Preliminary reconstructions of the 3D structure of electron bunches based on COTR using two methods

Ze Ouyang

Jan 16th, 2025

Content

- Overview of the inverse COTR problem
- Gradient-descent & Generative-neural-network reconstruction
- Several comparison
- Robustness of these two method
- Conclusion & Discussion

Overview

- Electron bunch $\rho(x_s, y_s, z_s)$ to COTR $C(i, j, \lambda_0)$

$$C(i, j, \lambda_0) = \hat{\mathcal{R}}(\rho(x_s, y_s, z_s))$$

ARTICLE Open Access

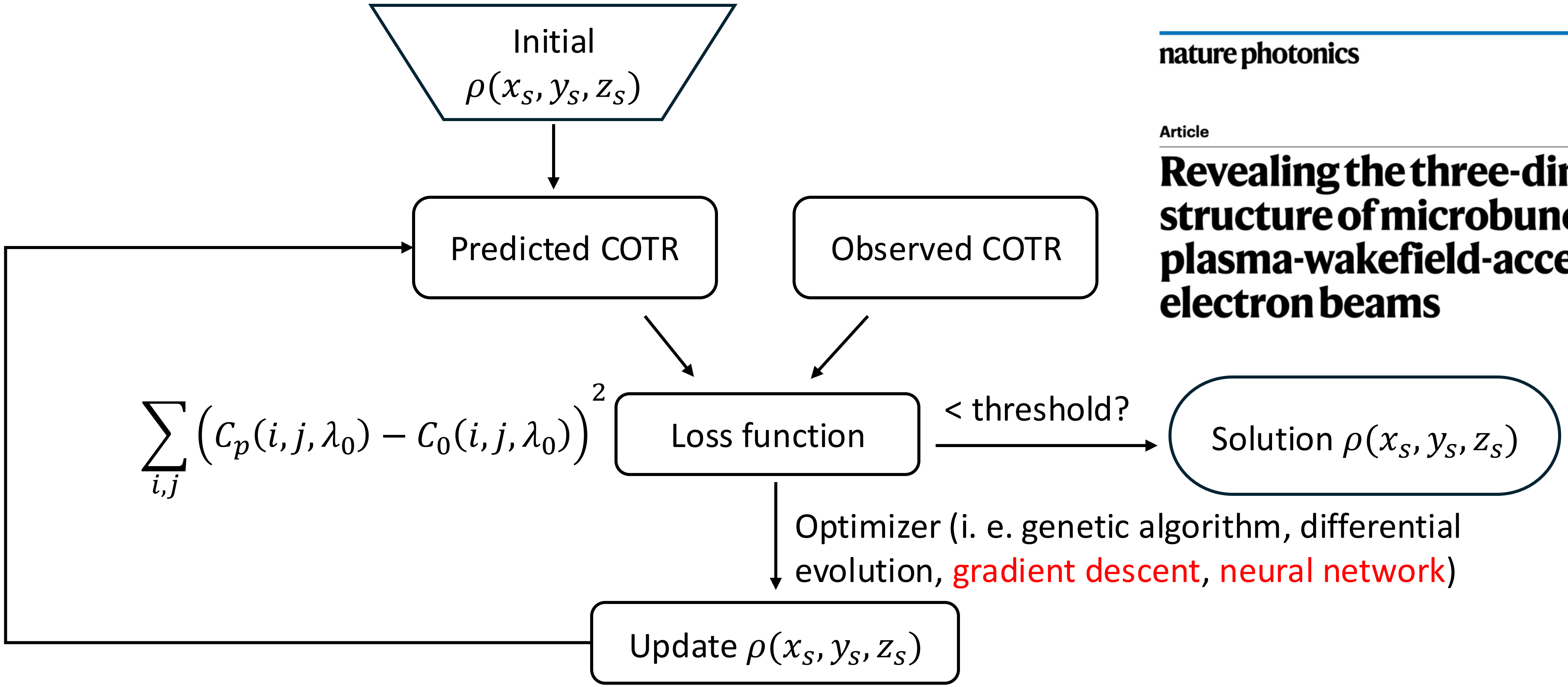
Electro-optic 3D snapshot of a laser wakefield accelerated kilo-ampere electron bunch

Kai Huang[1,2], Zhan Jin[2,3], Nobuhiko Nakanii[1,2], Tomonao Hosokai[2,3] and Masaki Kando[1,2]

nature photonics

Article https://d

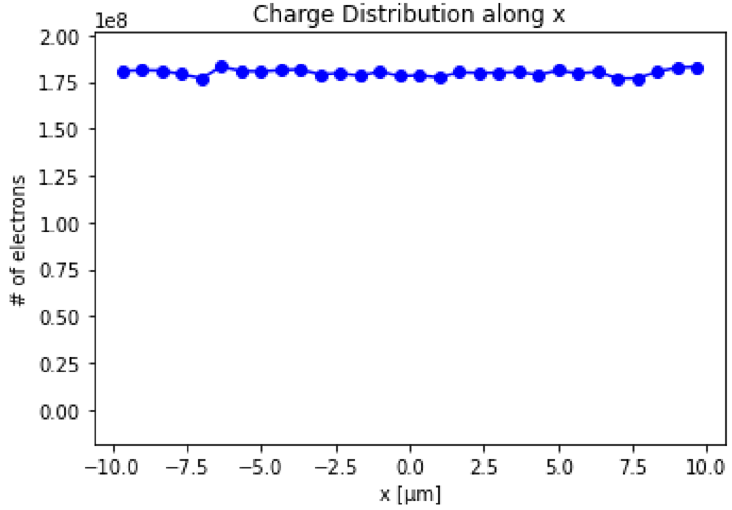
Revealing the three-dimensional structure of microbunched plasma-wakefield-accelerated electron beams

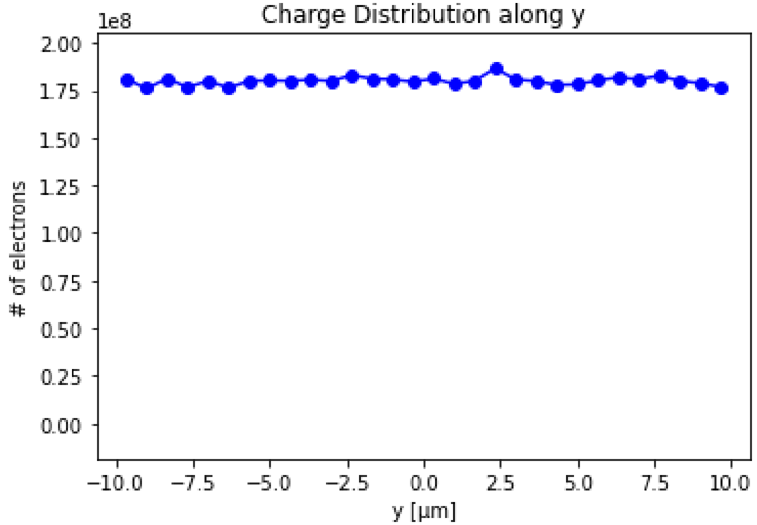


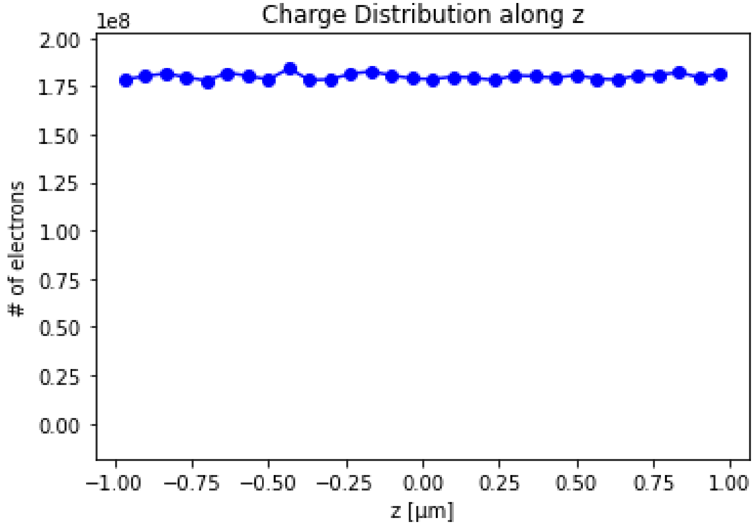
Description of $\rho(x_s, y_s, z_s)$

- 3D space: $L_x \times L_y \times L_z$ (10µm × 10µm × 1µm)
- Grids uniformly distributed in this space (30 × 30 × 30 = 27k)
- Each grid has certain number of electrons, 5.4e9 in total (865pC)

