

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

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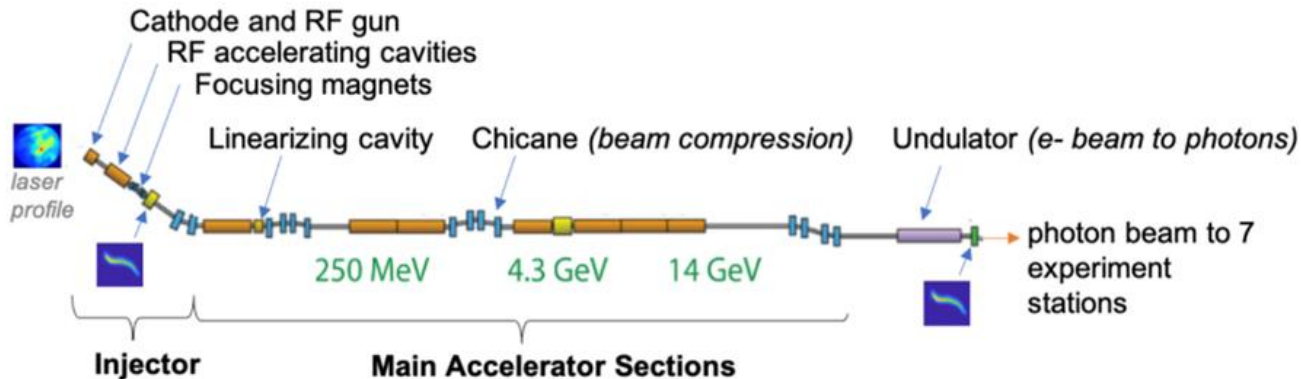
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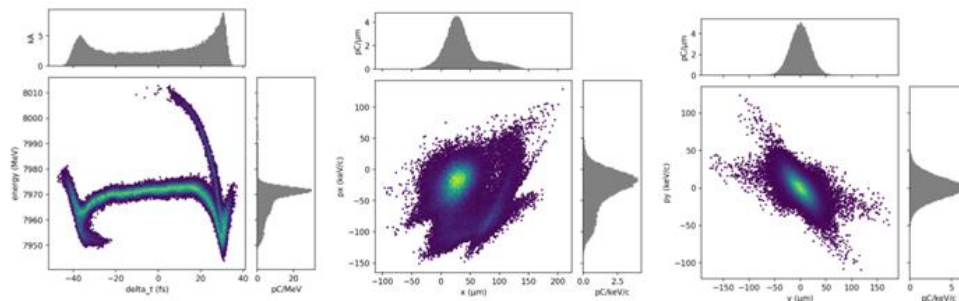
# Manipulating Beams in Phase Space



A. Edelen

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

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



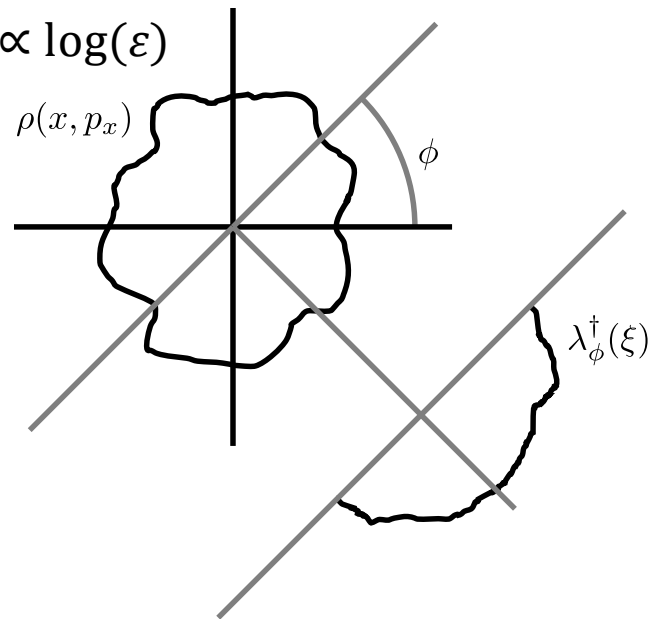
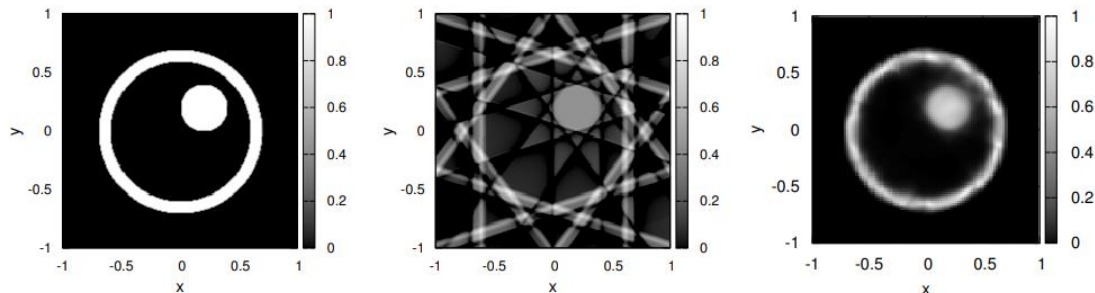
# Maximum Entropy Tomography (MENT)

Rotate phase space and reconstruct the distribution from 1D projections + **maximize the beam distribution entropy**

