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

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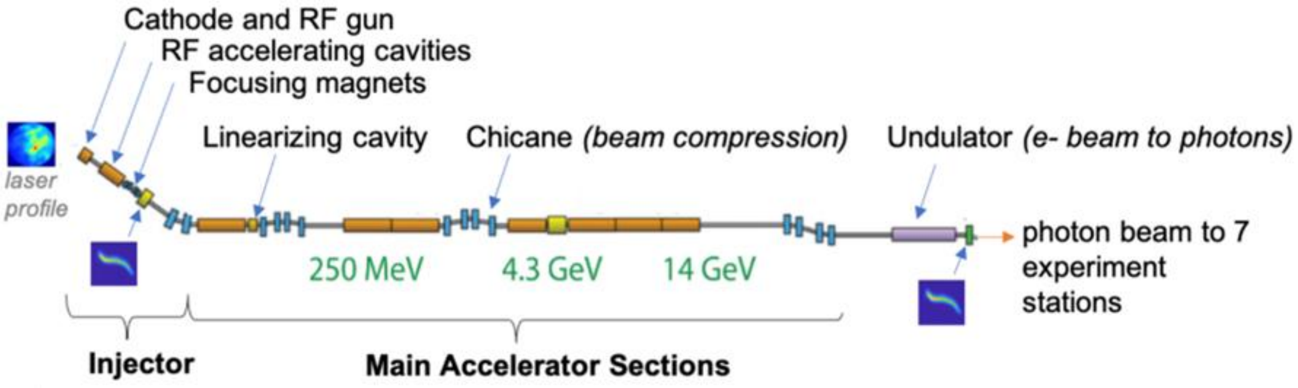
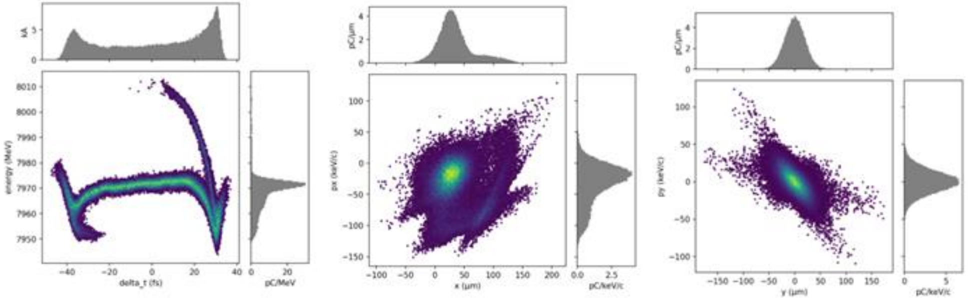
Manipulating Beams in Phase Space