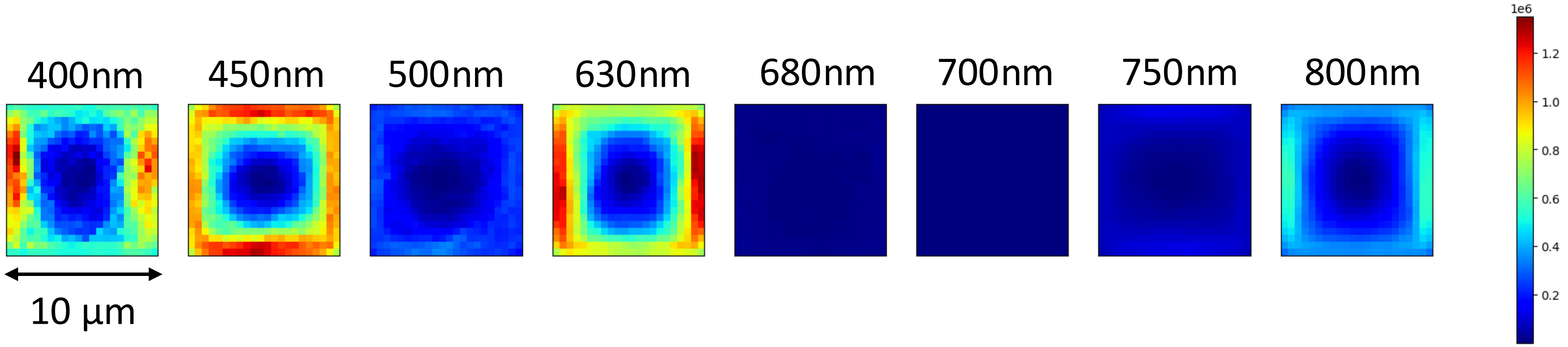
Task: Find a parameter set (grid charge) that minimizes the lost function





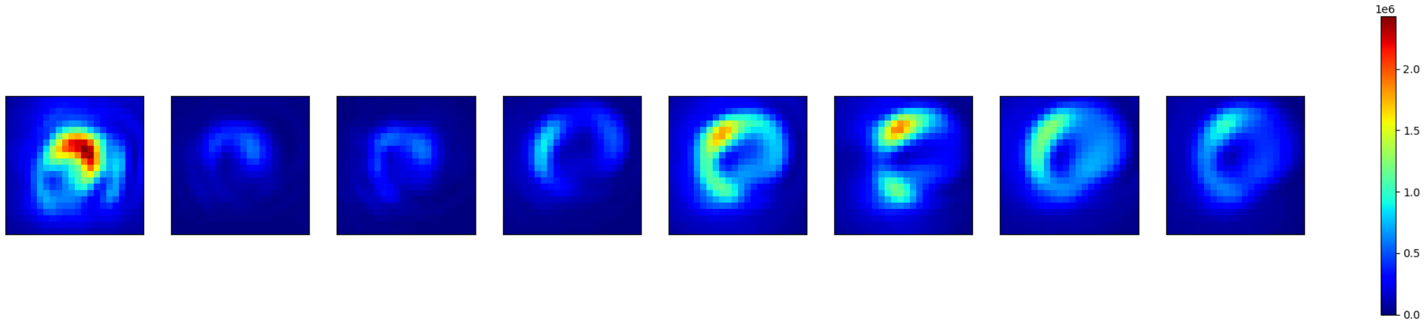


Synthetic COTR



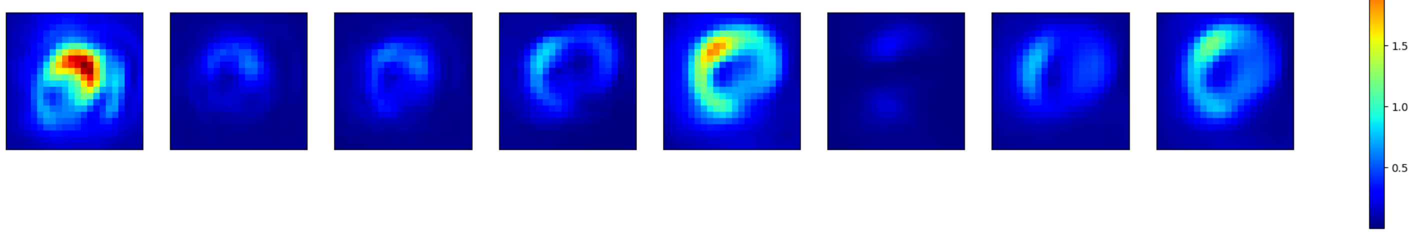
GD-based reconstruction from uniform $\rho(x_s, y_s, z_s)$

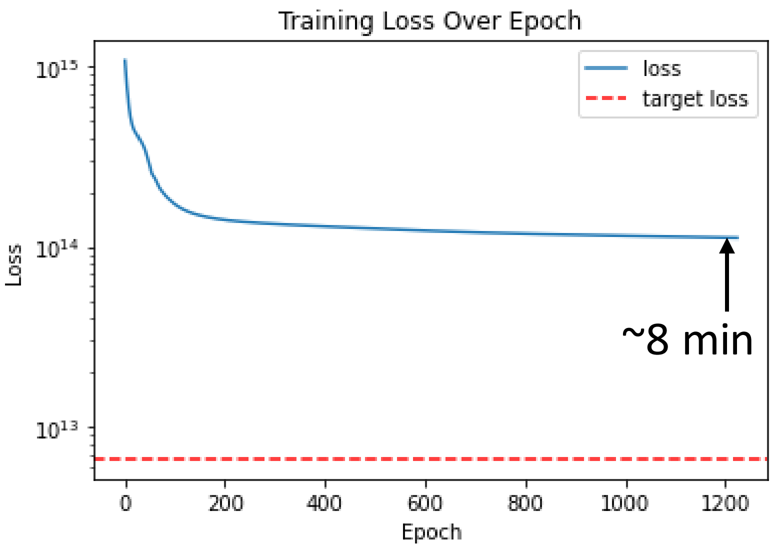
Experimental COTR



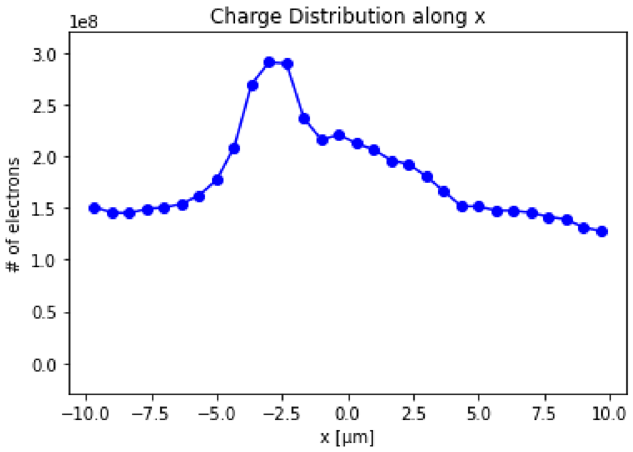
We start with quasi-uniformly distributed electron bunches!

