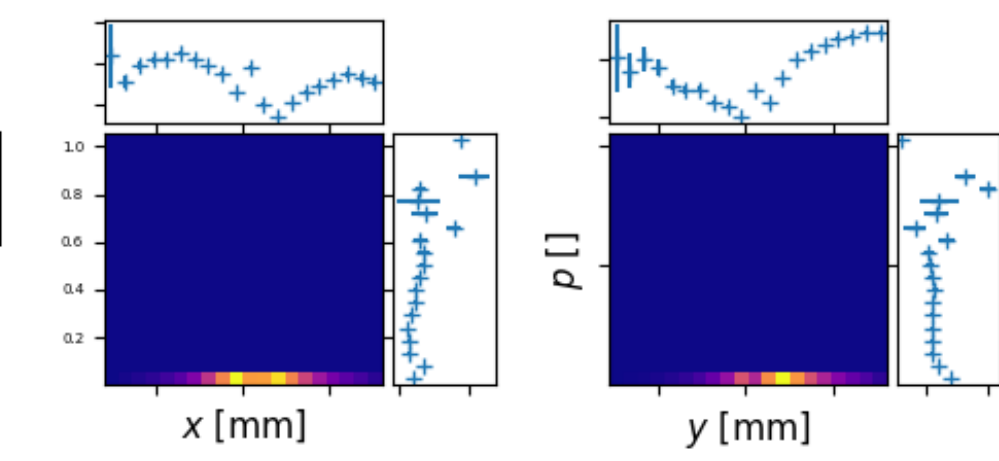




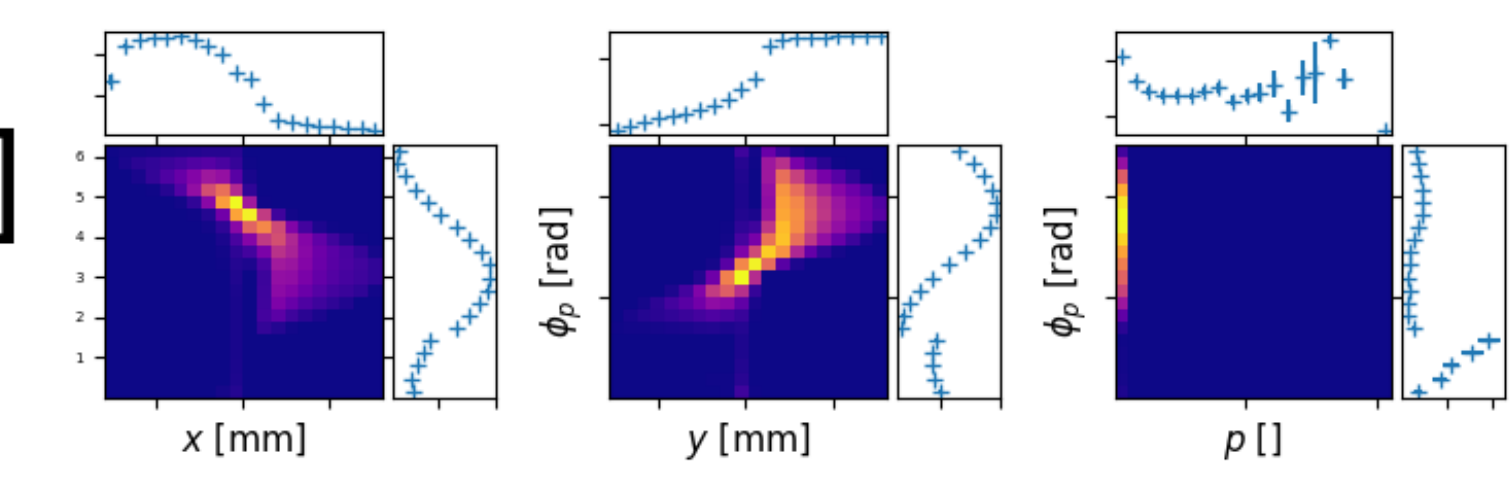
$y$  [mm]