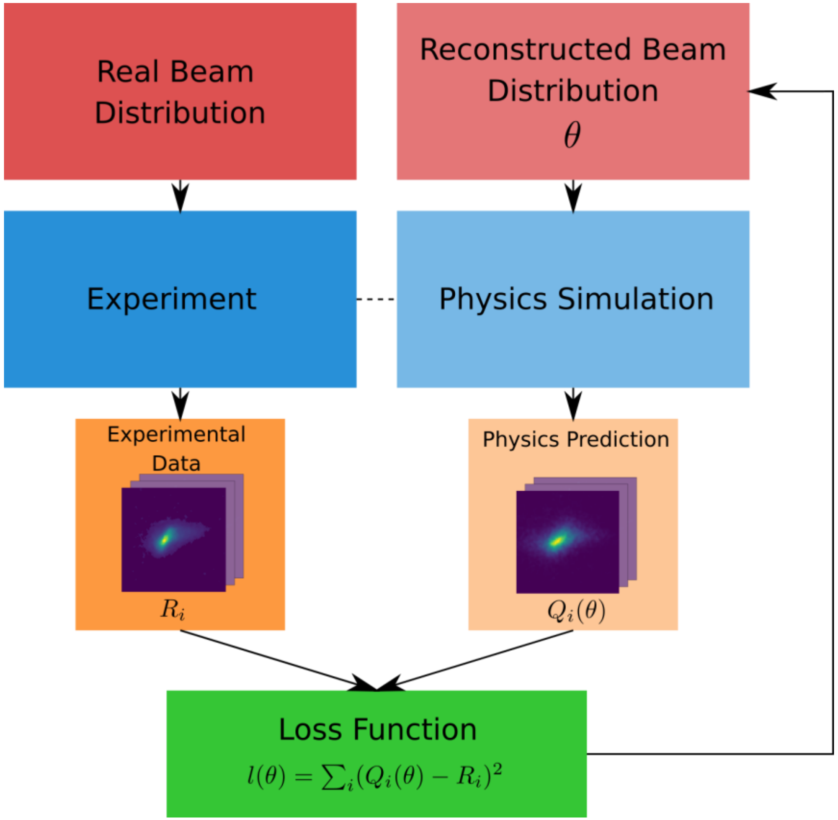
A. Edelen

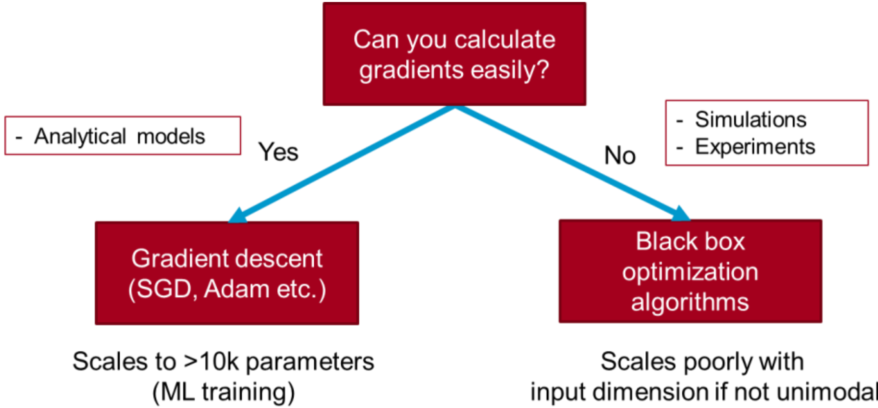


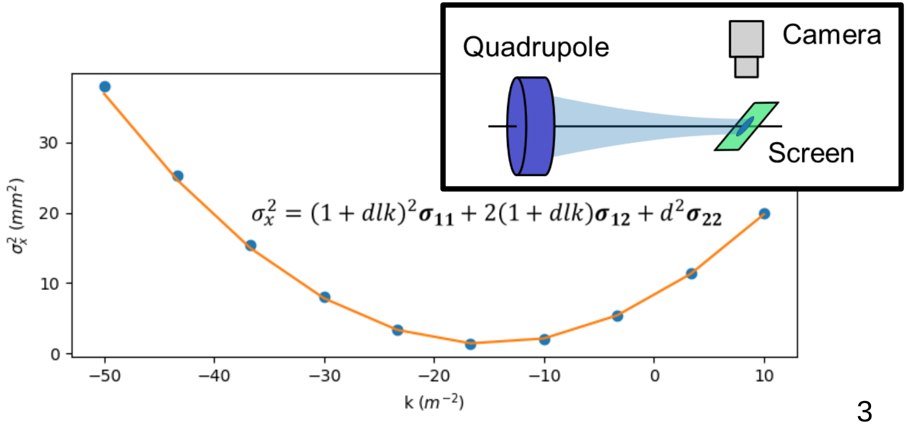
How do we measure particle beam distributions in 6D phase space?

$$\rho(x, p_x, y, p_y, z, \delta)$$

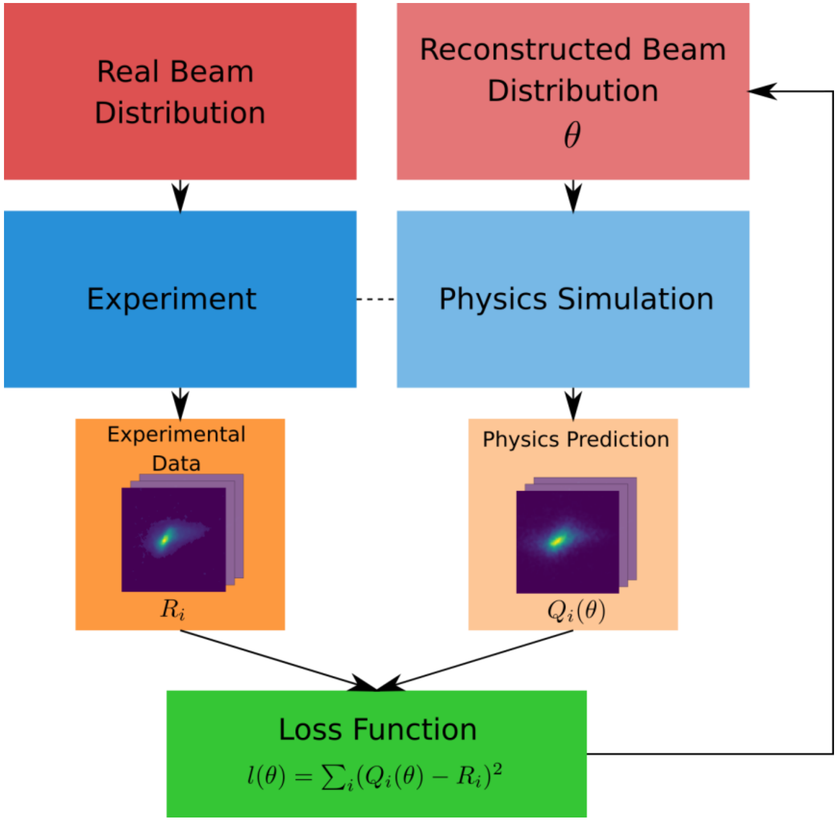
Inferring Beam Distributions Using Optimization