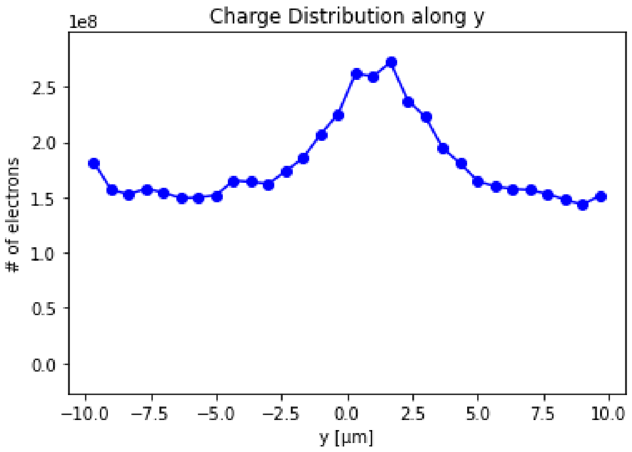
Reconstructed COTR by GD

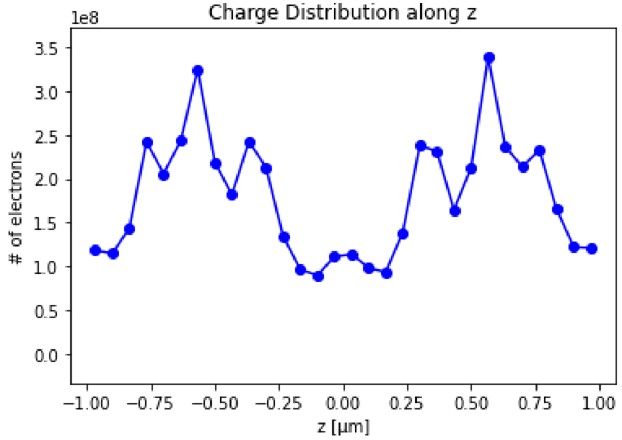




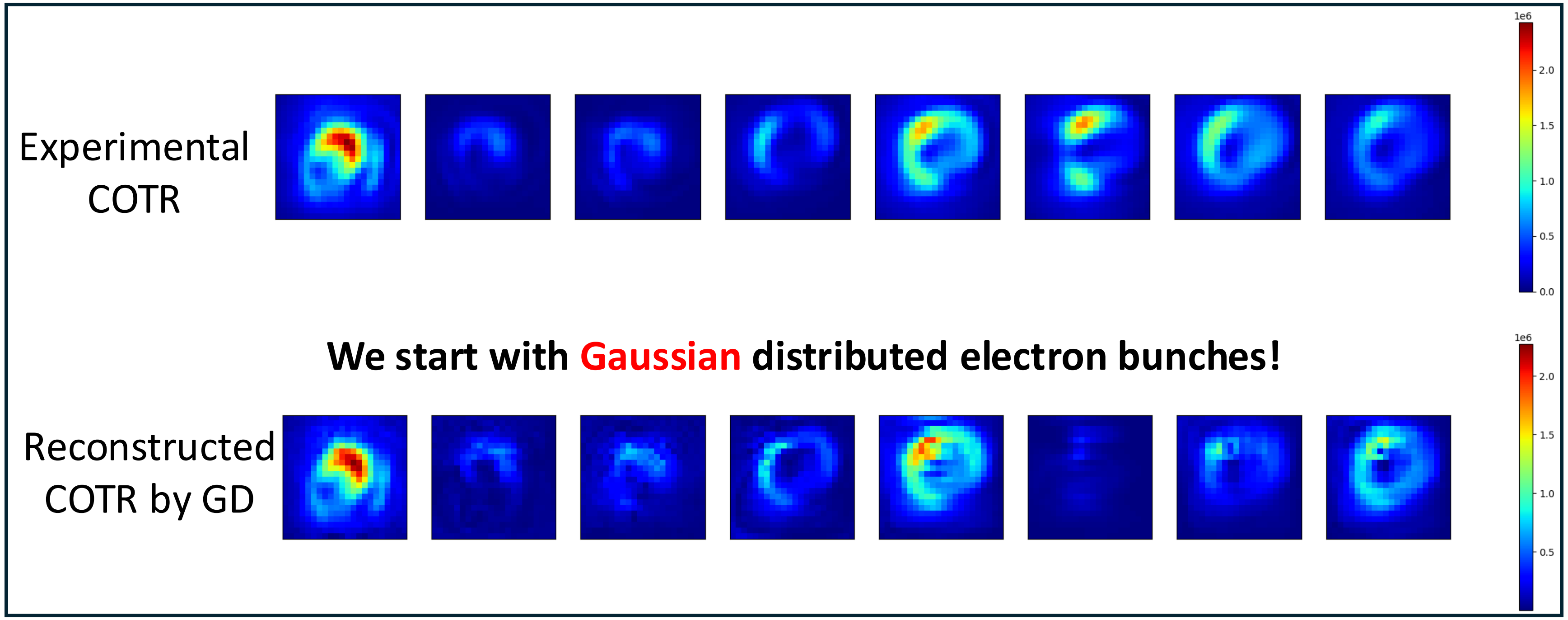
Target loss: difference of pixel <10%

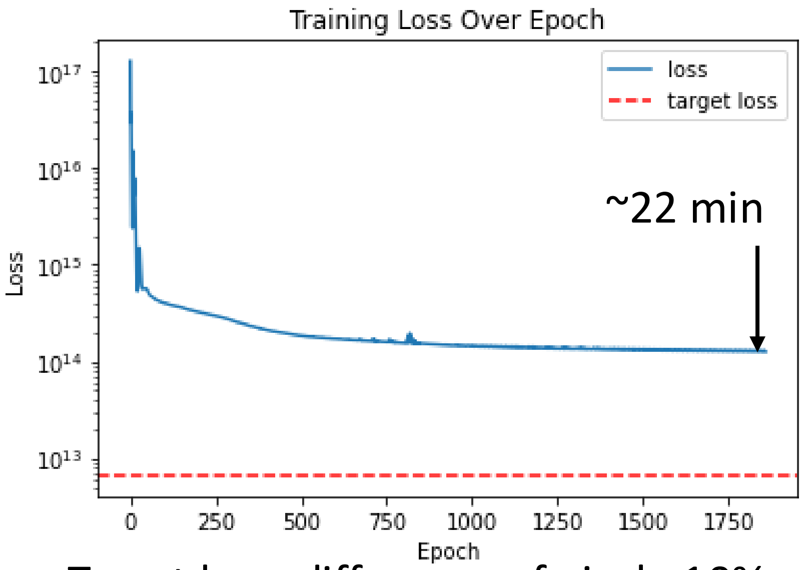




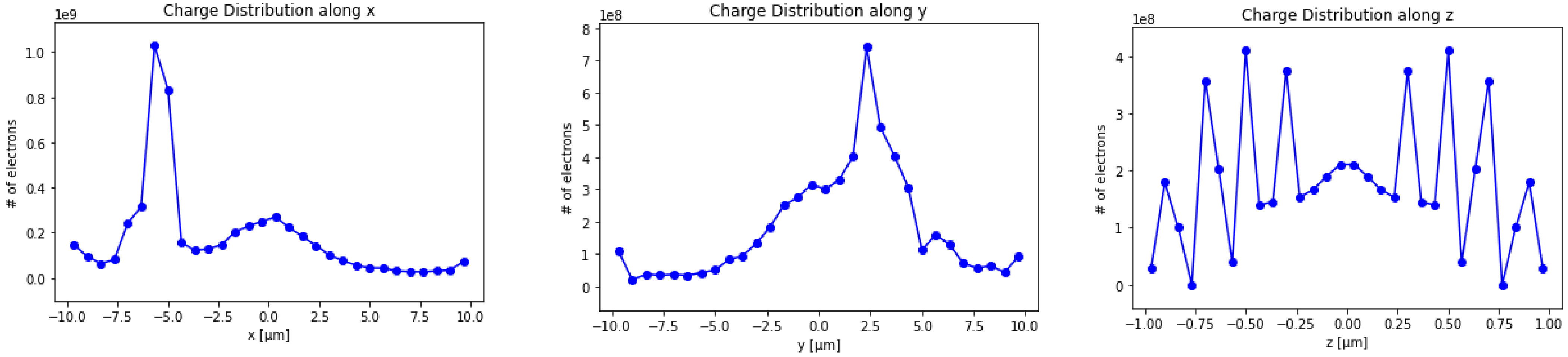


GD-based reconstruction from Gaussian $\rho(x_s, y_s, z_s)$





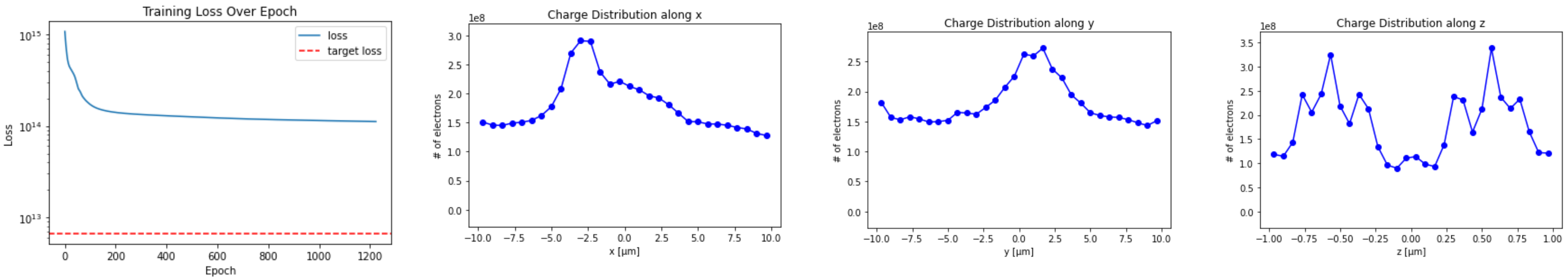
Target loss: difference of pixel <10%



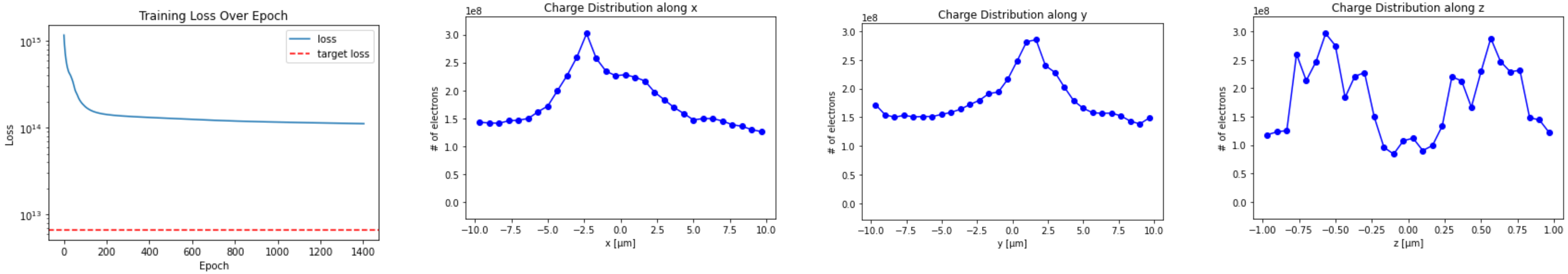
Uniqueness discussion on GD

We start with quasi-uniformly distributed electron bunches!