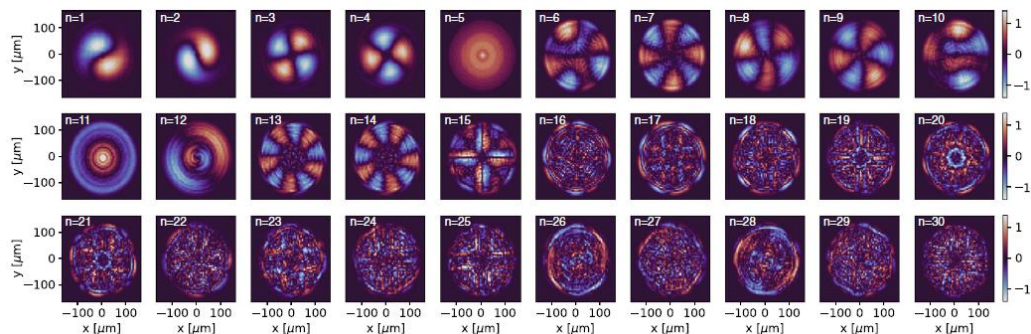
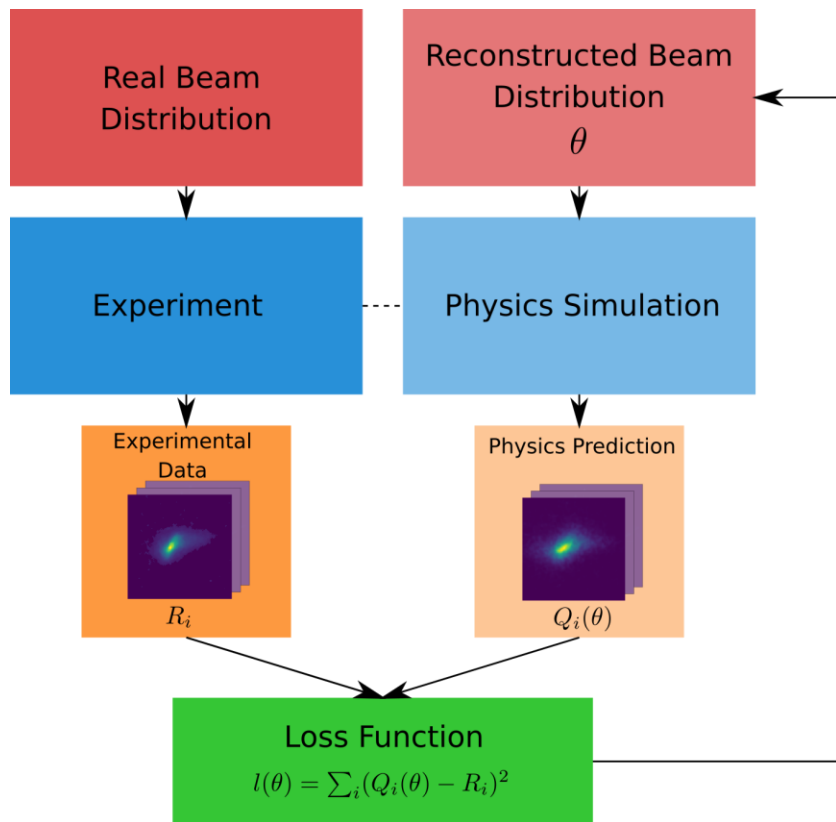
Note:  $H \propto \log(\varepsilon)$

$$\rho^* = \operatorname{argmin}\{-H(\rho) + \lambda f(\rho)\}$$

Distribution entropy      Lagrange multiplier      Measurement reconstruction



# Inferring Beam Distributions Using Optimization



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

Represent beam distribution with principal component analysis (PCA) and optimize weights to fit experimental measurements

# Optimization Strategies for Inference

Can you calculate gradients easily?

- Analytical models

Yes

Gradient descent  
(SGD, Adam etc.)

Scales to >10k parameters  
(ML training)

No

- Simulations  
- Experiments

Black box  
optimization  
algorithms

Scales poorly with  
input dimension if not unimodal

Go ahead, try it with simplex...

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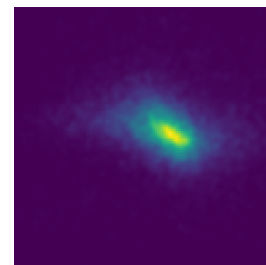
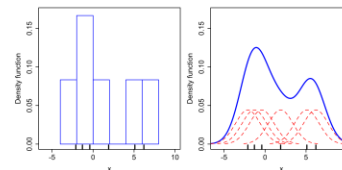
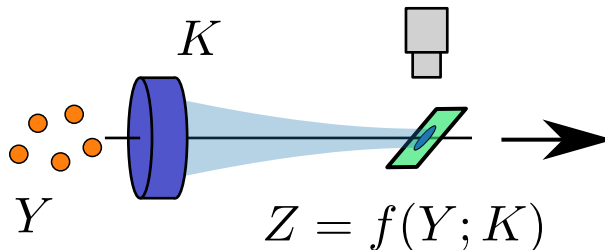
Go ahead, try it with simplex...

# 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.



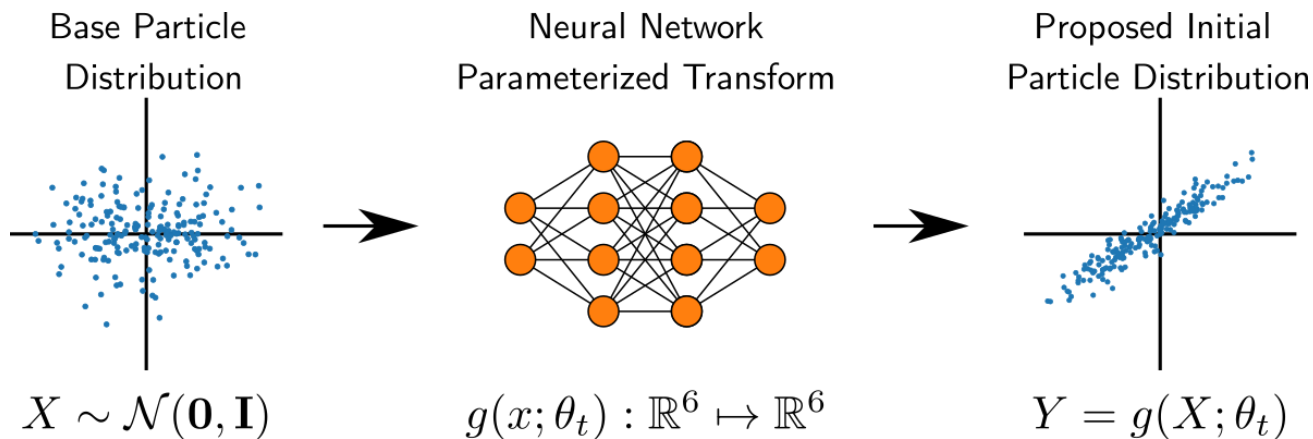
$$Q^{(i,j)} = \text{KDE}(Z)$$

$$\frac{\partial Z}{\partial Y}, \frac{\partial Z}{\partial K}, \frac{\partial \sigma_Z}{\partial K}, \dots$$