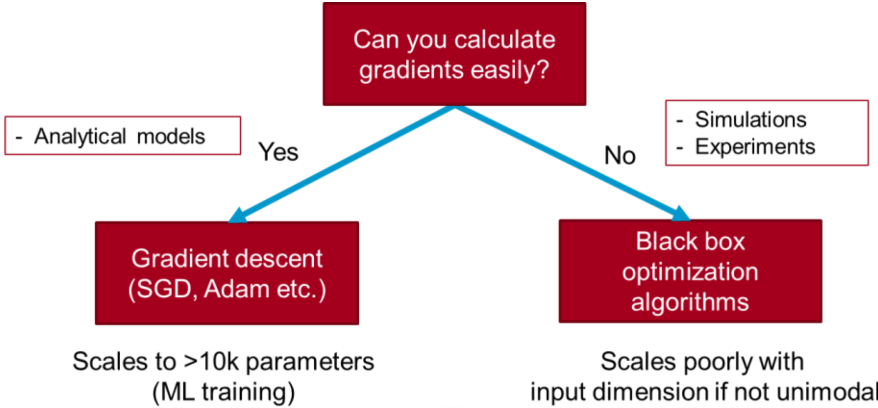


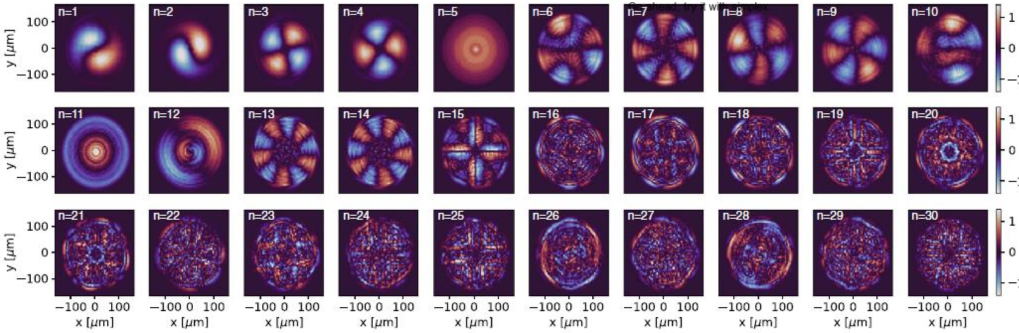




Inferring Beam Distributions Using Optimization







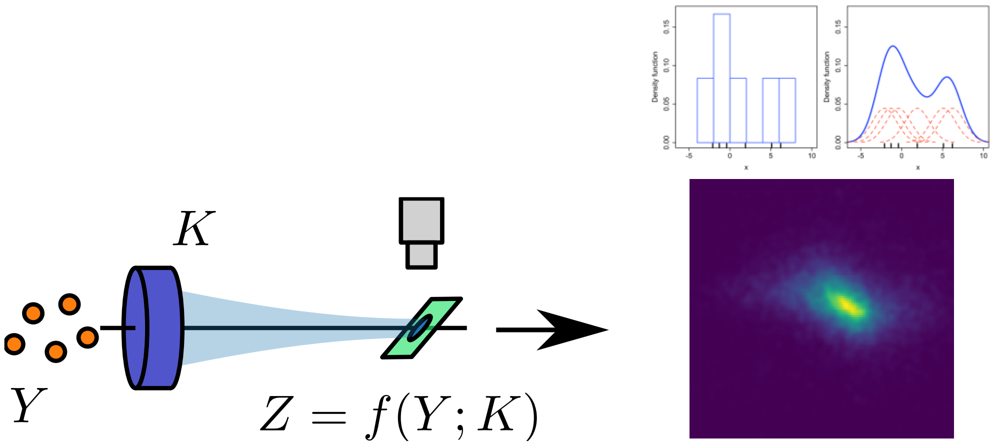
Scheinker, Alexander, et al *Scientific reports* 11.1 (2021): 1-11.

Differentiable Simulations

Keep track of derivative information during **every** calculation step.

Enables **gradient based optimization** of model error with respect to all free parameters using the chain rule.

Easily optimize models with >10k free parameters.

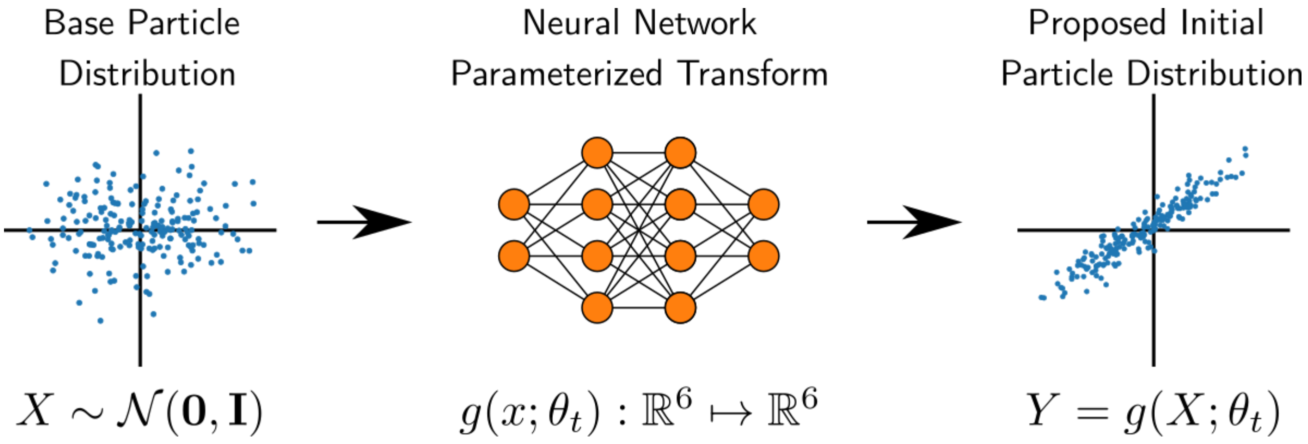


$$Q^{(i,j)} = \mathrm{KDE}(Z)$$

$$\frac{\partial Z}{\partial Y}, \frac{\partial Z}{\partial K}, \frac{\partial \sigma_Z}{\partial K}, \ldots \qquad \frac{\partial Q^{(i,j)}}{\partial Y}, \frac{\partial Q^{(i,j)}}{\partial K}$$

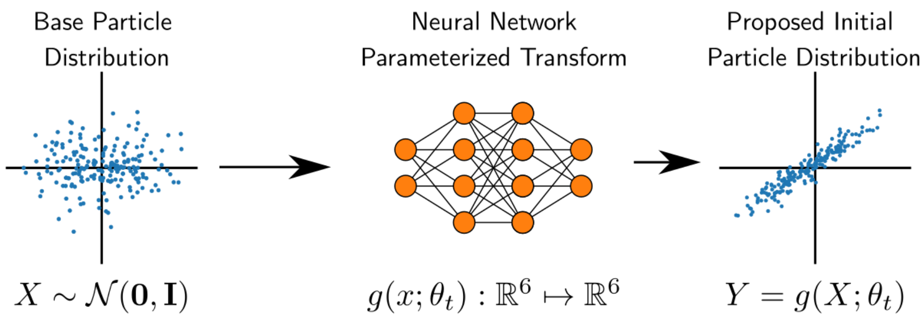
Neural Network Parameterization of Beam Distributions

Want to parameterize 6D phase space distributions with a function that is **flexible** and **learnable**.