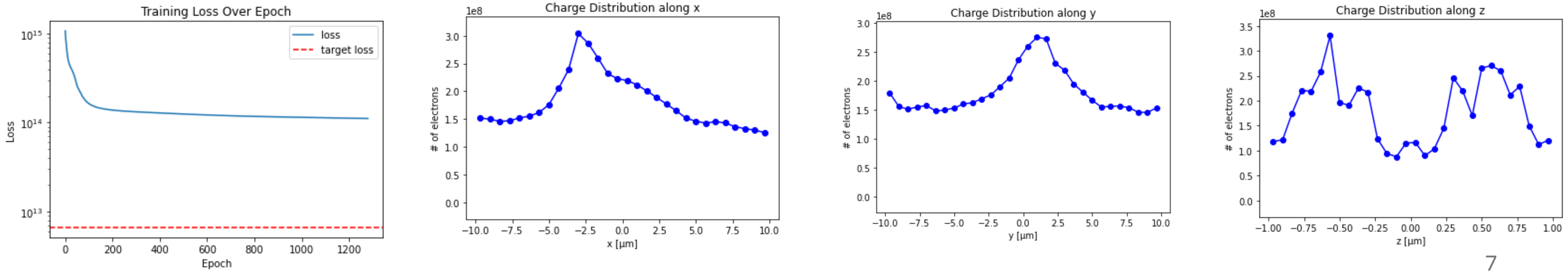
Solution 1



Solution 2



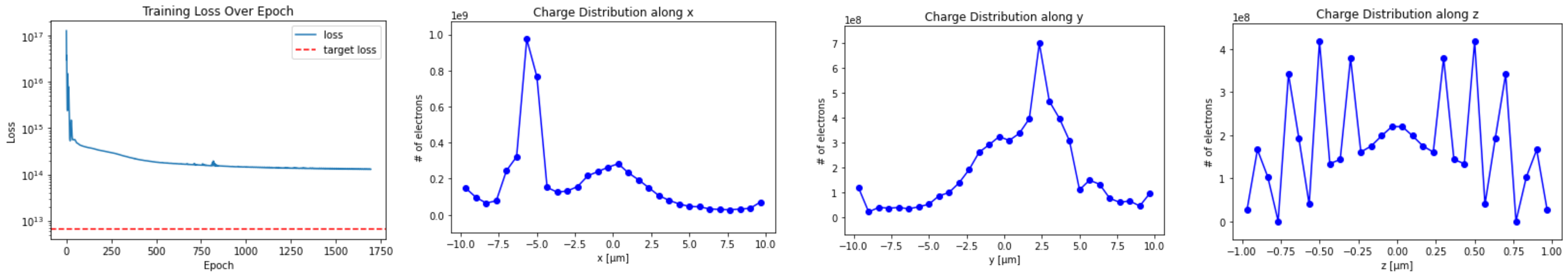
Solution 3



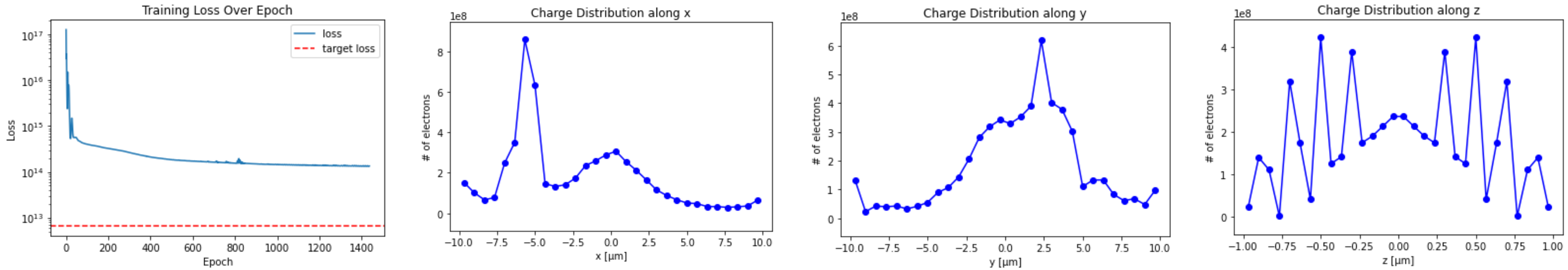
Uniqueness discussion on GD

We start with Gaussian distributed electron bunches!

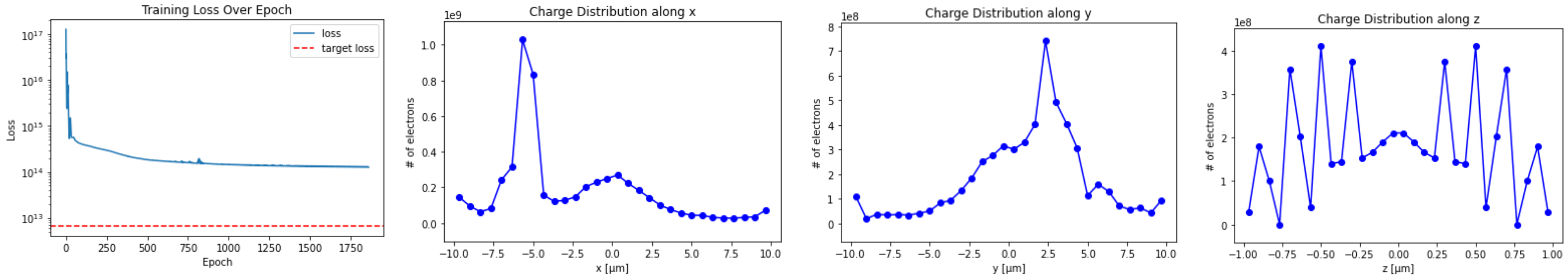
Solution 1



Solution 2



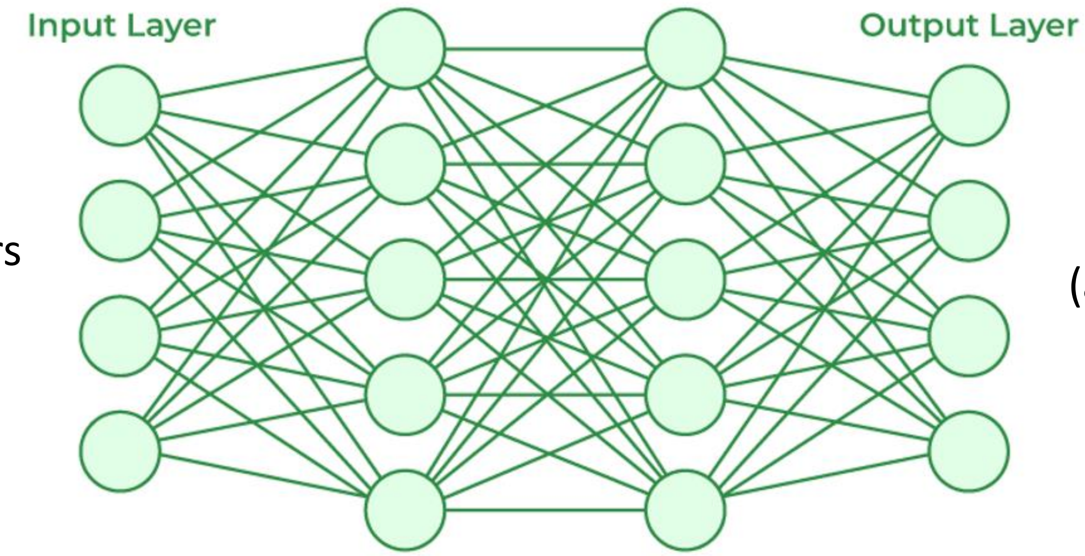
Solution 3



GNN-based reconstruction

Generative Neural Network

Noise
(array of 50 random numbers
between 0 to 1)



Grid charge
(array of 27k numbers)

Universal function approximator

- Rather than directly tune the grid charge in the GD method, here we tune the parameters of NN.
- Parameters of NN: Weights, Biases, # of layers, # of neurons per layer, activation function, et al.
- For the case here, we have ~200k parameters of the NN.

