Beam Condition Forecasting with Non-destructive Measurements at FACET-II

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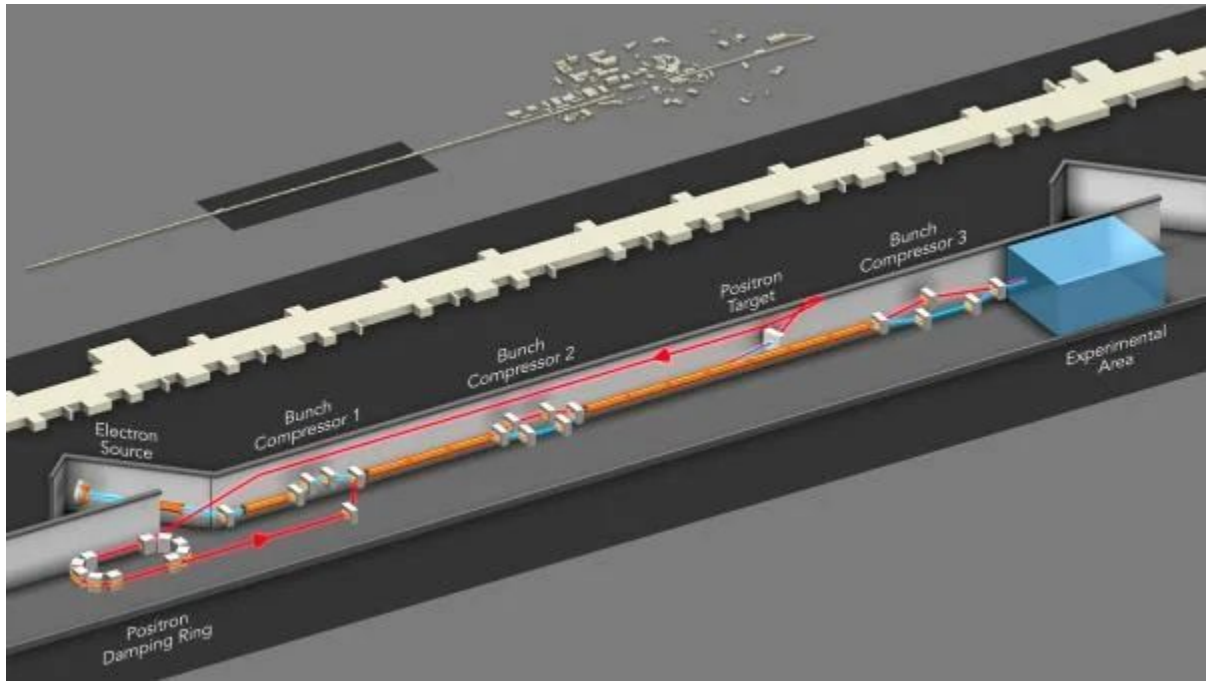
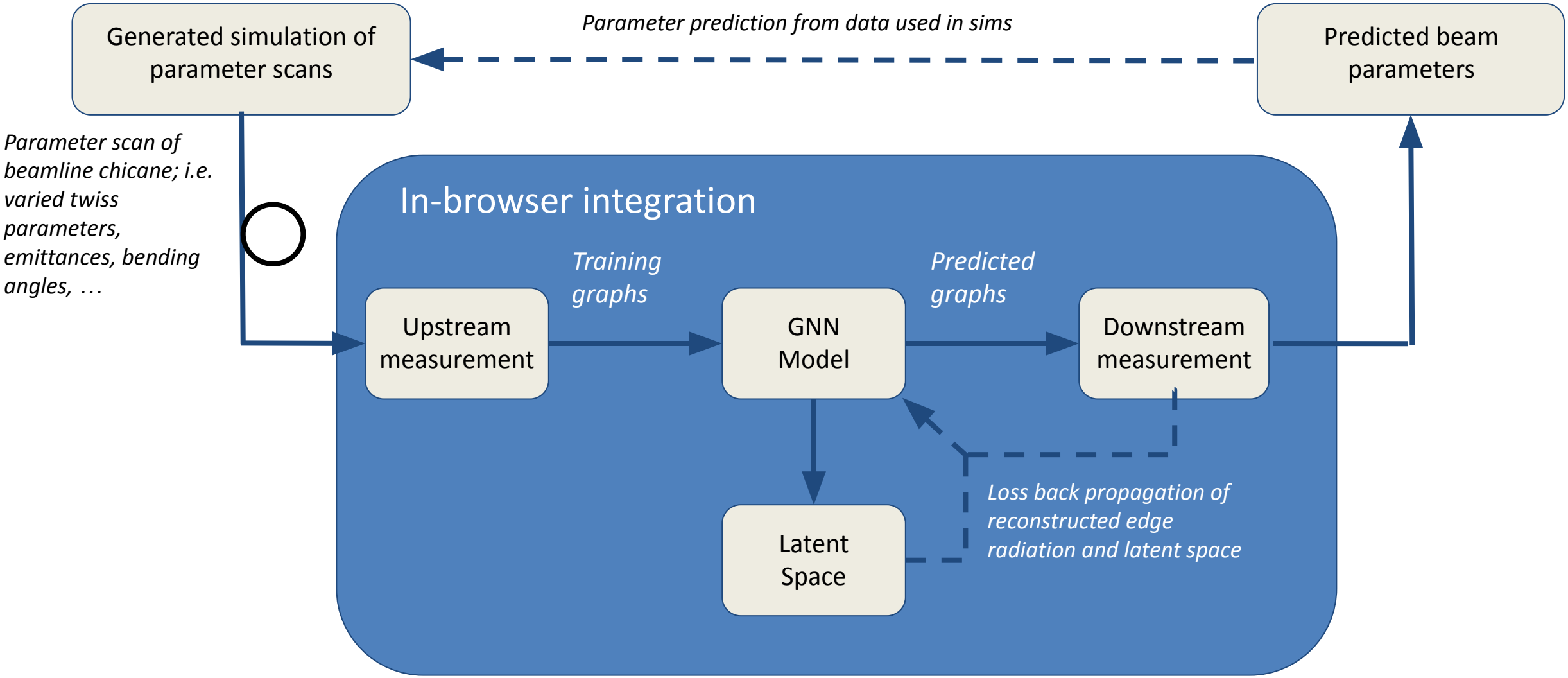
Measurements at FACET-II