$$\frac{\partial Q^{(i,j)}}{\partial Y}, \frac{\partial Q^{(i,j)}}{\partial K}$$

# Neural Network Parameterization of Beam Distributions

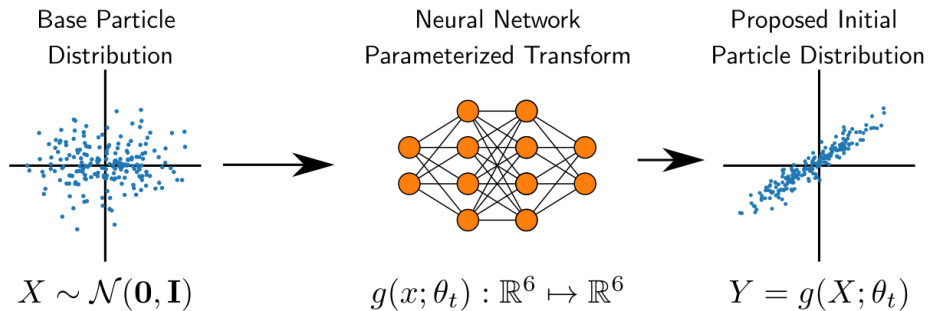
Want to parameterize 6D phase space distributions with a function that is **flexible** and **learnable**.



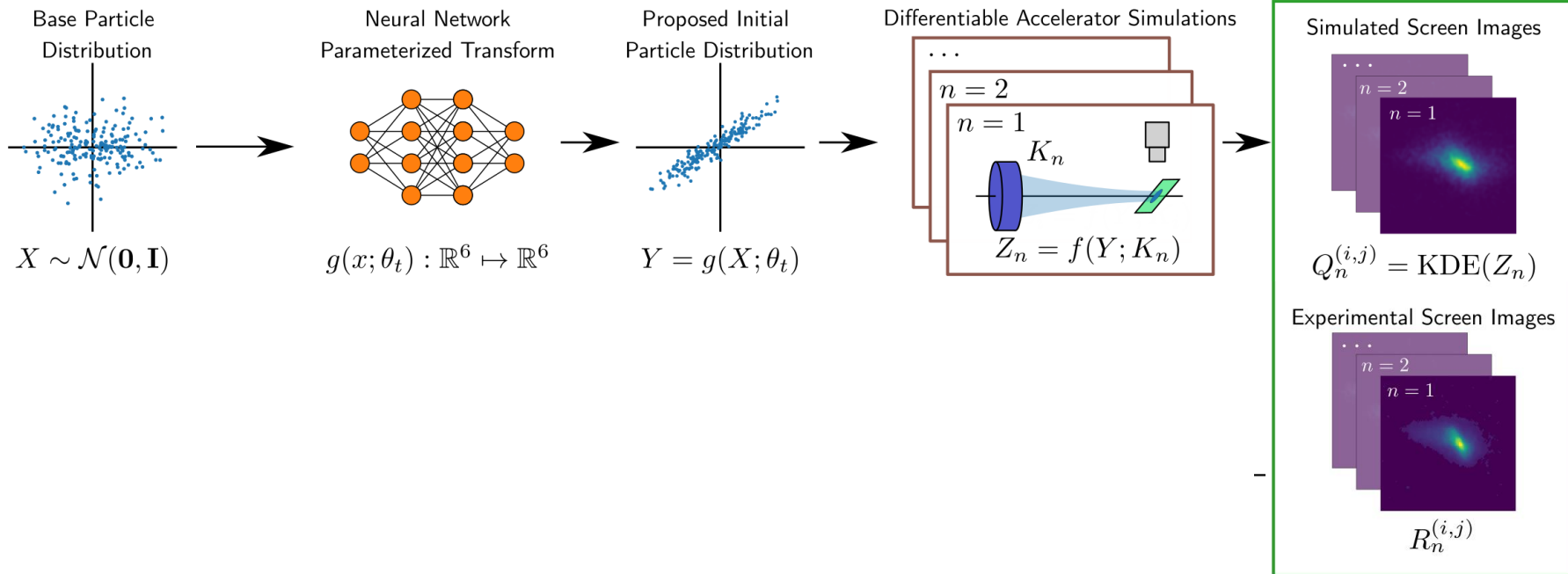
Fully connected NN with  $\sim O(1k)$  parameters