GNN-based reconstruction

PHYSICAL REVIEW LETTERS **130,** 145001 (2023)

Phase Space Reconstruction from Accelerator Beam Measurements Using Neural Networks and Differentiable Simulations

R. Roussel,* A. Edelen, C. Mayes, and D. Ratner
SLAC National Accelerator Laboratory, Menlo Park, California 94025, USA

PHYSICAL REVIEW ACCELERATORS AND BEAMS **27,** 094601 (2024)
Editors' Suggestion

Efficient six-dimensional phase space reconstructions from experimental measurements using generative machine learning

Ryan Roussel,[1] Juan Pablo Gonzalez-Aguilera,[2] Eric Wisniewski,[3] Alexander Ody,[3] Wanming Liu,[3] John Power,[3] Young-Kee Kim,[2] and Auralee Edelen[1]
[1]*SLAC National Accelerator Laboratory, Menlo Park, California 94025, USA*
[2]*Department of Physics and Enrico Fermi Institute, University of Chicago, Chicago, Illinois 60637, USA*
[3]*Argonne National Laboratory, Lemont, Illinois 60439, USA*

PHYSICAL REVIEW ACCELERATORS AND BEAMS **27,** 074601 (2024)

Four-dimensional phase-space reconstruction of flat and magnetized beams using neural networks and differentiable simulations

Seongyeol Kim,[1,*] Juan Pablo Gonzalez-Aguilera,[2,†] Philippe Piot,[1,3] Gongxiaohui Chen,[1] Scott Doran,[1] Young-Kee Kim,[2] Wanming Liu,[1] Charles Whiteford,[1] Eric Wisniewski,[1] Auralee Edelen,[4] Ryan Roussel,[4] and John Power[1]

This recent paper from our friends at AAC appears relevant to our discussion on Tuesday. MD

From: ResearchGate <no-reply@researchgatemail.net>
Date: Saturday, September 14, 2024 at 3:22 AM
To: Downer, Michael <downer@physics.utexas.edu>
Subject: M.C., a recent article cited your research

M.C., we found a recent citation of your research:

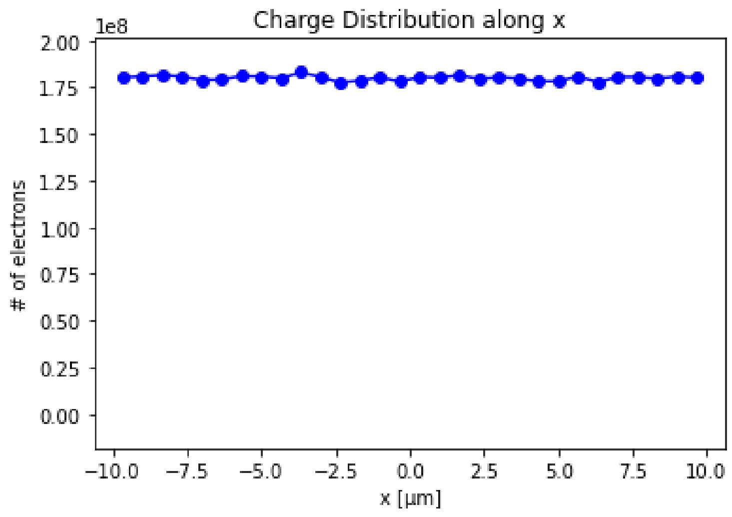
Efficient six-dimensional phase space reconstructions from experimental measurements using generative machine learning

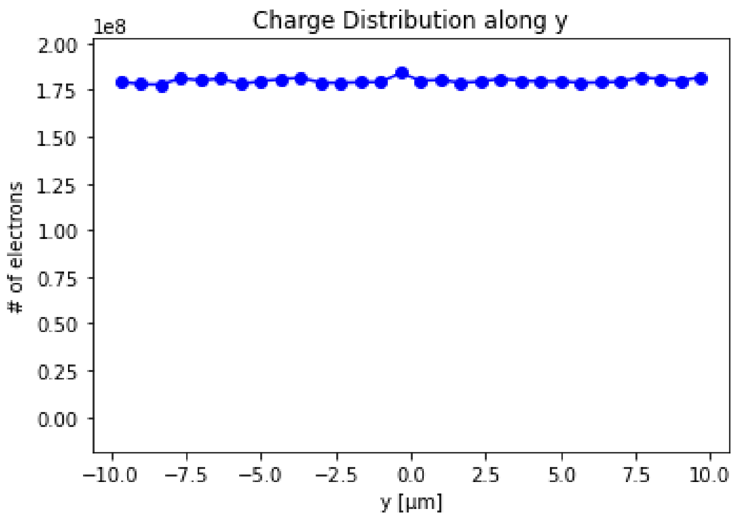
Citing article

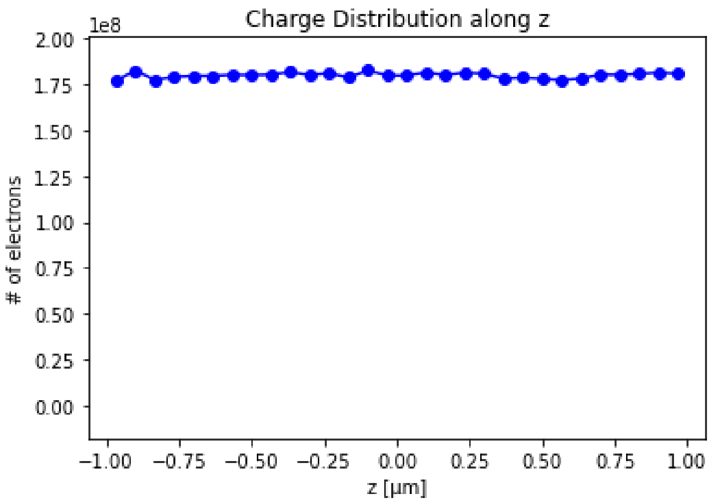
Sep 2024

GNN-based reconstruction

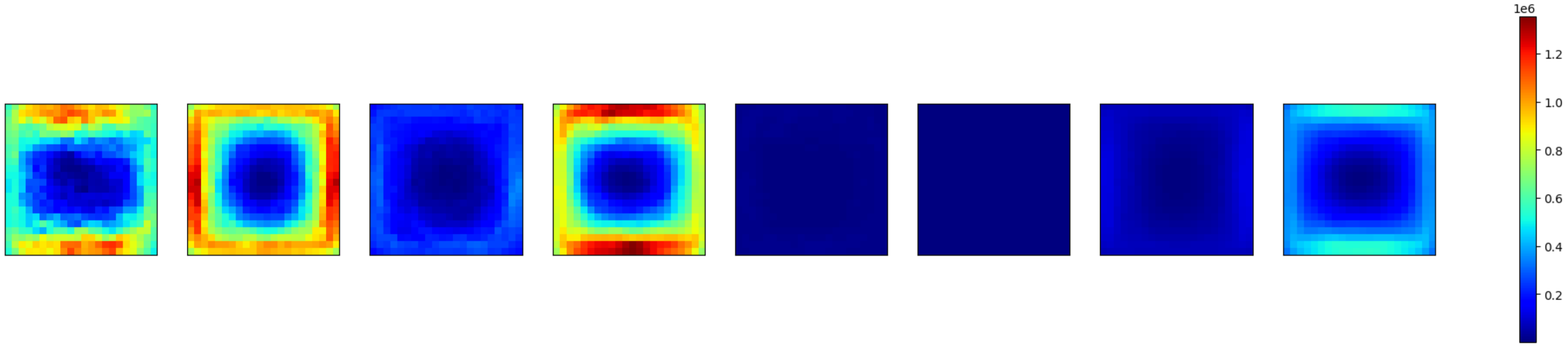
Initial electron bunches from random noise & initialized GNN