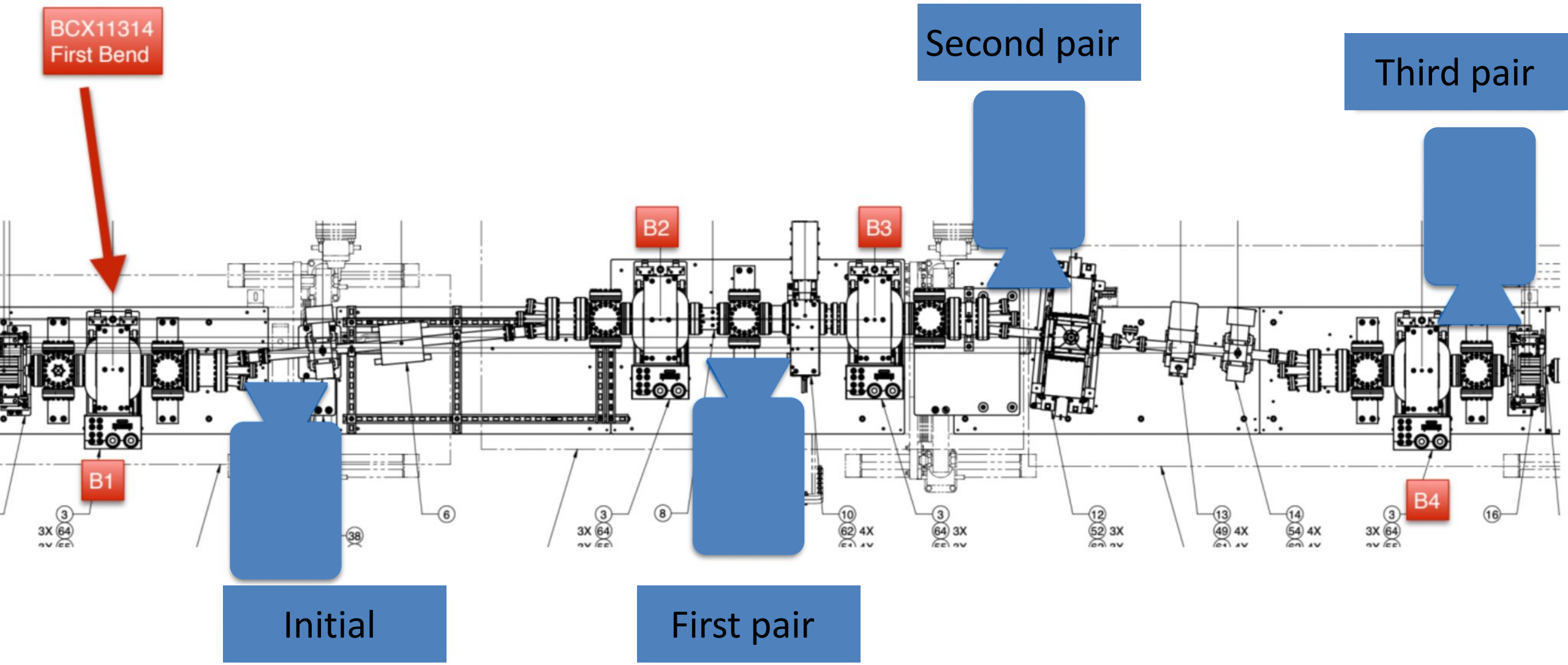
- Test facility with user access
  - Provides high energy electron beam to samples at the end of the beamline
  - Beam diagnostic techniques using both destructive and non-destructive methods
  - Significant efforts made to improve non-destructive measurement techniques
- Benefits to non-destructive measurements
  - Non-destructive measurements can be run during experiments
  - Many accelerator facilities utilize both measurement types
  - FACET-II upgraded cameras in mid-2023
  - Cameras measure non destructive edge radiation
- Edge radiation
  - Charged particle emits radiation due to far-field magnetic field effects
  - Depends on a variety of factors such as magnetic bending length