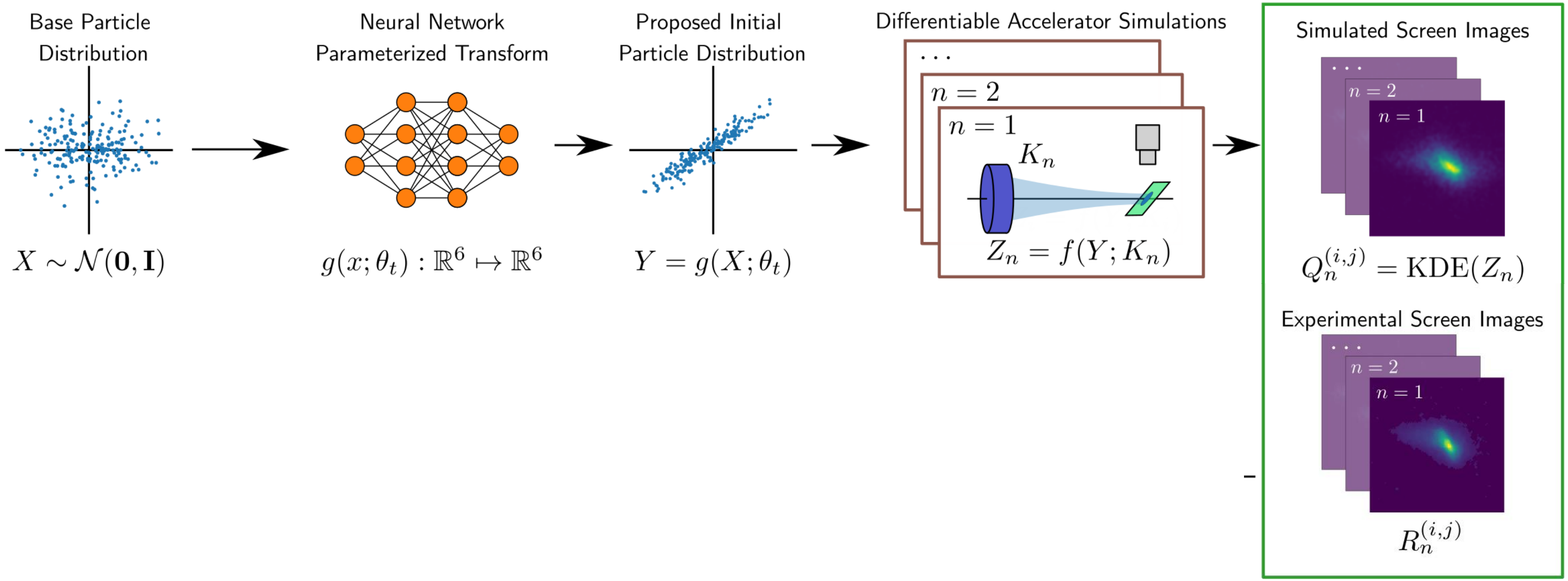


Fully connected NN with ~O(1k) parameters

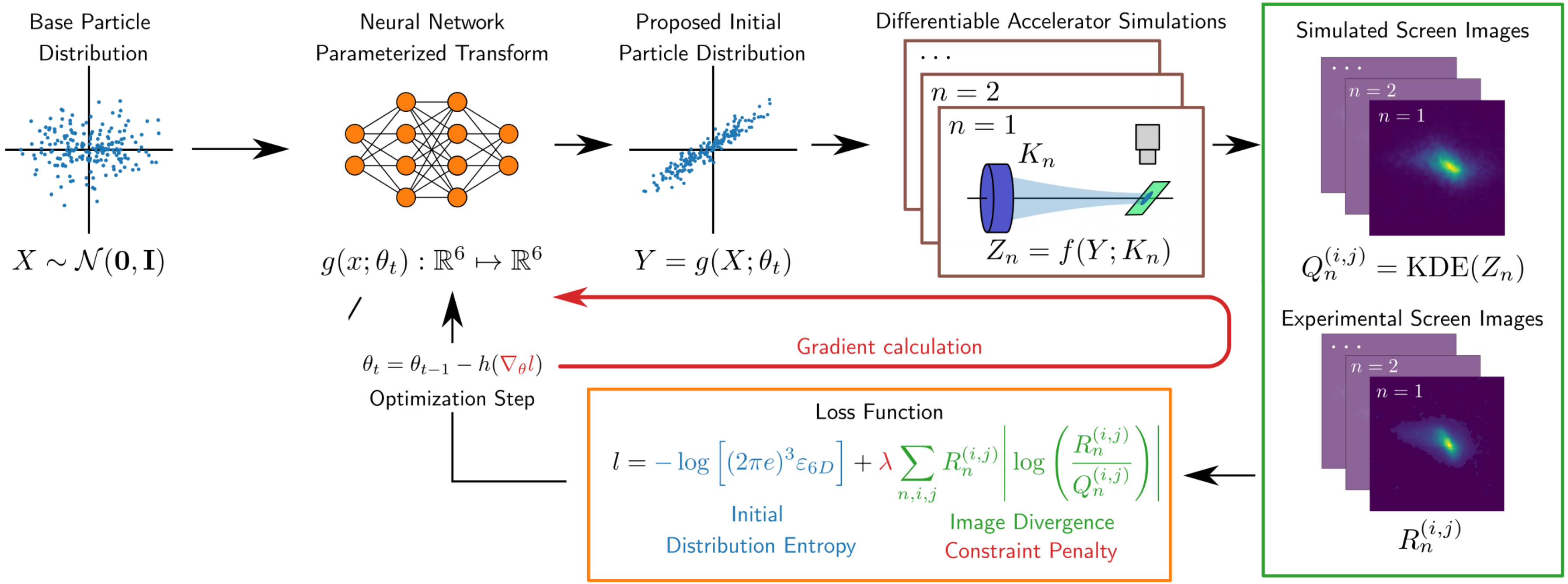
Phase Space Reconstruction Pipeline



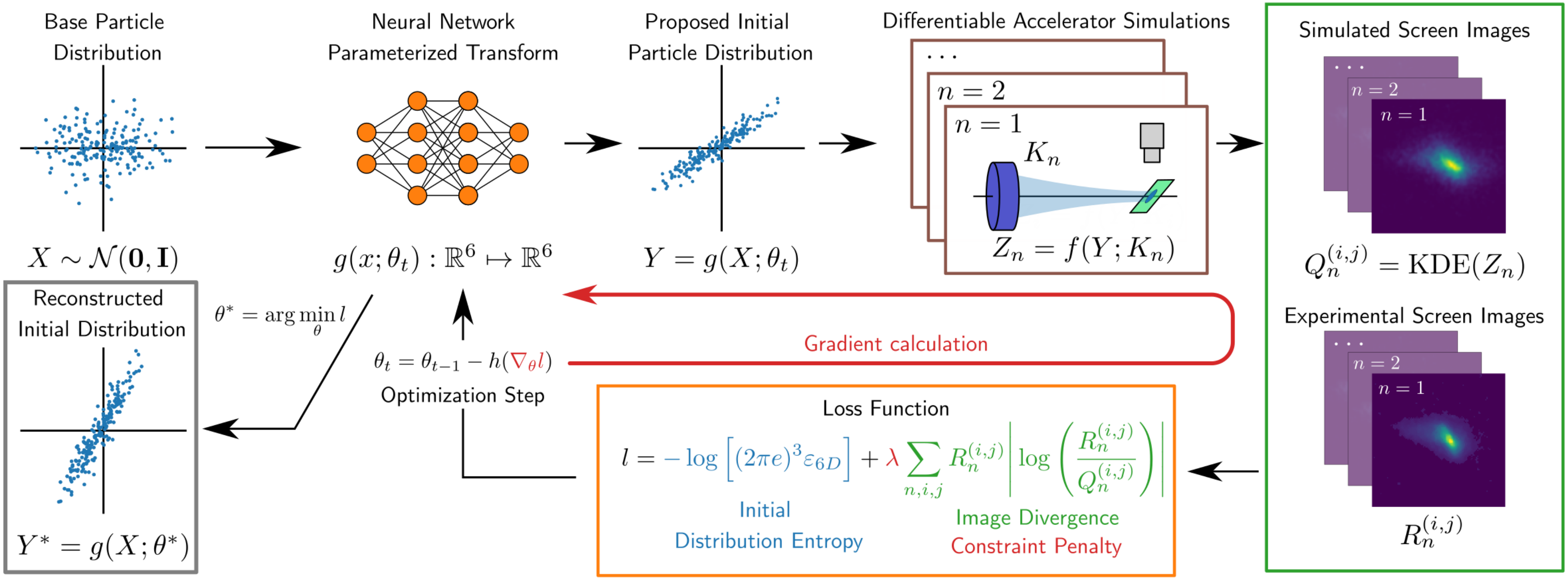
Phase Space Reconstruction Pipeline



Phase Space Reconstruction Pipeline