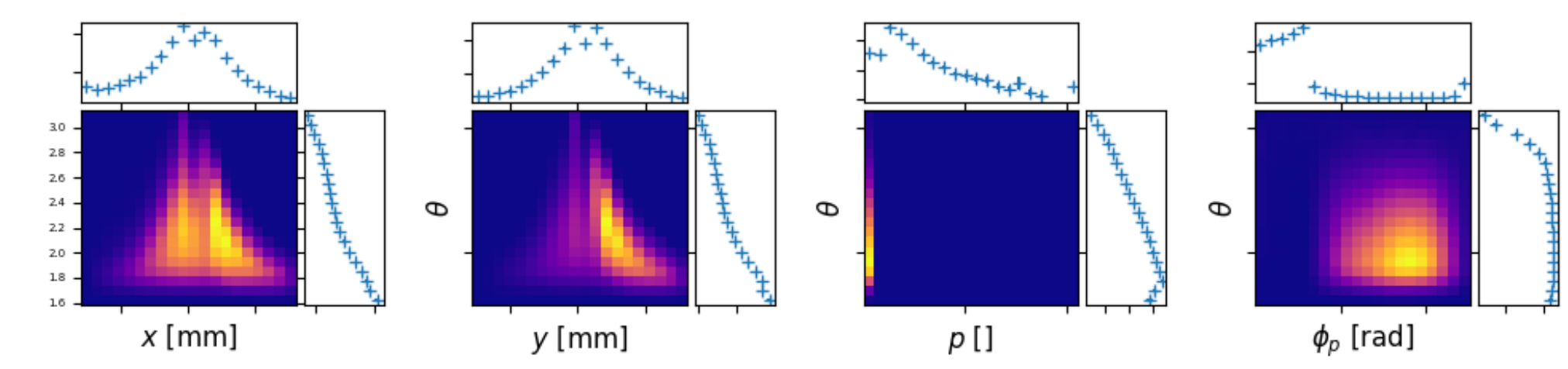
$p$  []



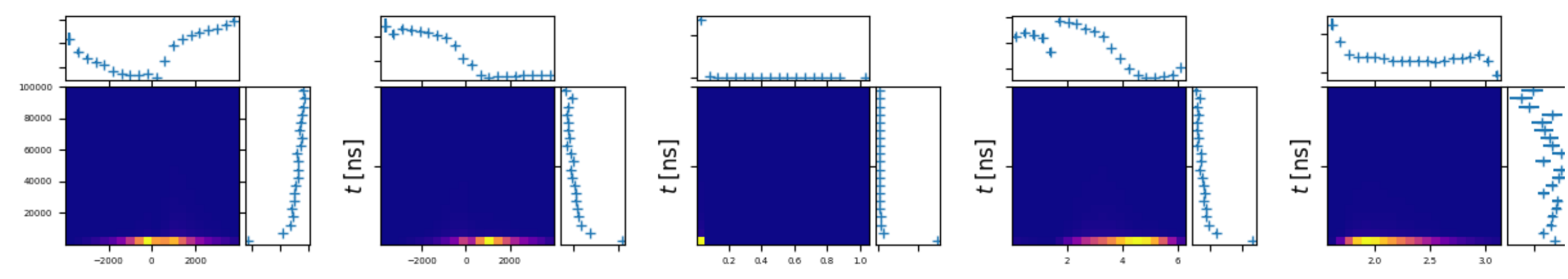
$\phi_p$  [rad]



$\theta$



$t$  [ns]



$x$  [mm]

$y$  [mm]

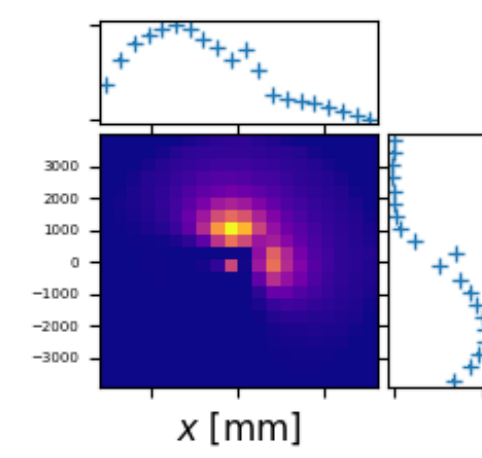
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$\phi_p$  [rad]