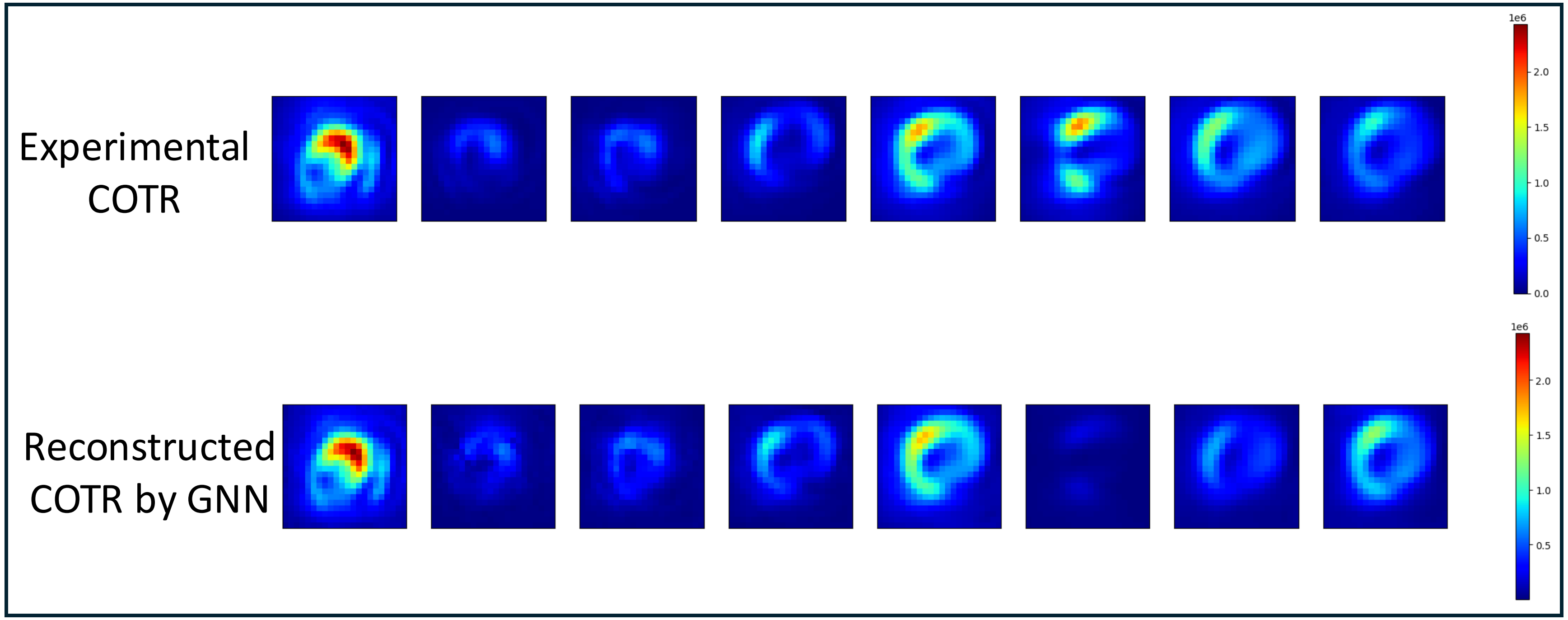


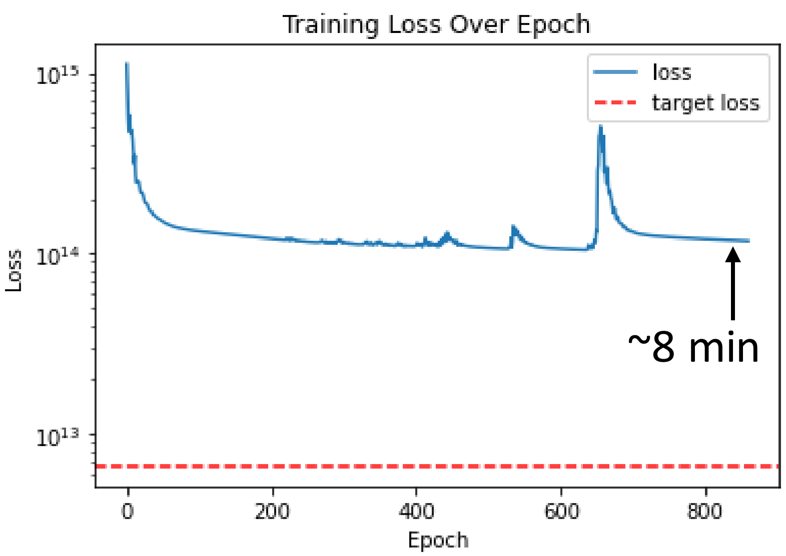


Synthetic COTR

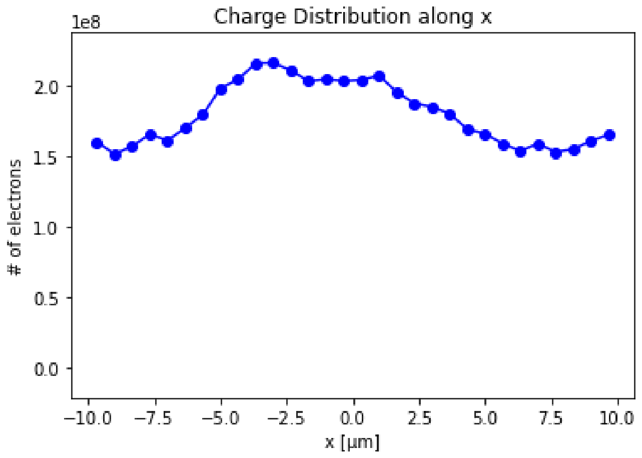


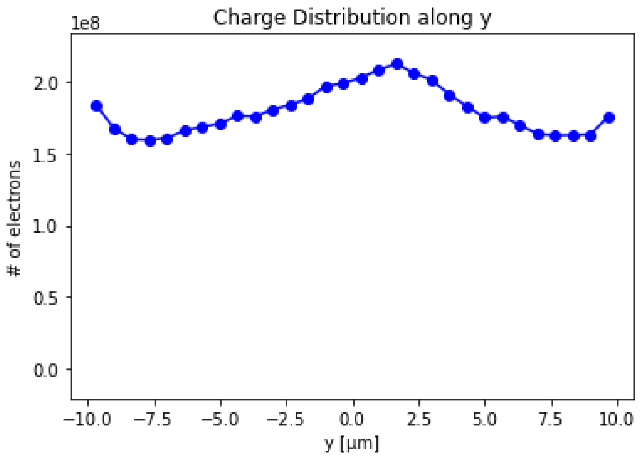
GNN-based reconstruction

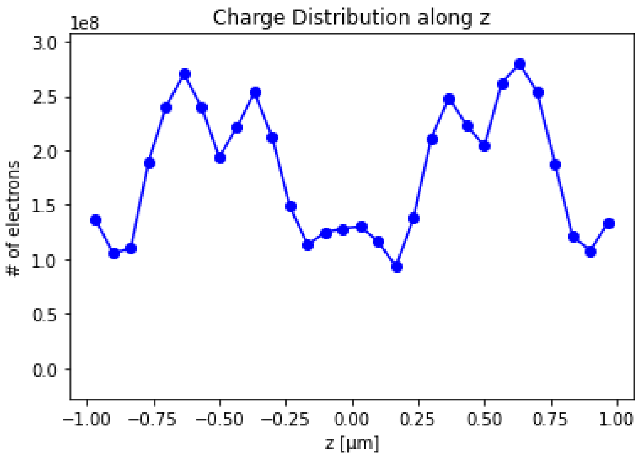




Target loss: difference of pixel <10%

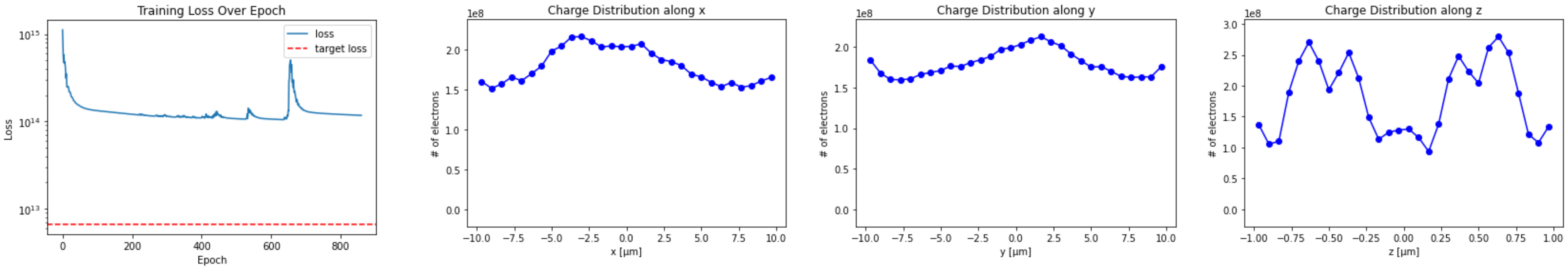




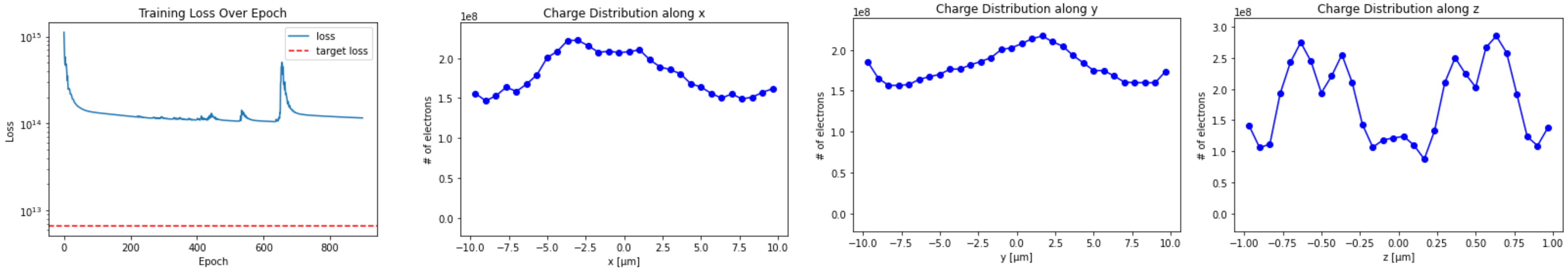


Uniqueness discussion on GNN from seed (71)