Phase Space Reconstruction Pipeline



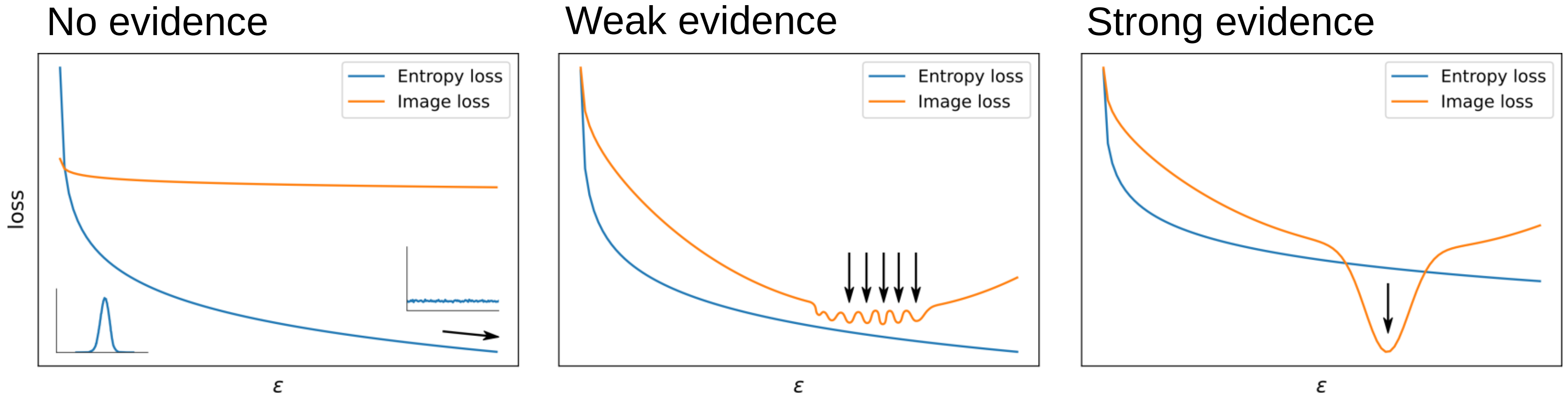
Maximum Entropy Loss Function

$$l = -\log\left[(2\pi e)^3 \varepsilon_{6D}\right] + \lambda \sum_{n,i,j} R_n^{(i,j)} \left| \log\left(\frac{R_n^{(i,j)}}{Q_n^{(i,j)}}\right) \right|$$