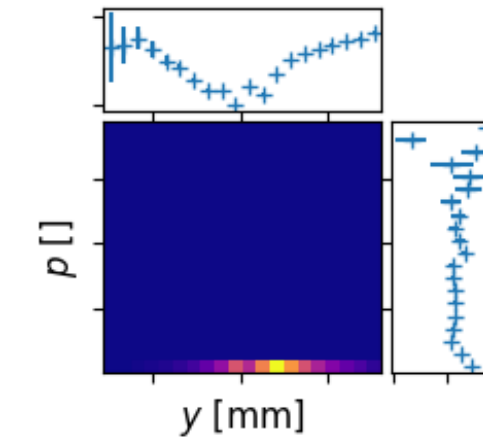
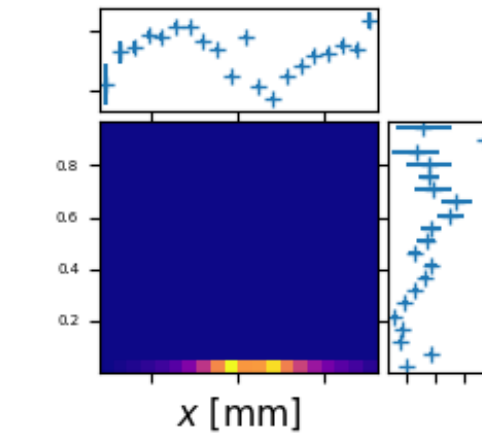
$\theta$

FullSim

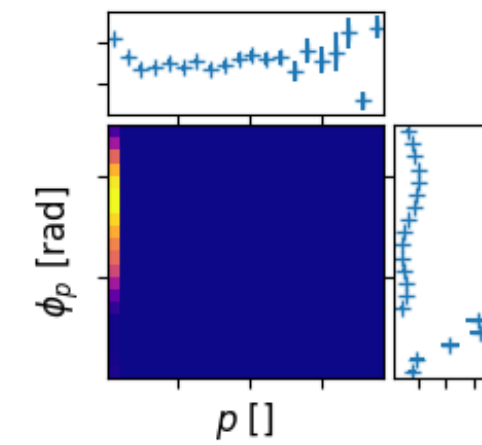
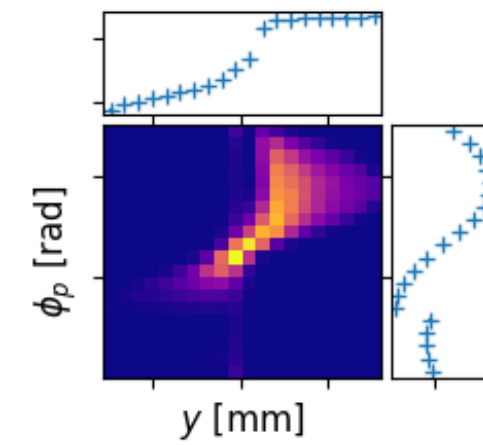
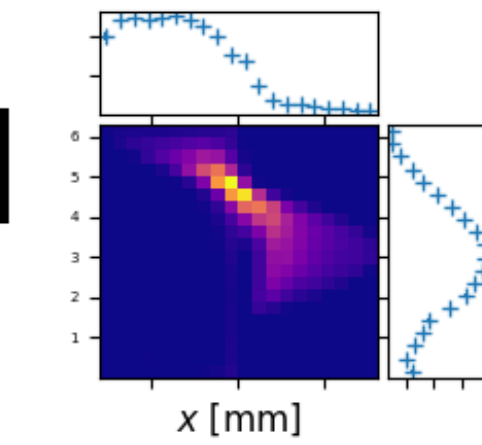
$y$  [mm]