Data Pipeline



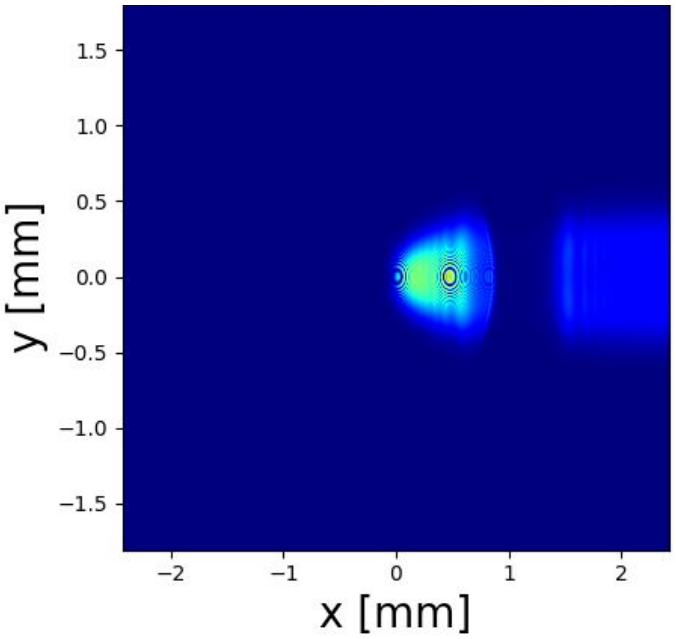
Beamline Setup



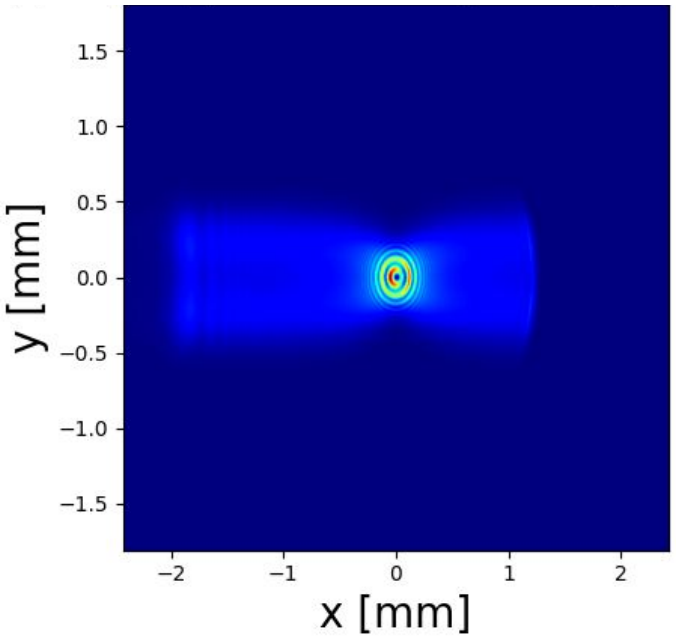
Beam Measurement Design

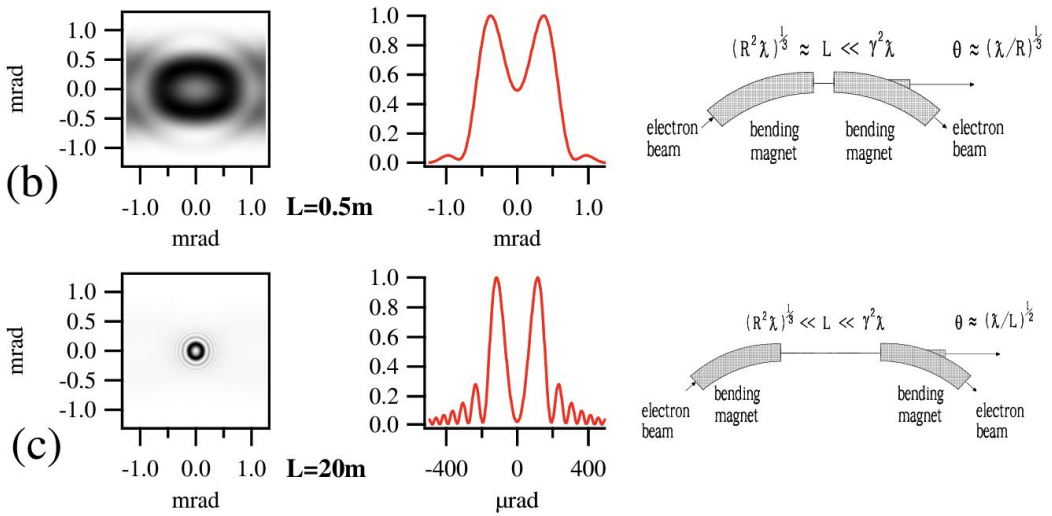
- Three pairs of bending magnets
  - Electron beam travels through chicane for beam quantification
  - Each pair of magnet edges provide constructive/deconstructive interference for measurement

First pair



Second pair

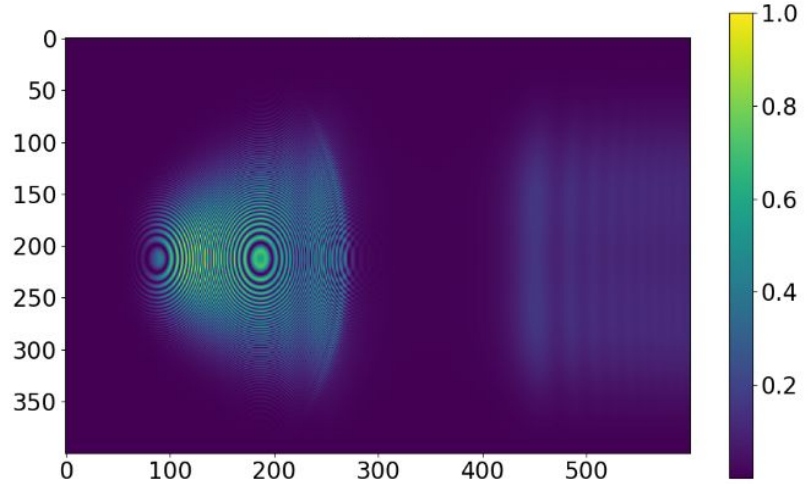