Initial Distribution Entropy

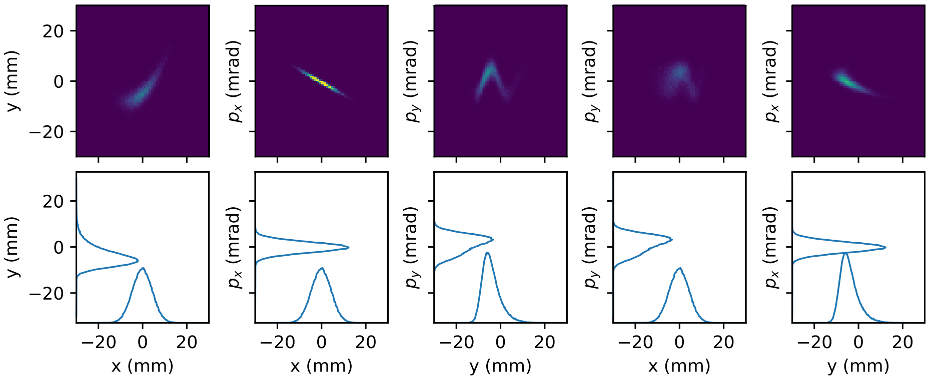
Image Divergence

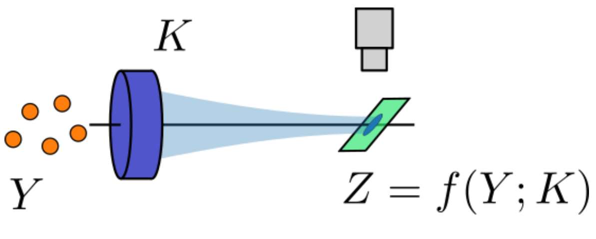
Constraint Penalty



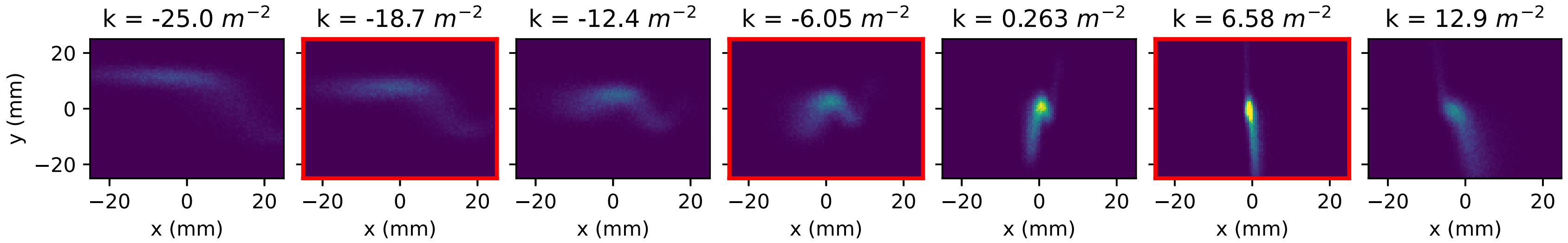
Synthetic Example

Synthetic beam distribution in simulation

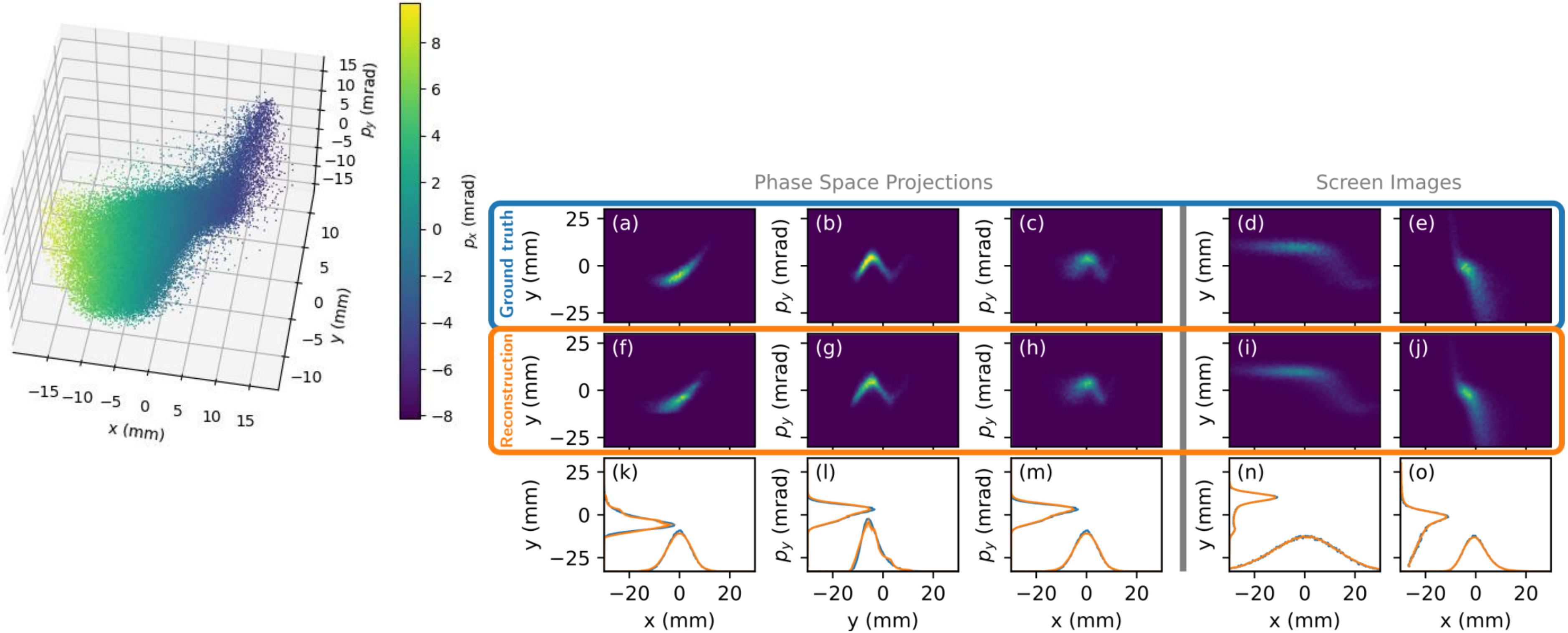




Screen images

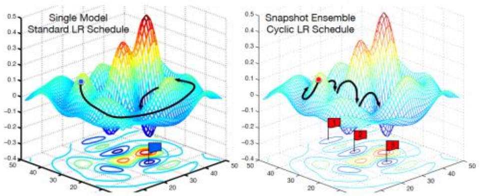


Synthetic Example Reconstruction

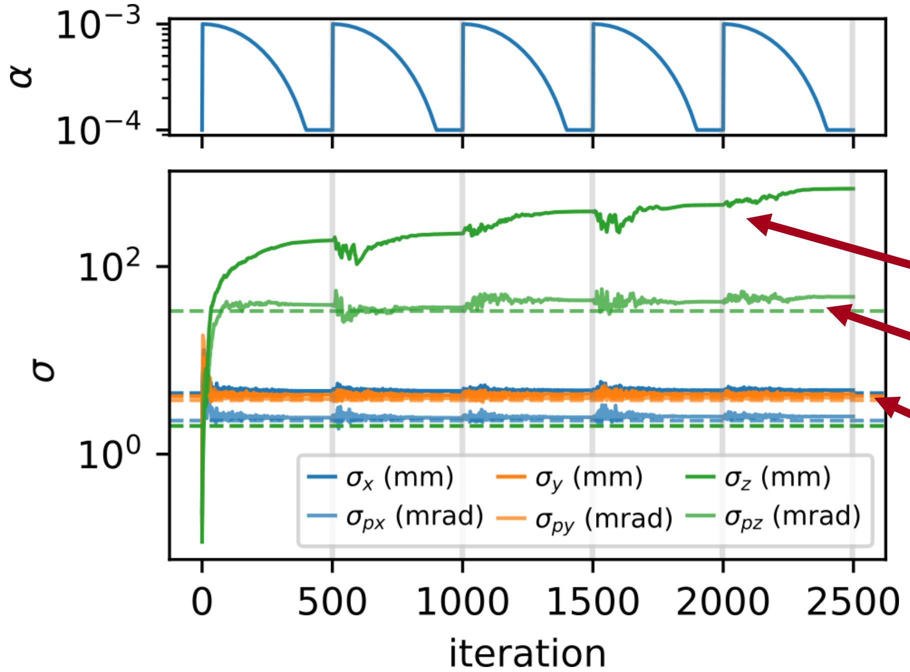


Measuring Model Uncertainty and Convergence

Snapshot ensembling



Huang G. et al., ICLR 2017



Loss Function

$$l = -\log\left[(2\pi e)^3 \varepsilon_{6D}\right] + \lambda \sum_{n,i,j} R_n^{(i,j)} \left| \log\left(\frac{R_n^{(i,j)}}{Q_n^{(i,j)}}\right)\right|$$