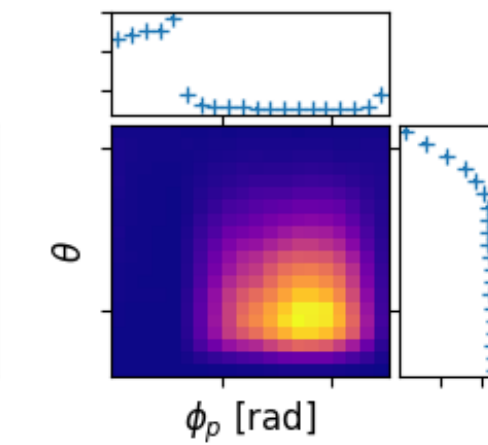
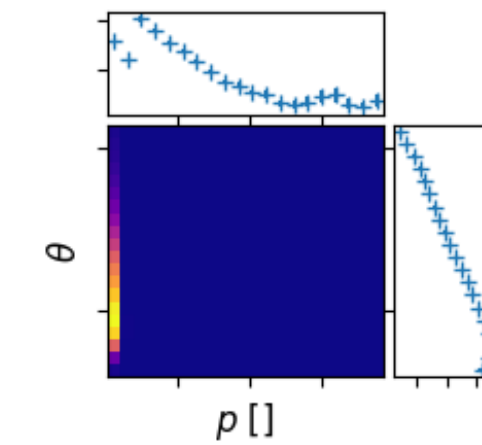
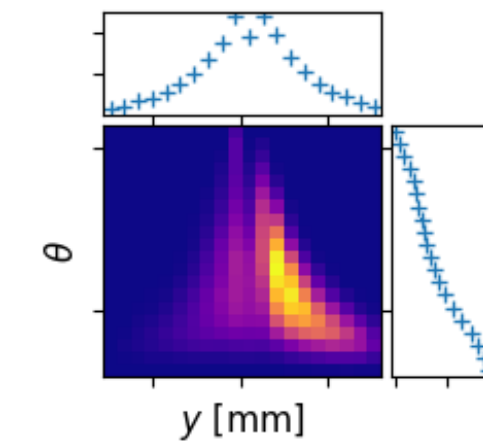
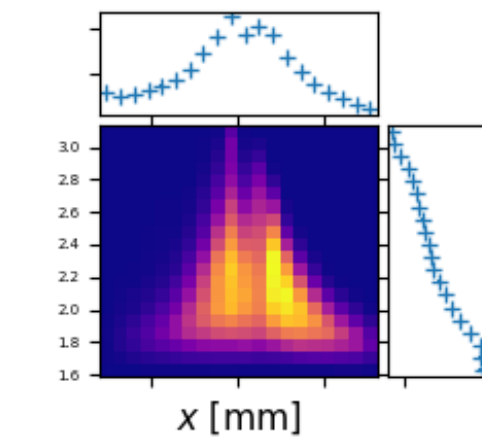
$p$  []



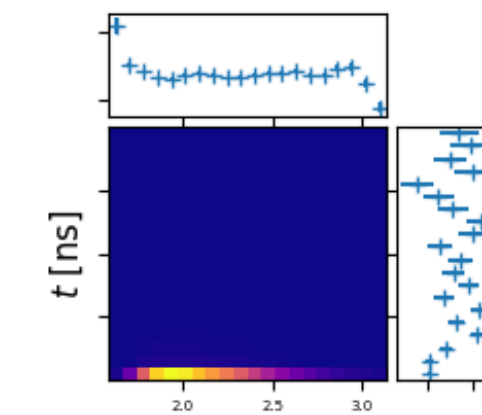
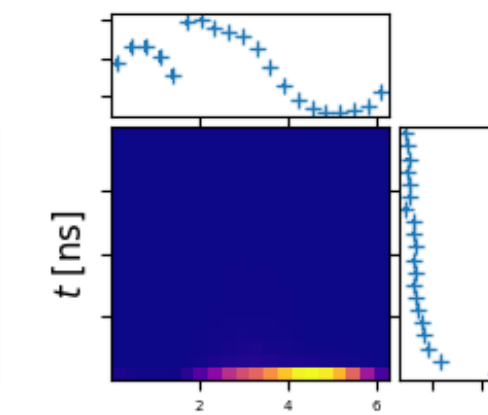
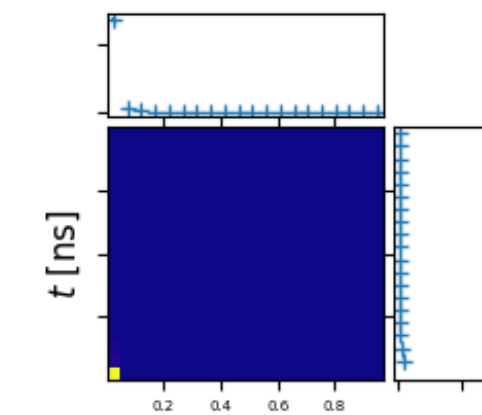
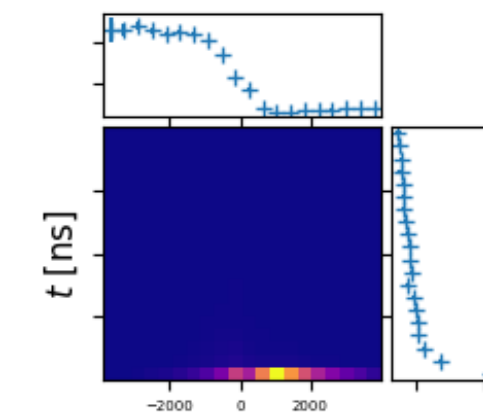
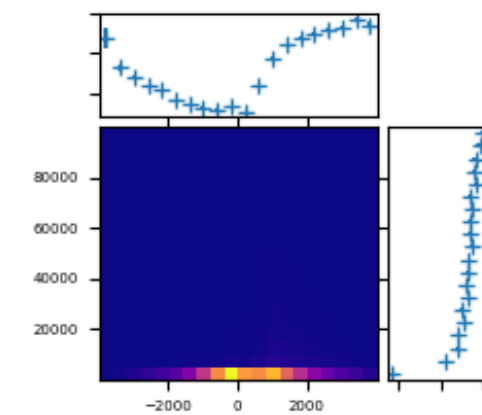
$\phi_p$  [rad]