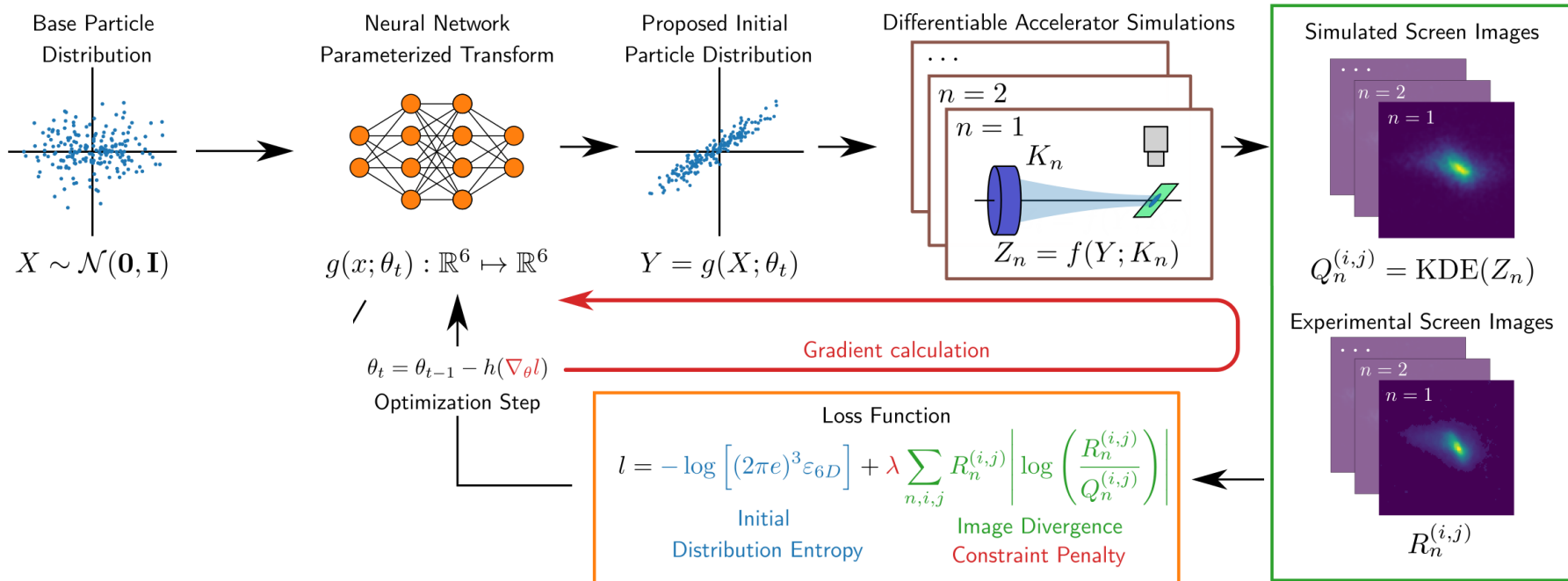
# Phase Space Reconstruction Pipeline



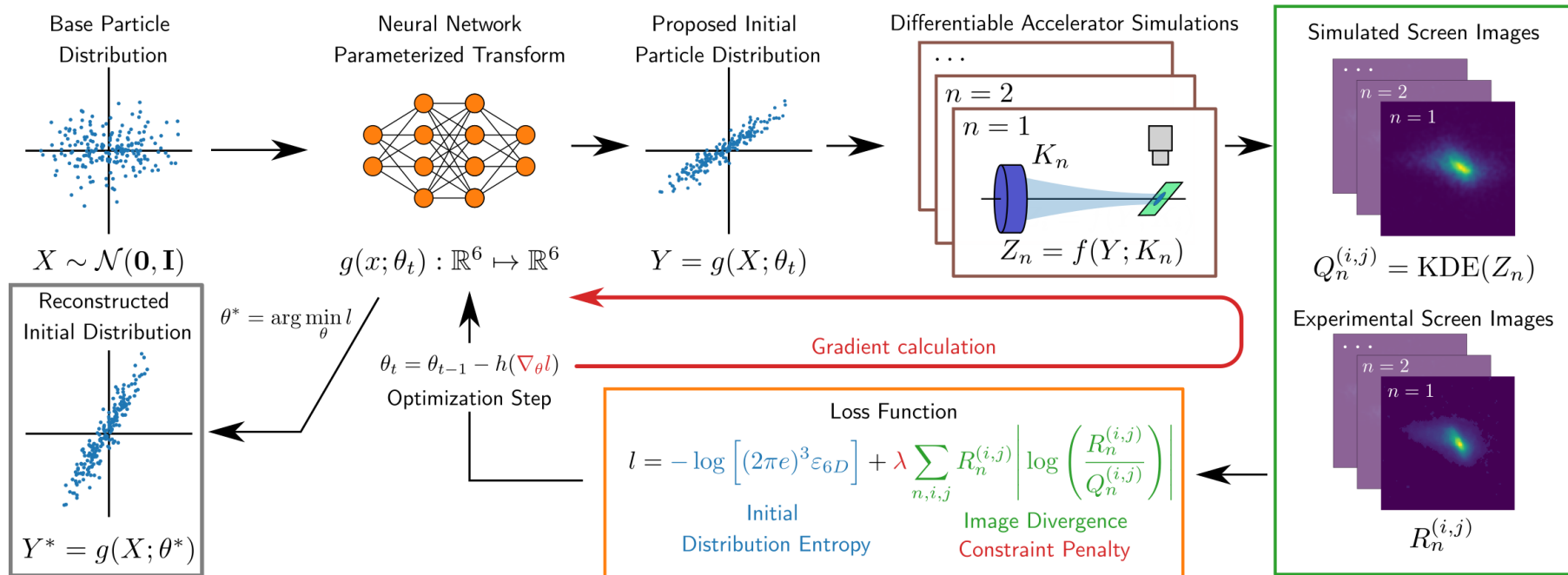
# Phase Space Reconstruction Pipeline



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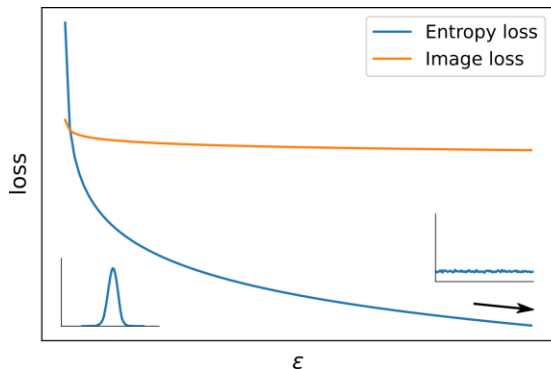
# Phase Space Reconstruction Pipeline



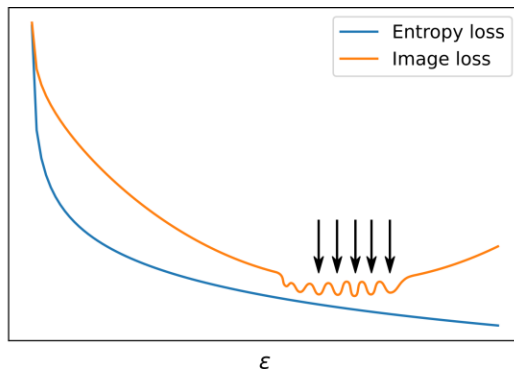
# Maximum Entropy Loss Function

$$l = \underbrace{-\log \left[ (2\pi e)^3 \varepsilon_{6D} \right]}_{\text{Initial Distribution Entropy}} + \lambda \underbrace{\sum_{n,i,j} R_n^{(i,j)}}_{\text{Image Divergence}} \left| \log \left( \frac{R_n^{(i,j)}}{Q_n^{(i,j)}} \right) \right|_{\text{Constraint Penalty}}$$