Initial Distribution Entropy

Image Divergence Constraint Penalty

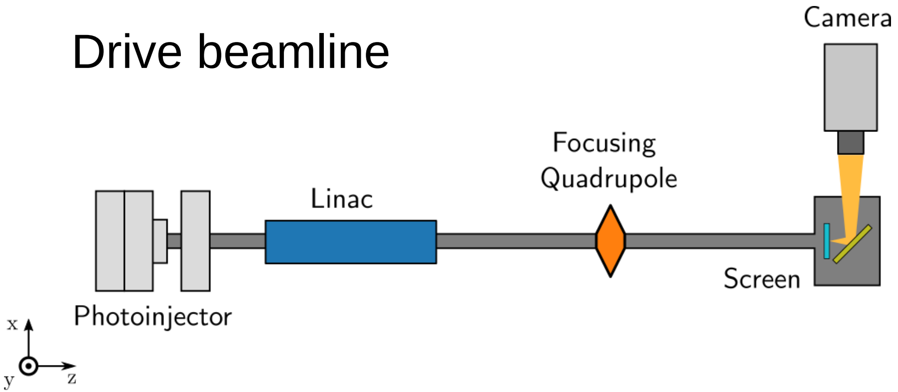
No information

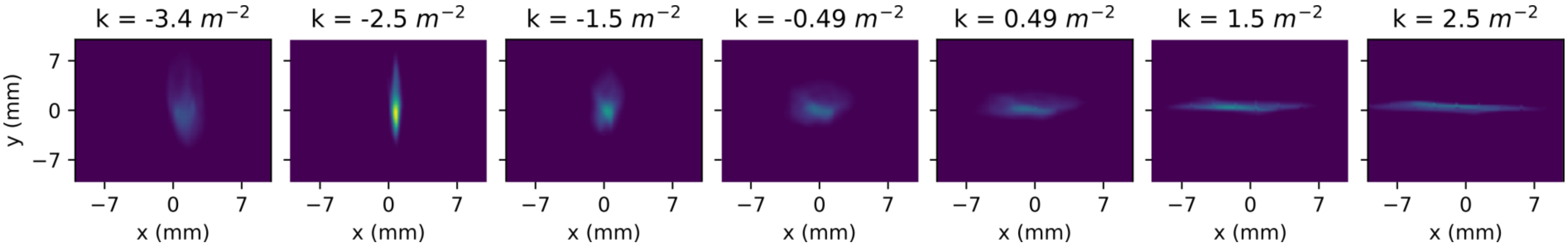
Some information

Lots of information

Tomography Example from AWA

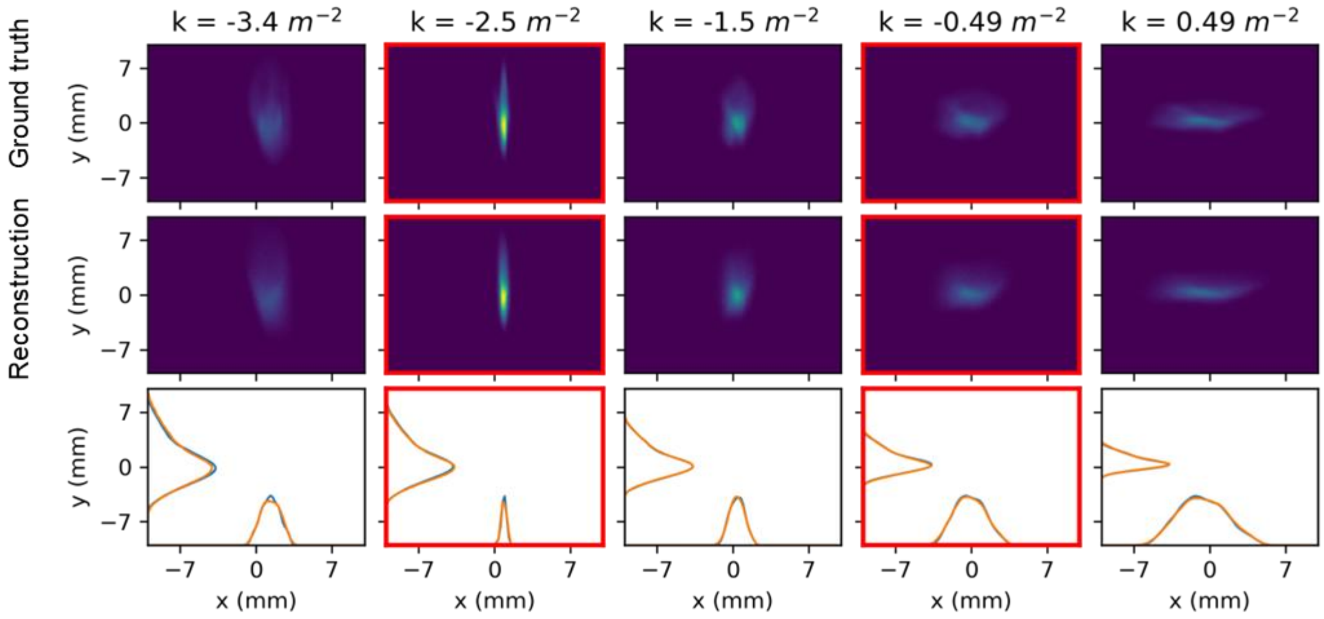
Drive beamline





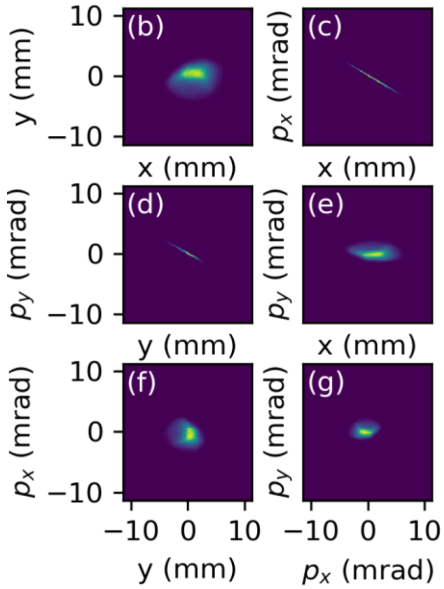
AWA Reconstruction Results

Measurement predictions



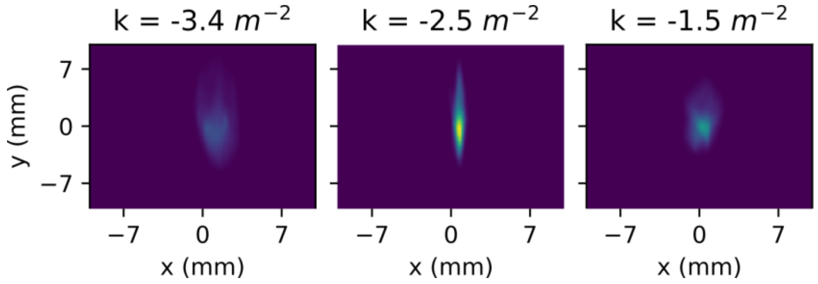
Red border denotes test samples

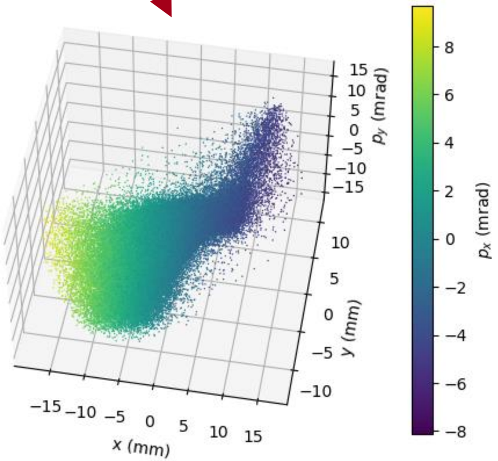
Reconstruction



Conclusions

- We can create **detailed reconstructions of beam phase spaces** from simple tomographic accelerator measurements without special diagnostics