$\theta$



$t$  [ns]



$x$  [mm]

$y$  [mm]

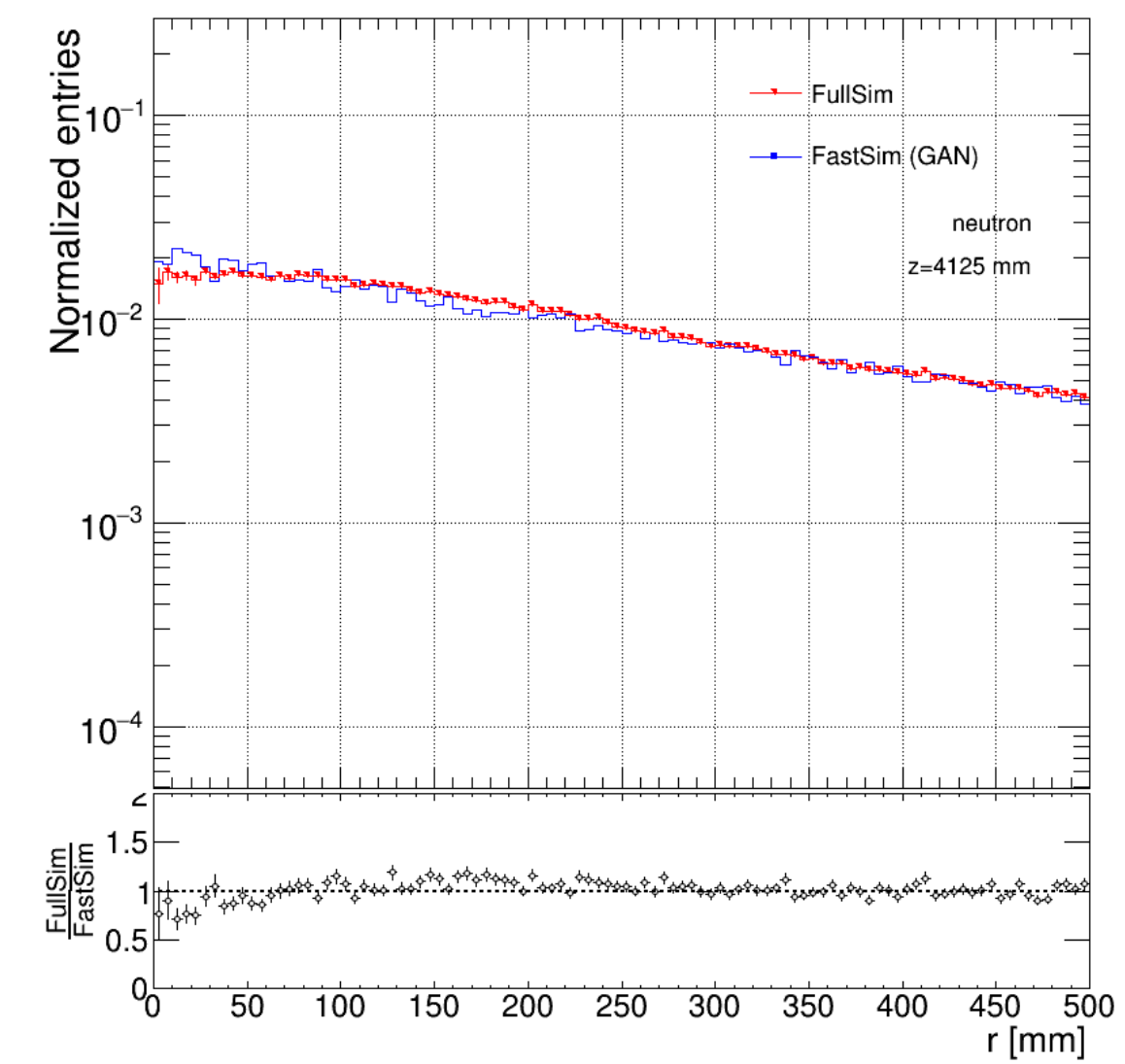
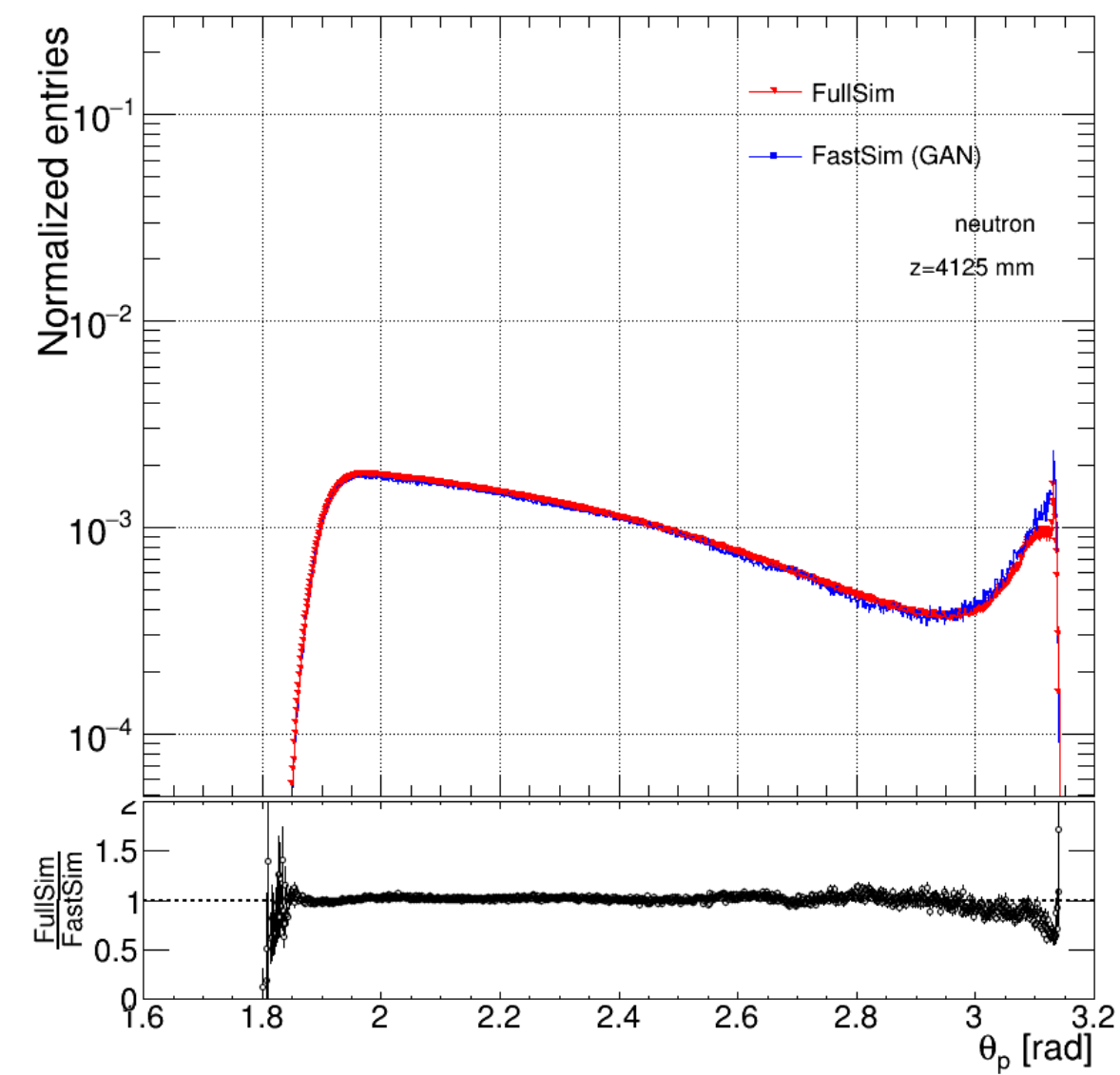