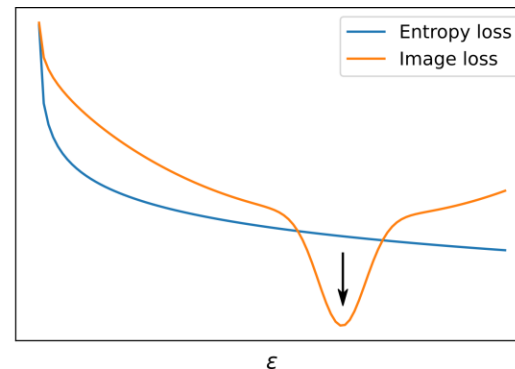
No evidence



Weak evidence

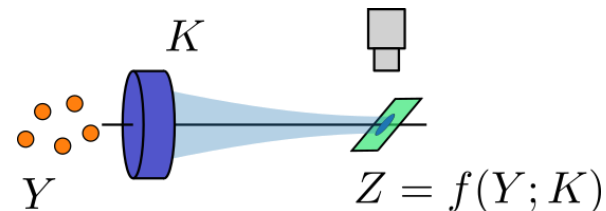
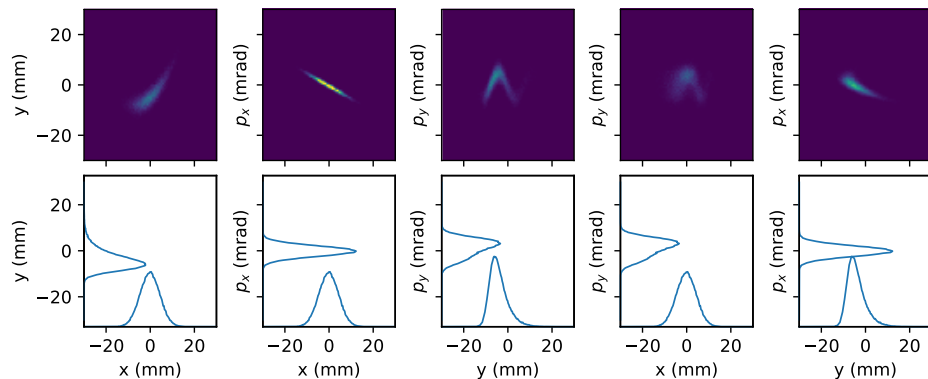


Strong evidence

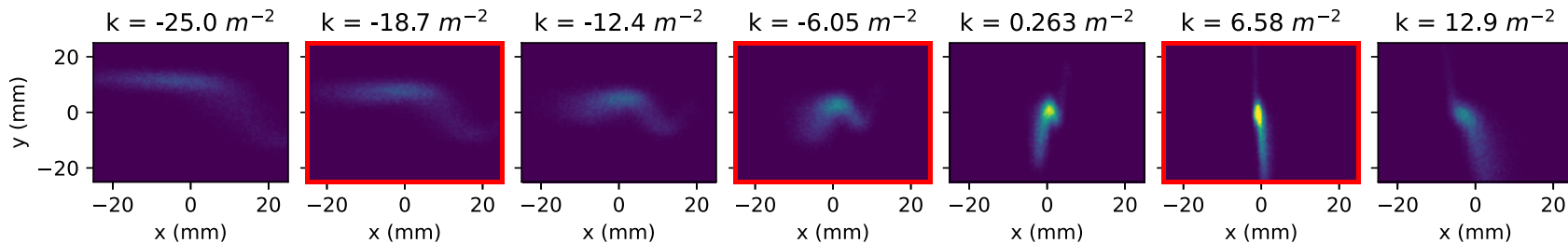


# Synthetic Example

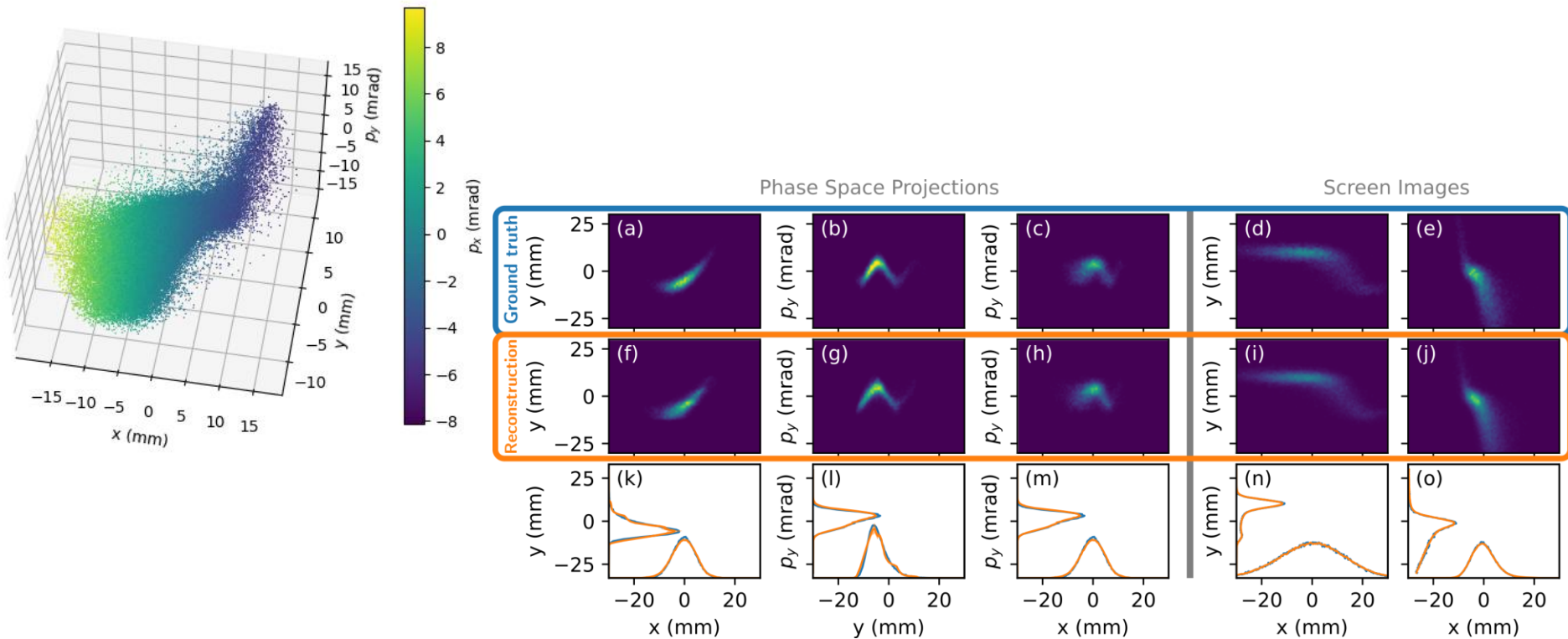
## Synthetic beam distribution in simulation