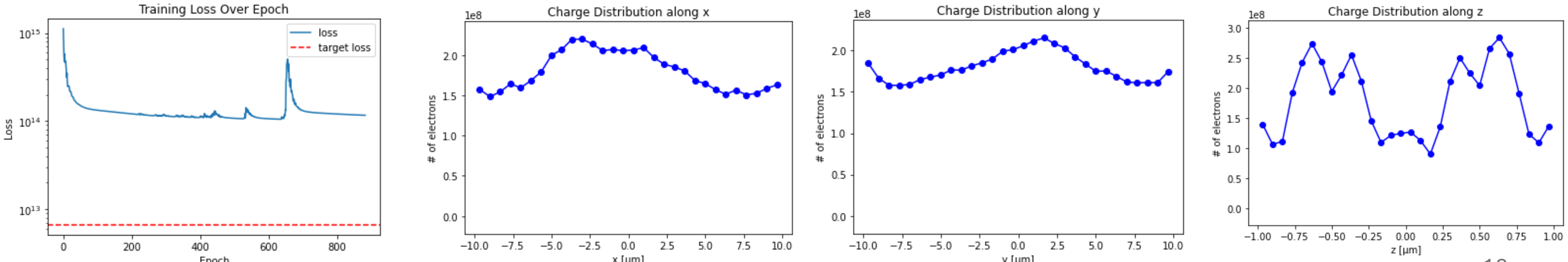
Solution 1



Solution 2

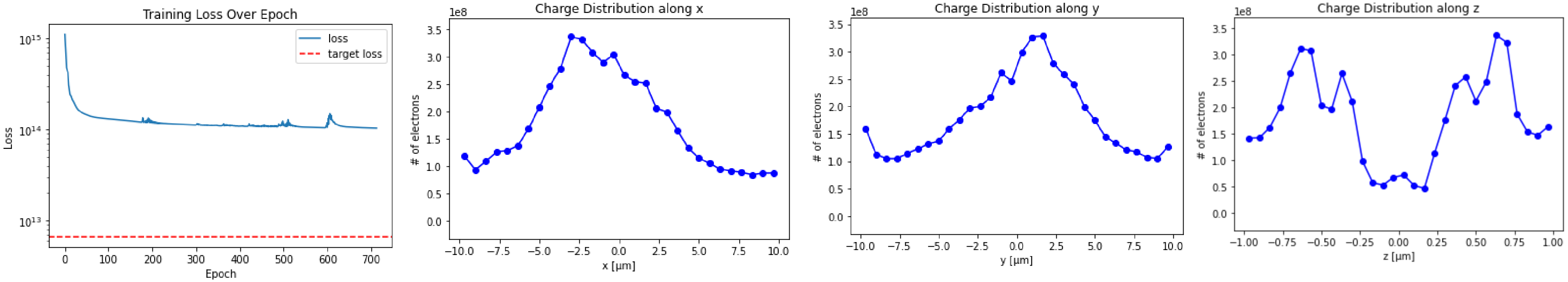


Solution 3

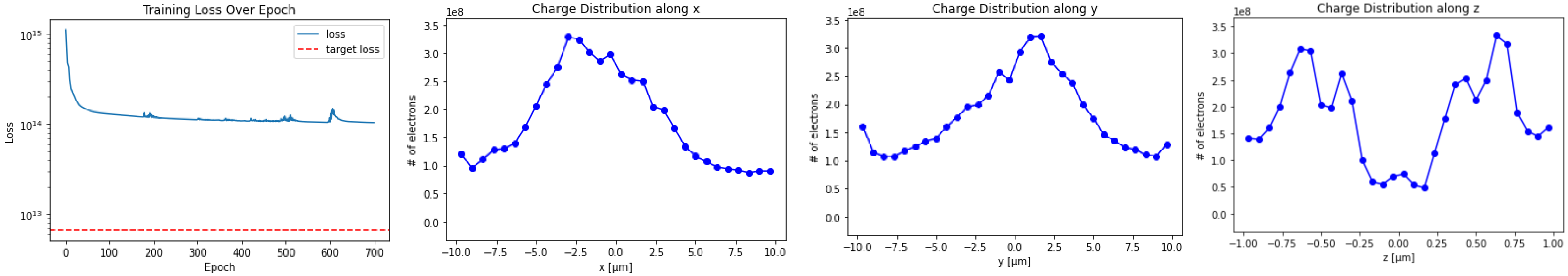


Uniqueness discussion on GNN from seed (51)