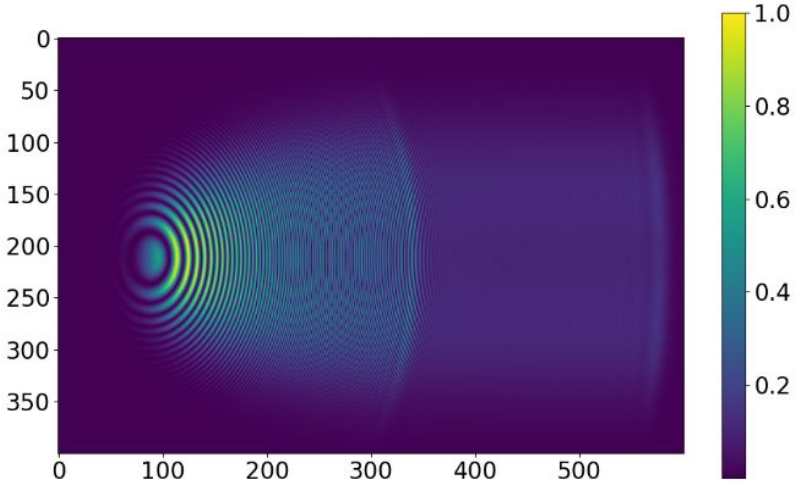
Simulating Edge Radiation

- Synchrotron Radiation Workshop (SRW) simulation
  - Calculation of detailed characteristics of SR generated by relativistic electrons in B fields
  - Robust simulation of the frequency range
  - Parameter scanning to many datasets
  - Noise can be added to simulation to replicate real data
  - Inputs are any upstream measurement and output is any downstream measurement