## Screen images

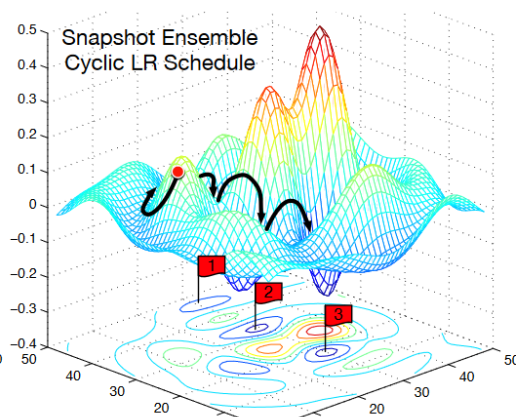
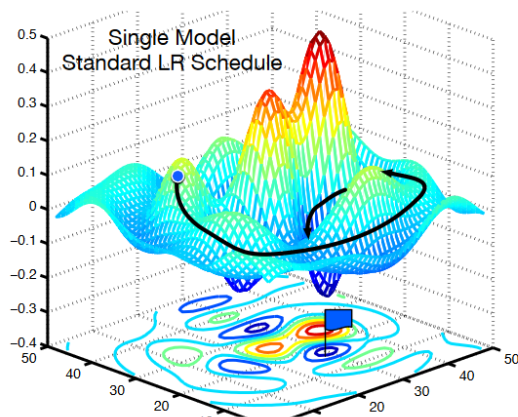
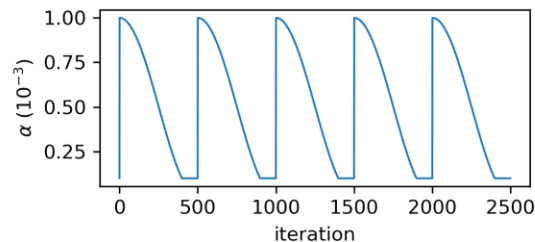


# Synthetic Example Reconstruction



# Measuring Model Uncertainty

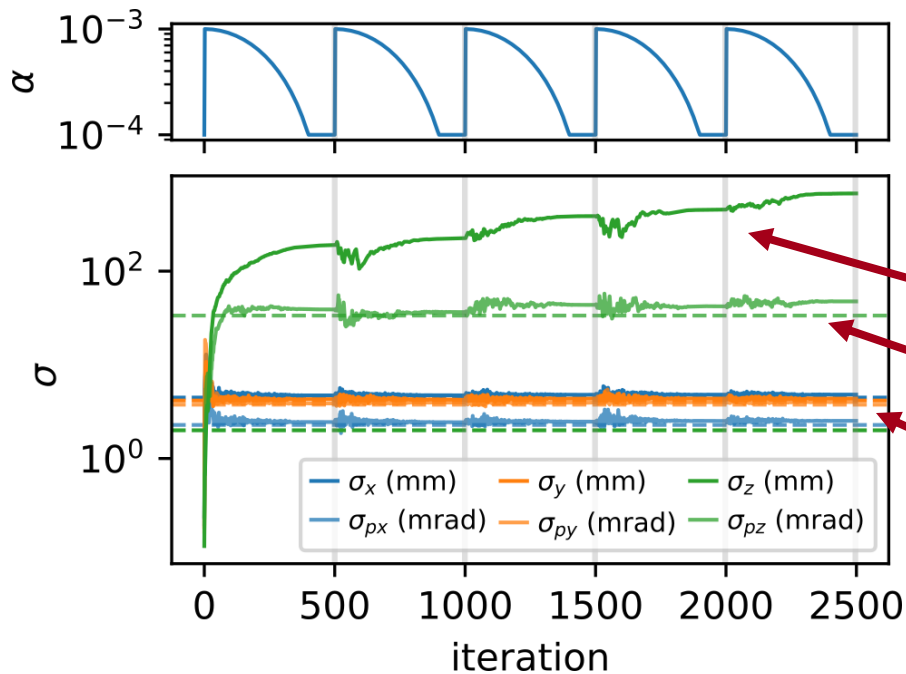
Create a snapshot ensemble to measure uncertainty by cycling the learning rate