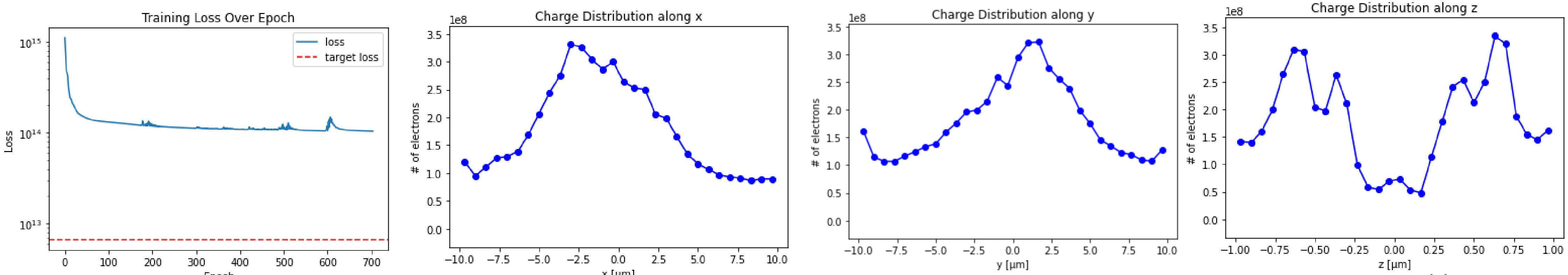
Solution 1



Solution 2



Solution 3

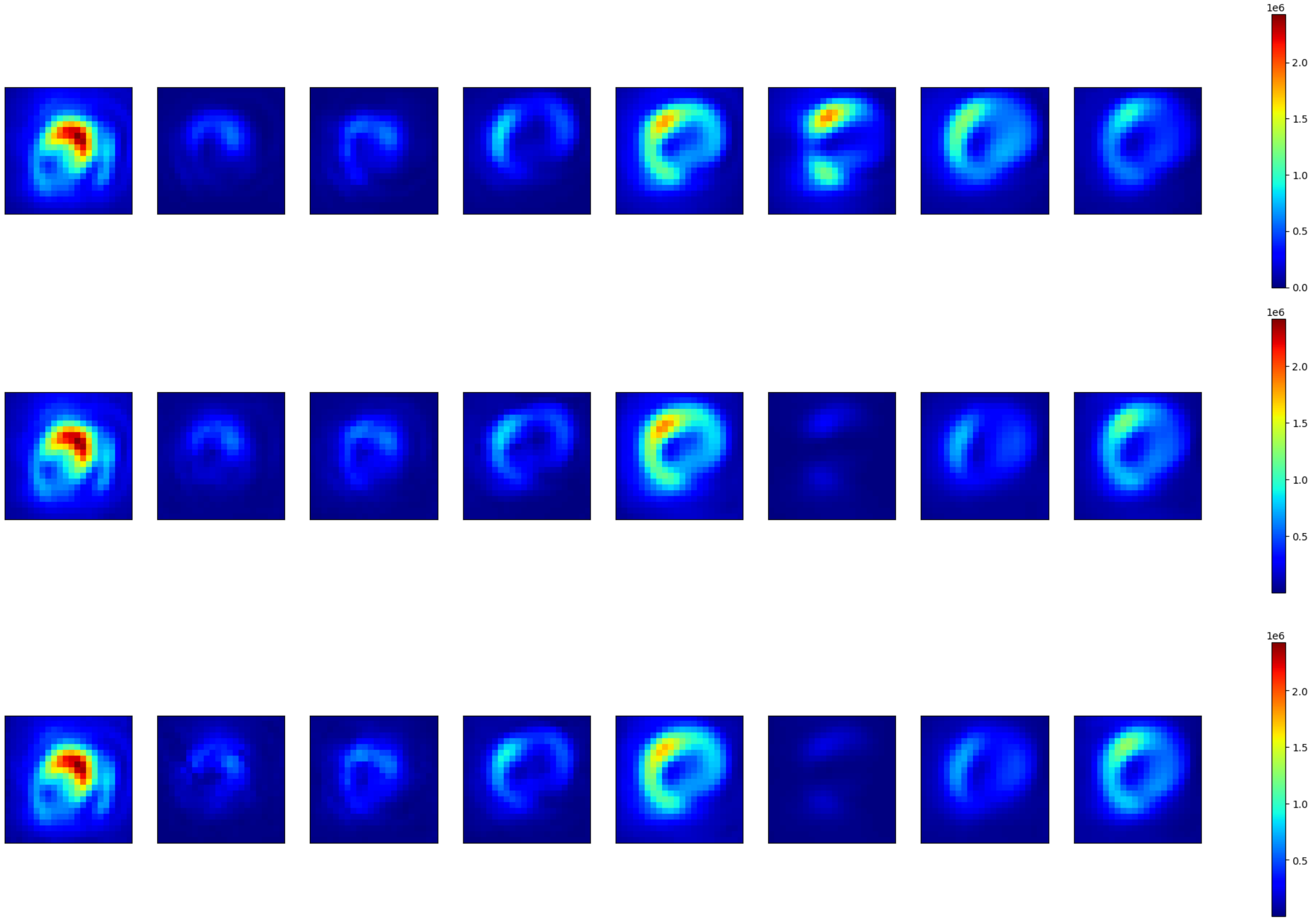


Robustness of GD & GNN, shot 228

Experimental COTR

Reconstructed COTR by Gradient Descent

Reconstructed COTR by Generative Neural Network

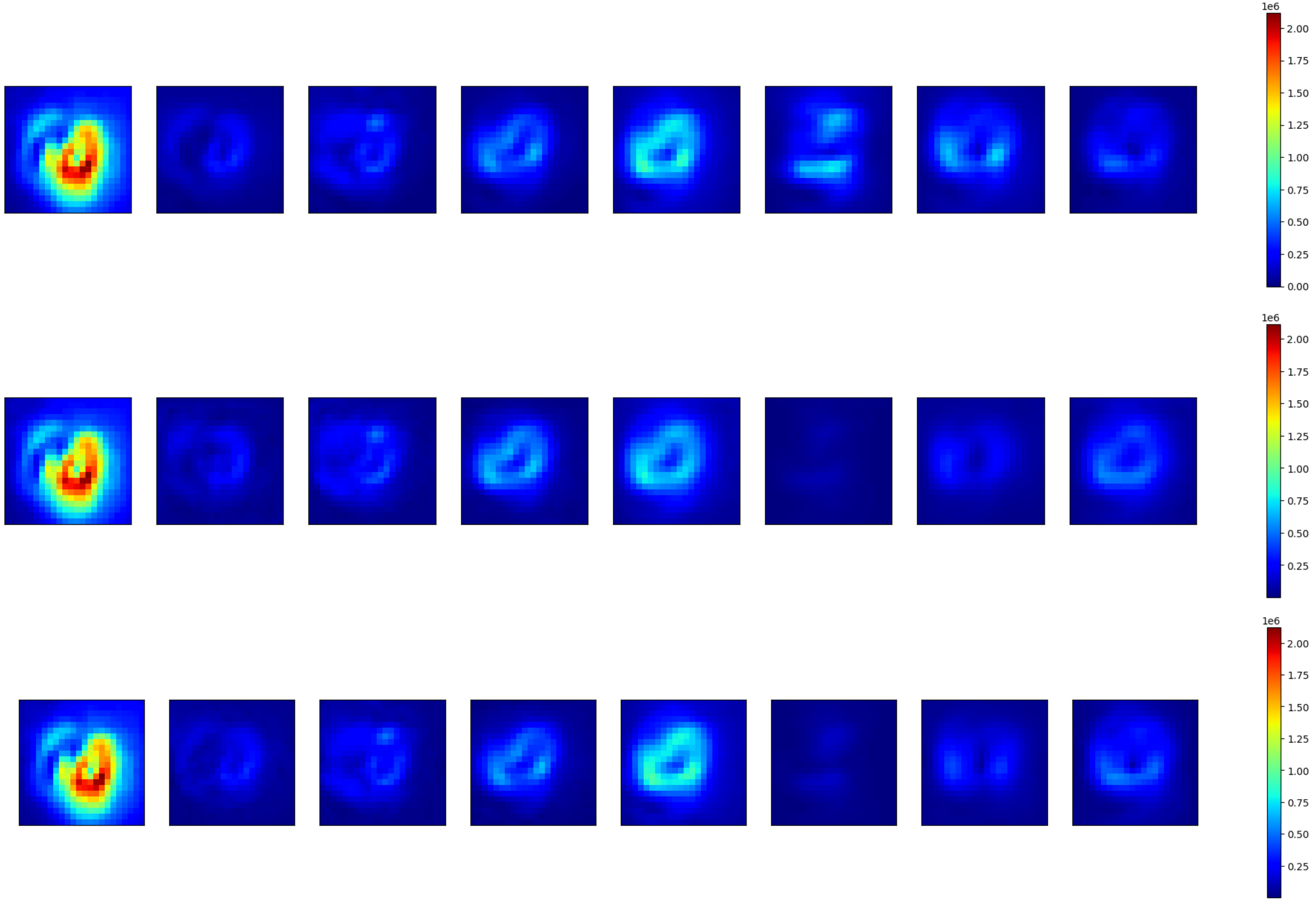


Robustness of GD & GNN, shot 237

Experimental COTR

Reconstructed COTR by Gradient Descent

Reconstructed COTR by Generative Neural Network

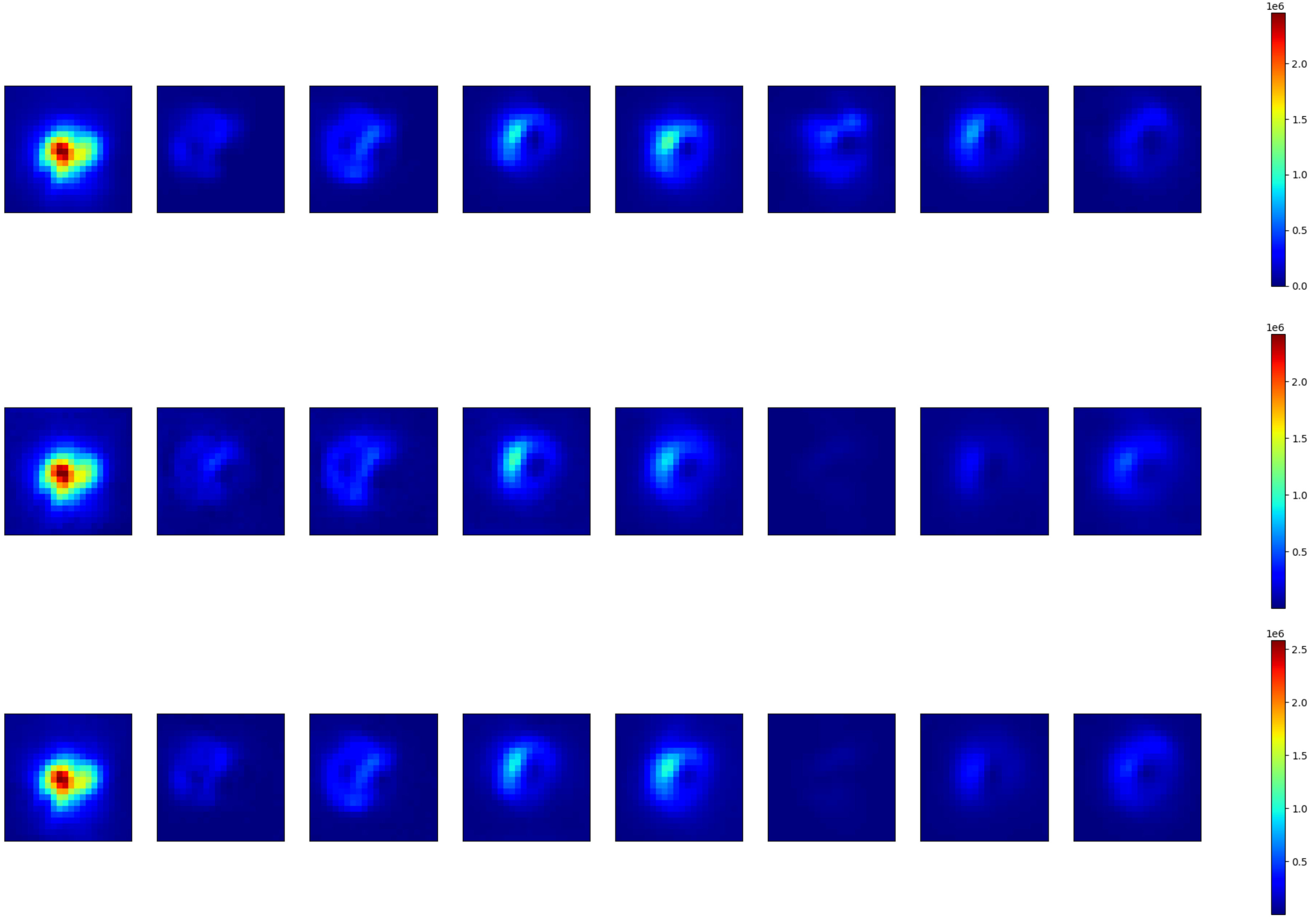


Robustness of GD & GNN, shot 526

Experimental COTR

Reconstructed COTR by Gradient Descent

Reconstructed COTR by Generative Neural Network



Conclusion & Discussion

Conclusion

1. In both methods, same seed leads to same reconstructed electron bunches; but different seeds lead to different reconstructed electron bunches.
2. Our methods show robustness on multiple shots.
3. Two-wavelength-figures don't match well in all situations.

Discussion

1. Why loss stuck at a certain level? Model, initial condition, fine-tuned parameters
2. Other ways to describe electron bunches
3. Other use of NN: reduction of parameters, Physics-informed NN,
4. dataset generation
5. Initial parameters of electron bunches
6. Physically-reasonable converged electron bunches
7. Combination with prior knowledge of electron bunches, i.e. z- distribution