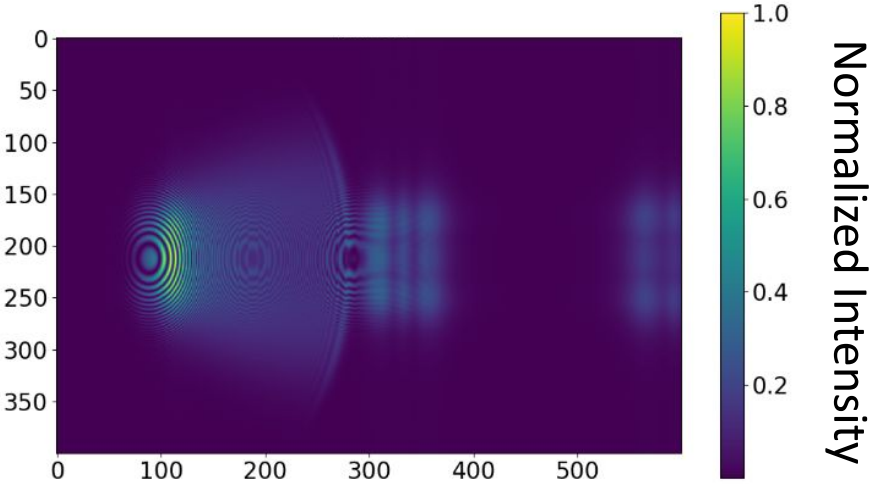
First pair



Second pair

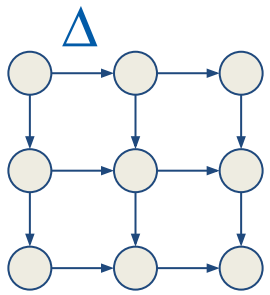


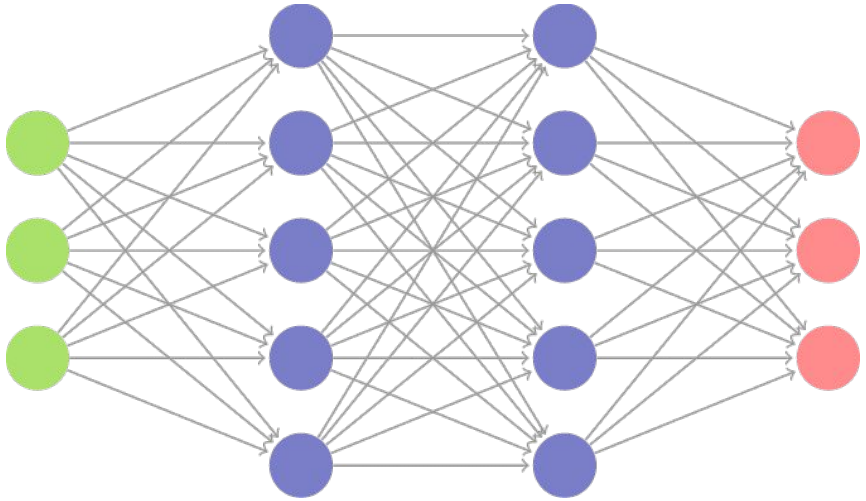
Third pair

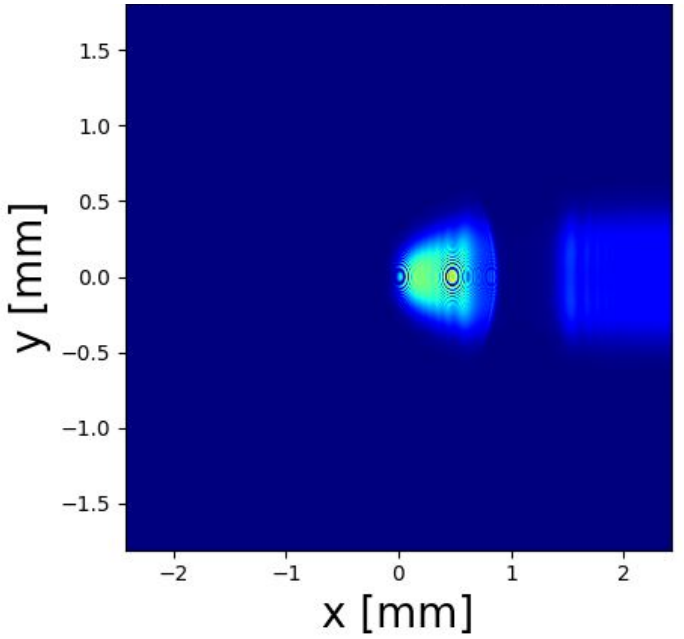


Building the Model

- Graph representation
  - Each pixel is represented as a node
  - Intensities are used as node features
  - Pixel gradients are edge weights
  - Image sizes are 1024 by 1024
- Feedforward GNN
  - First bending image is fed through to then reconstruct second bending image
  - Can be any pair of images as long as the latter is downstream