Huang G. et al., ICLR 2017



# Measuring Model Uncertainty and Convergence



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

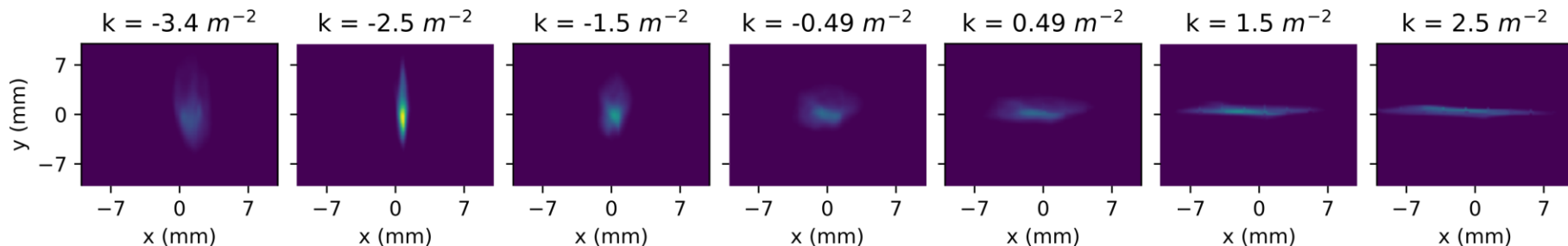
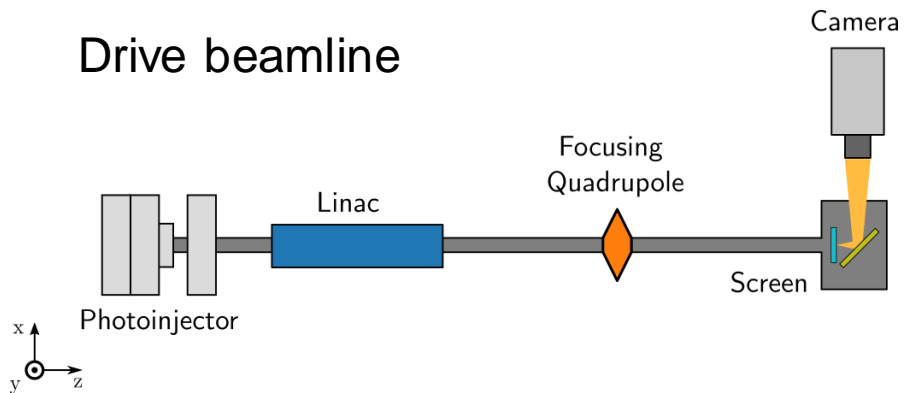
Some information