- Theoretically we are only limited by model accuracy and computational complexity (improved by GPUs), **need further investment in differentiable simulations**
- Need to expand our idea of what can be used as a diagnostic





Details https://arxiv.org/abs/2209.04505

Thanks!

SLAC

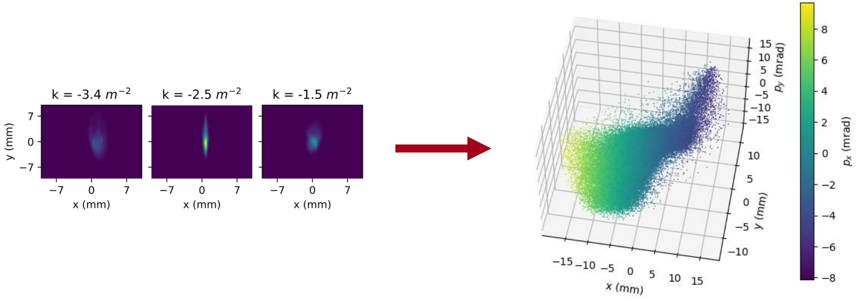
- Auralee Edelen
- Chris Mayes
- Daniel Ratner

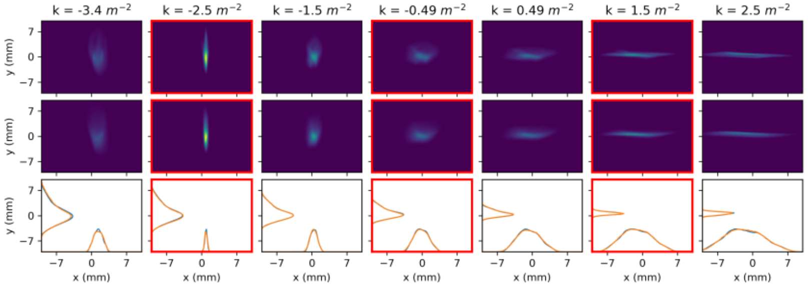
UChicago

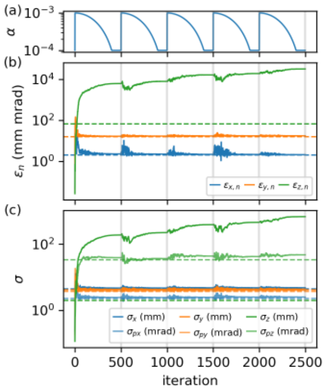
- Juan Pablo Gonzalez-Aguilera

Argonne Wakefield Accelerator

- Seongyeol Kim
- John Power
- Eric Wisniewski







Questions?