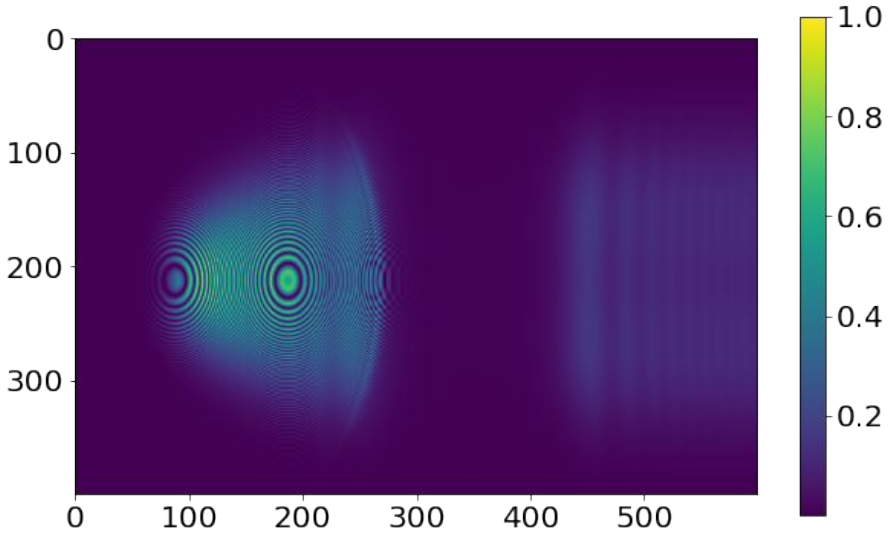


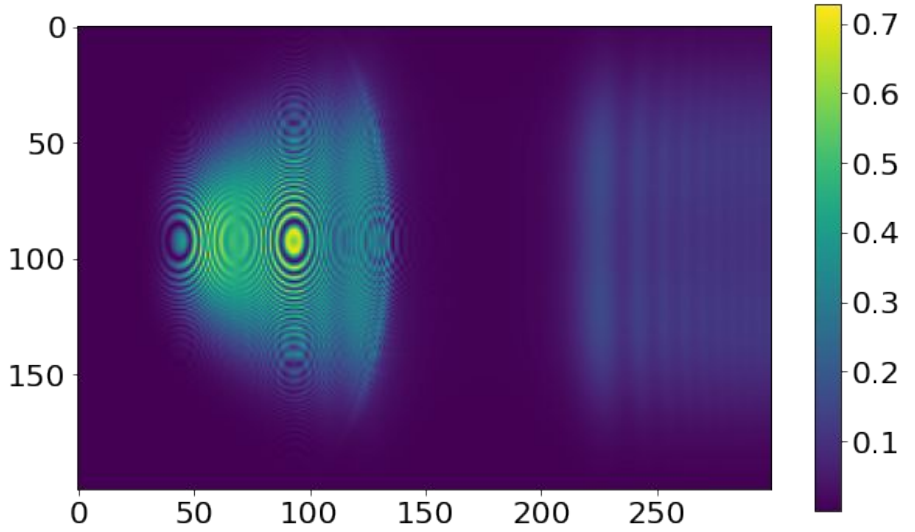


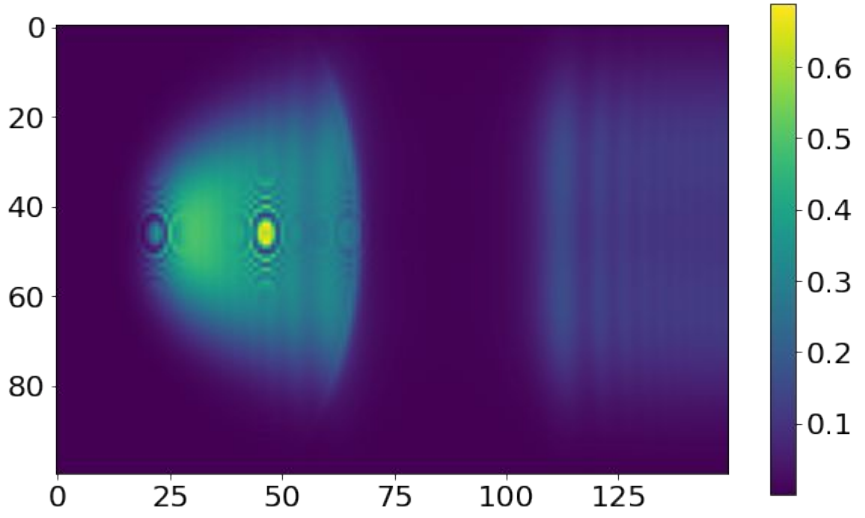


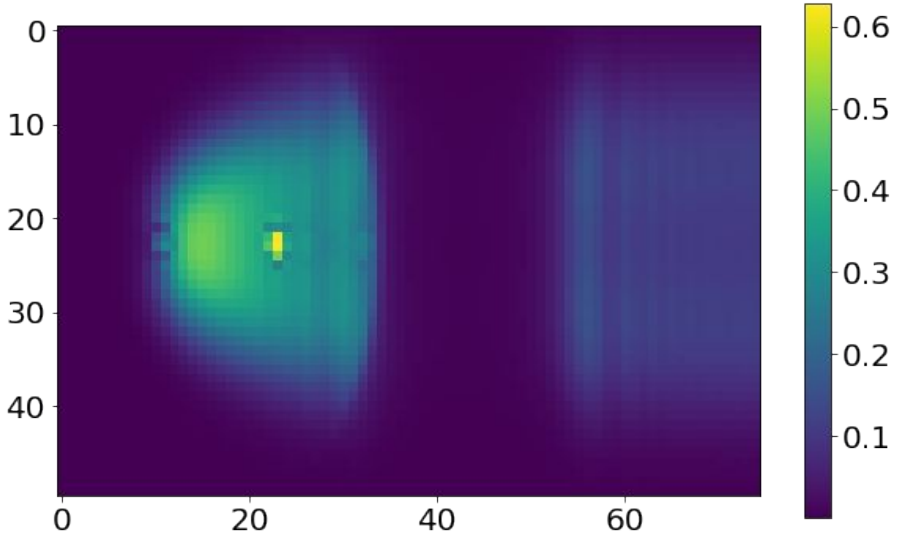
$$X^{(l+1)} = AX^{(l)}W^{(l)}$$

Image Resampling



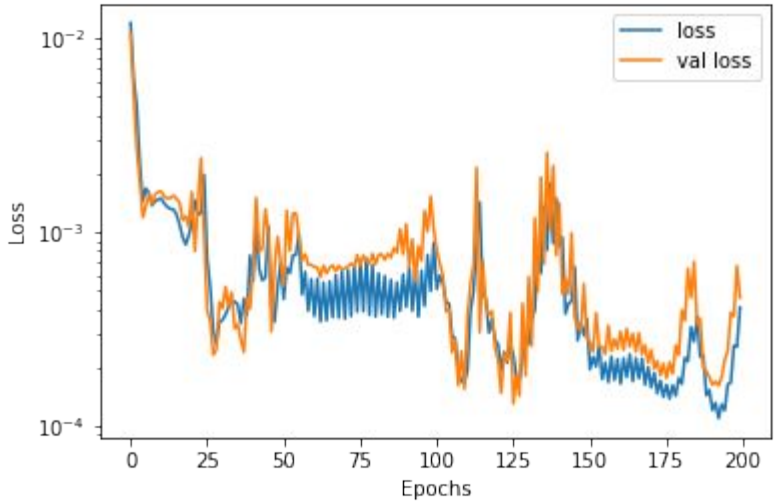