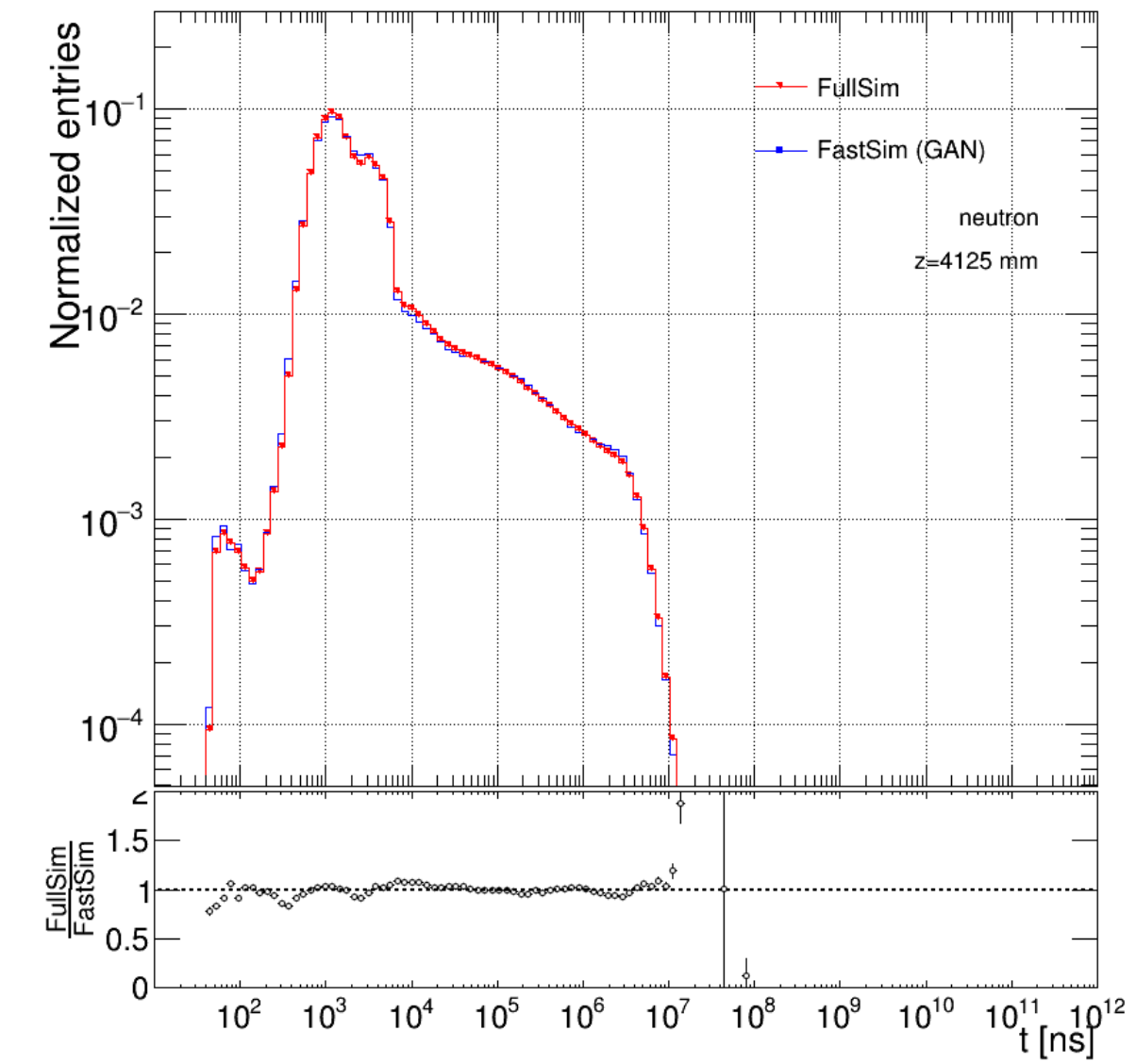
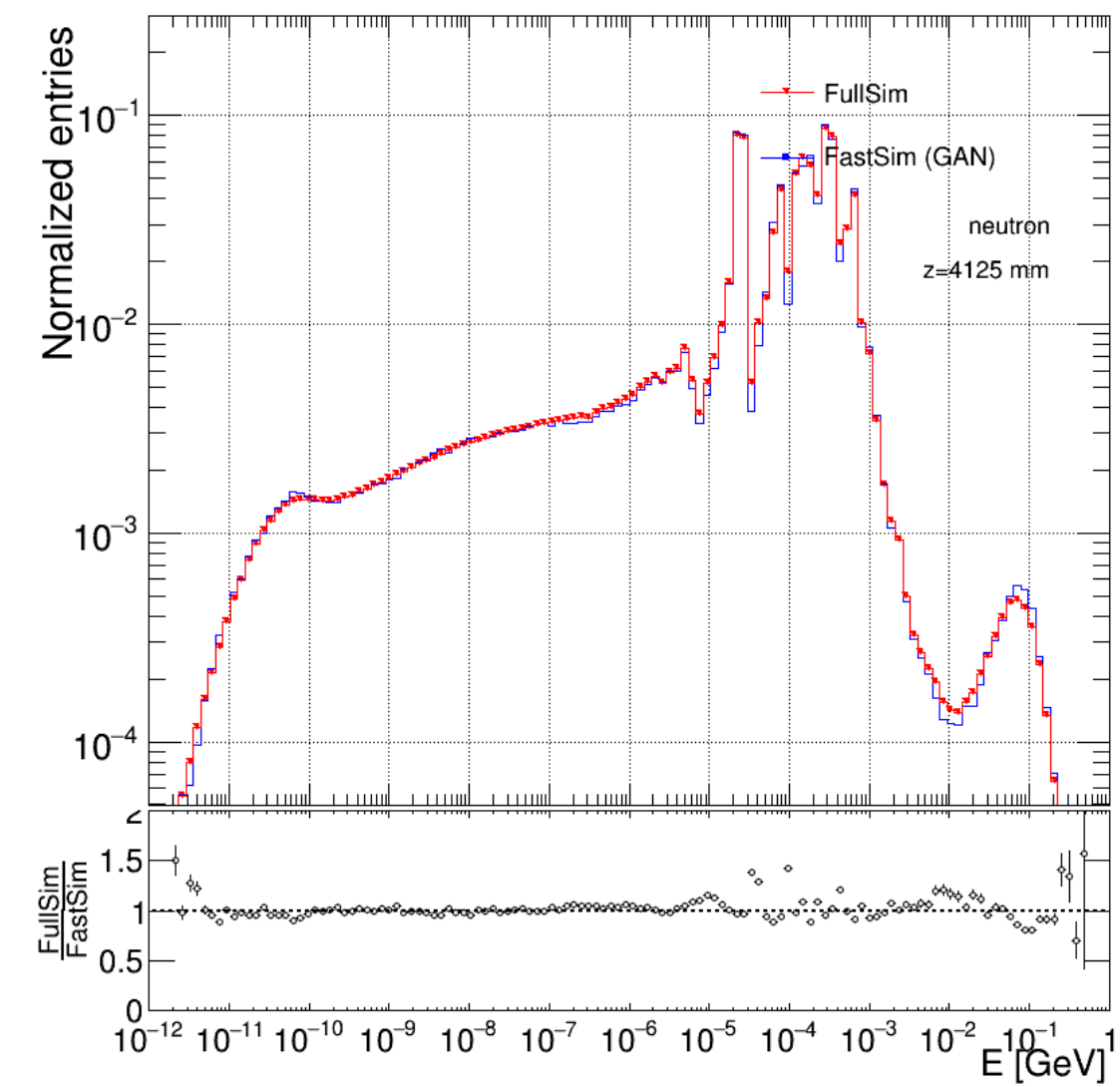
$p$  []

$\phi_p$  [rad]

$\theta$

FastSim

# At tracker surface



# Further steps

- Quantifying how well the distributions match
- Applying the same method to different particle types
- Extracting actual background from generated events



**Thank you!**