Lots of information

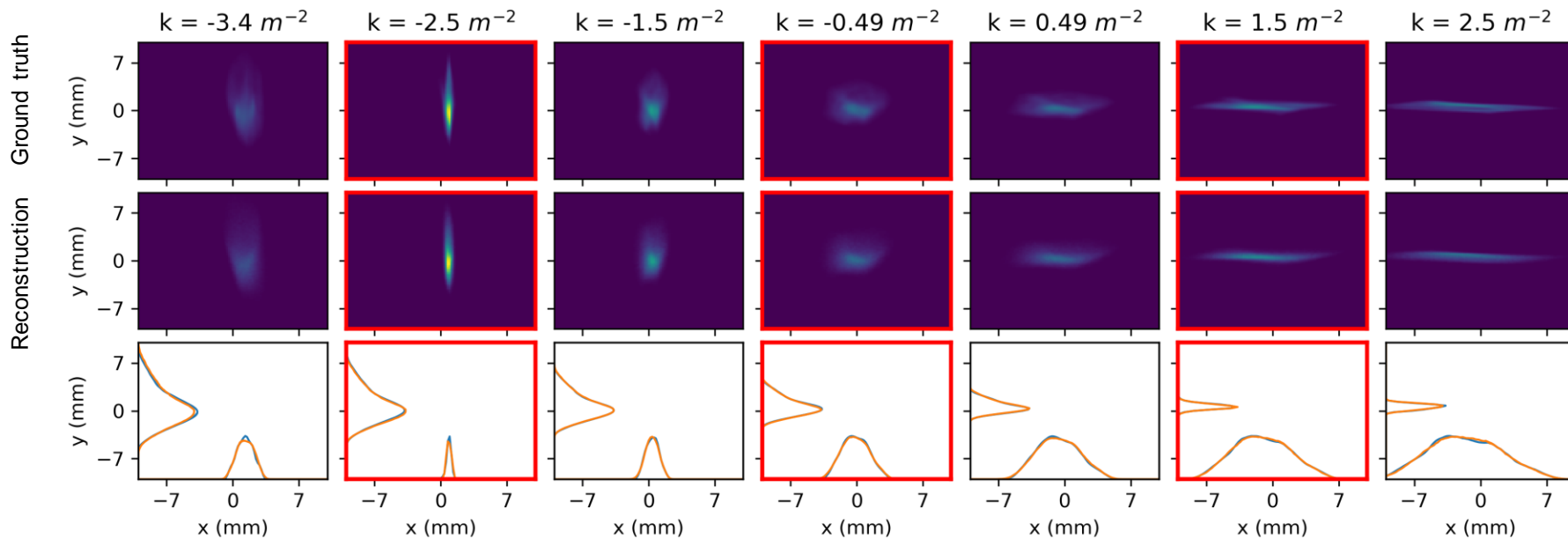
# Tomography Example from AWA



## Drive beamline

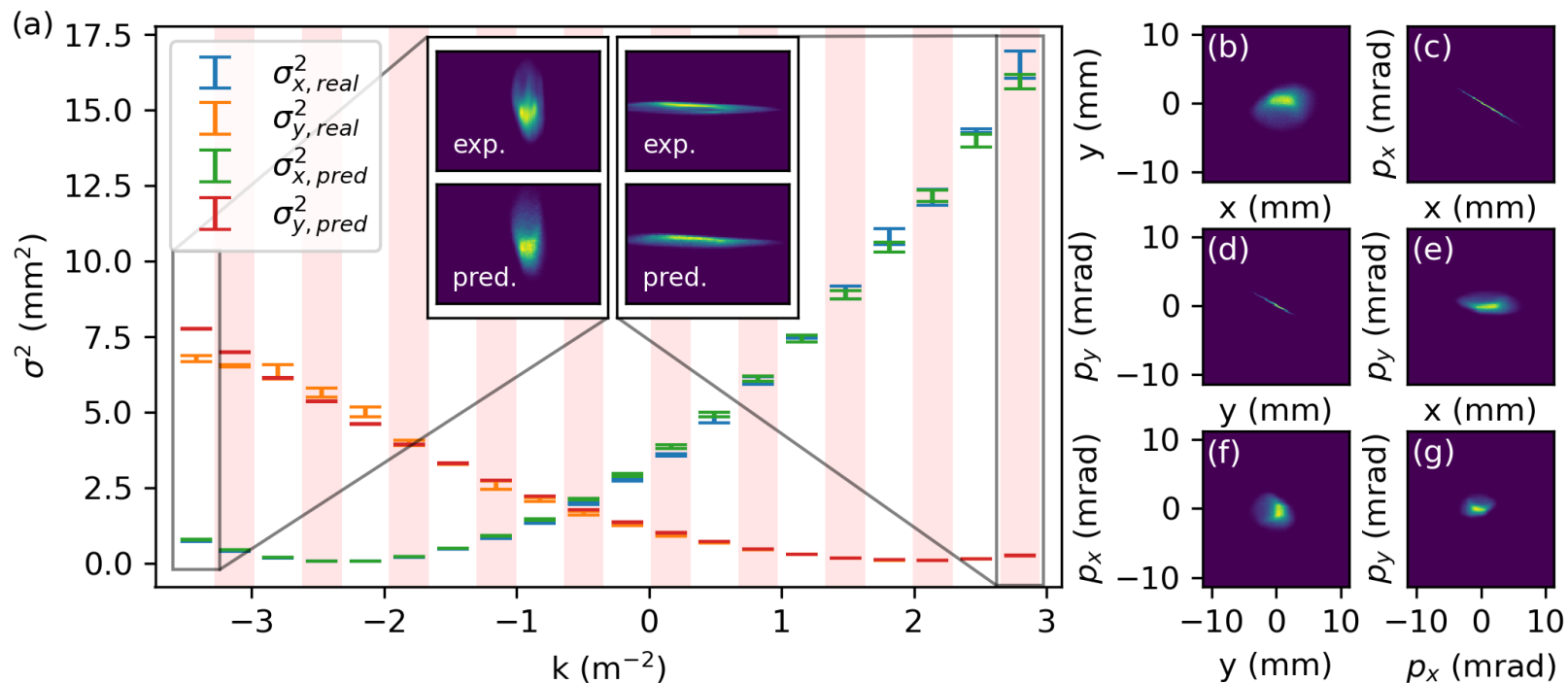


# AWA Reconstruction Results



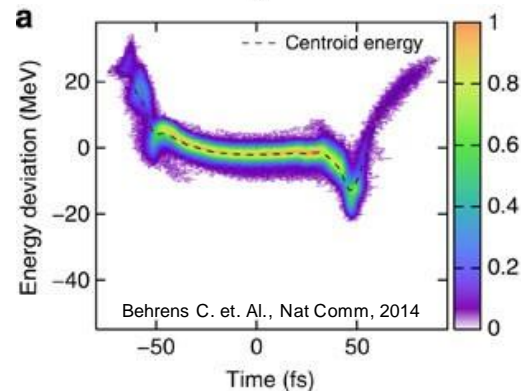
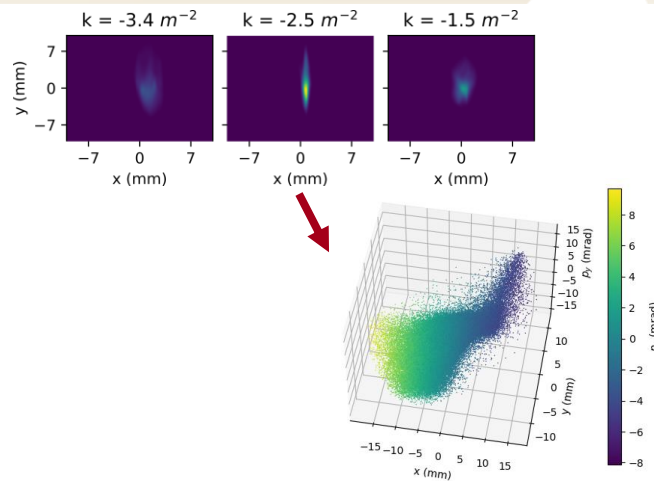
Red border denotes test samples

# AWA Reconstruction Results



# Conclusions

- We can create **detailed reconstructions of beam phase spaces** from simple tomographic accelerator measurements without special diagnostics
- Reconstructions from differentiable simulations **are not limited** by analytical tractability, number of free parameters
- Theoretically we are only limited by model detail and accuracy, **need further investment in differentiable simulations**
- Need to expand our idea of what can be used as a diagnostic



# Thanks!

## SLAC

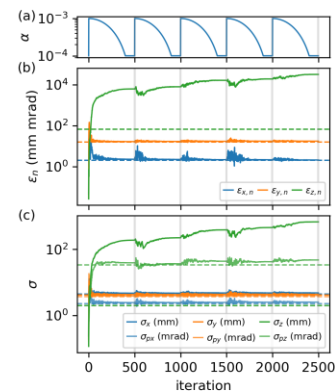
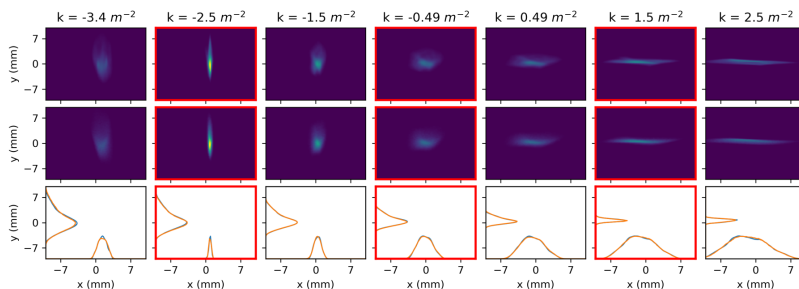
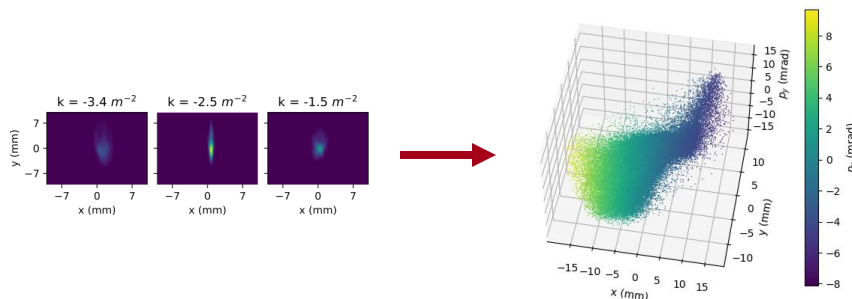
- Auralee Edelen
- Chris Mayes
- Daniel Ratner

## UChicago

- Juan Pablo Gonzalez-Aguilera

## Argonne Wakefield Accelerator

- Seongyeol Kim
- John Power
- Eric Wisniewski



# Questions?