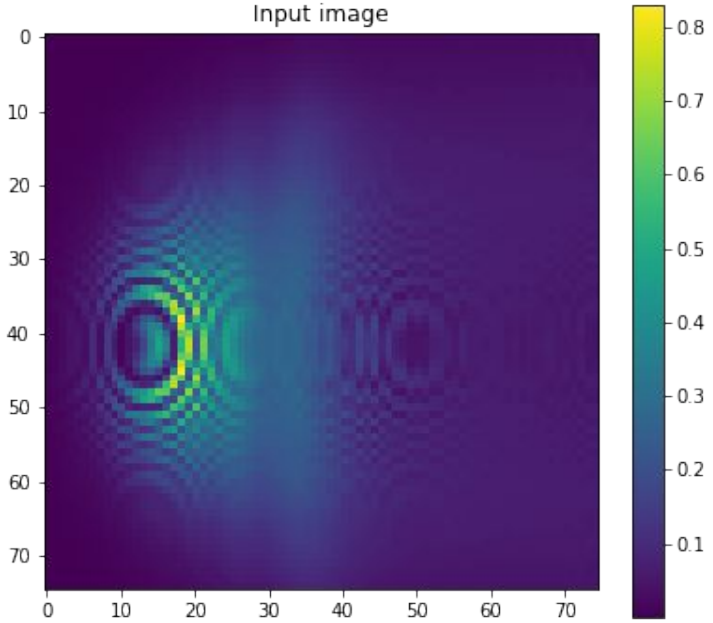


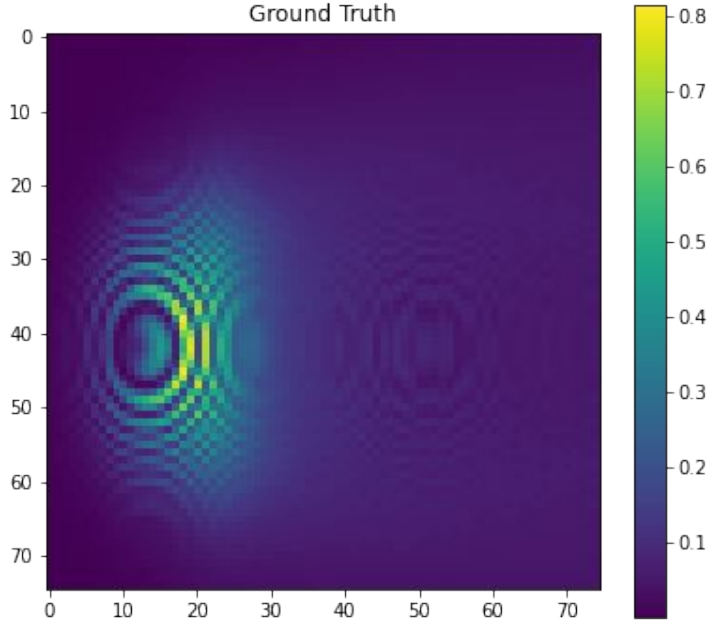


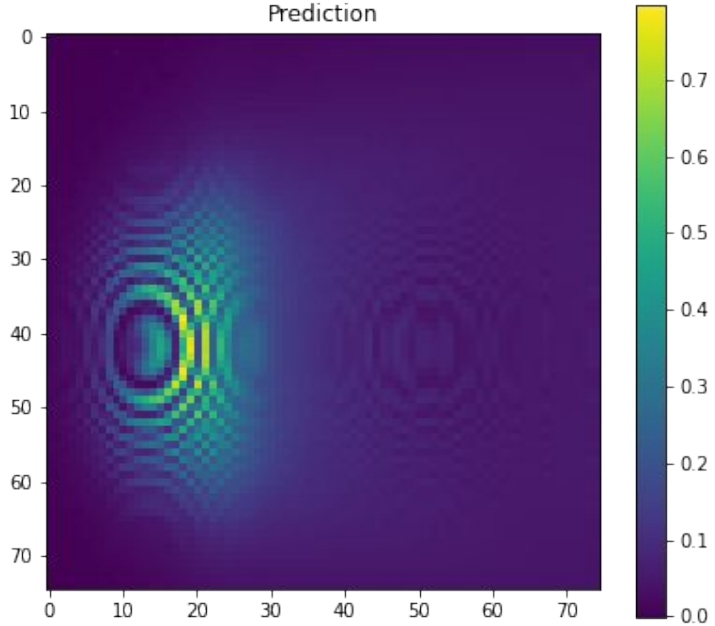
Training and Reconstruction

- Simple feed forward
  - Model is able to accurately reconstruct downstream radiation
  - Simple methods provide an overfitted model
  - Provides stepping stone to more complex methods
- Reconstruction on unseen test data
  - Accurately shows topology









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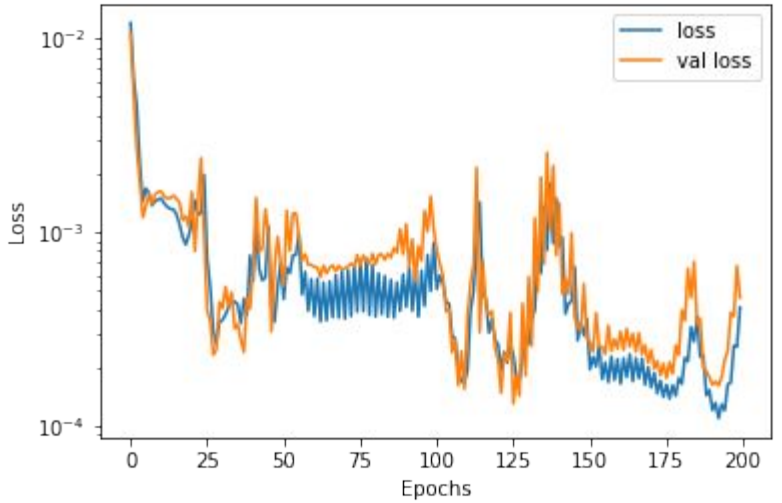
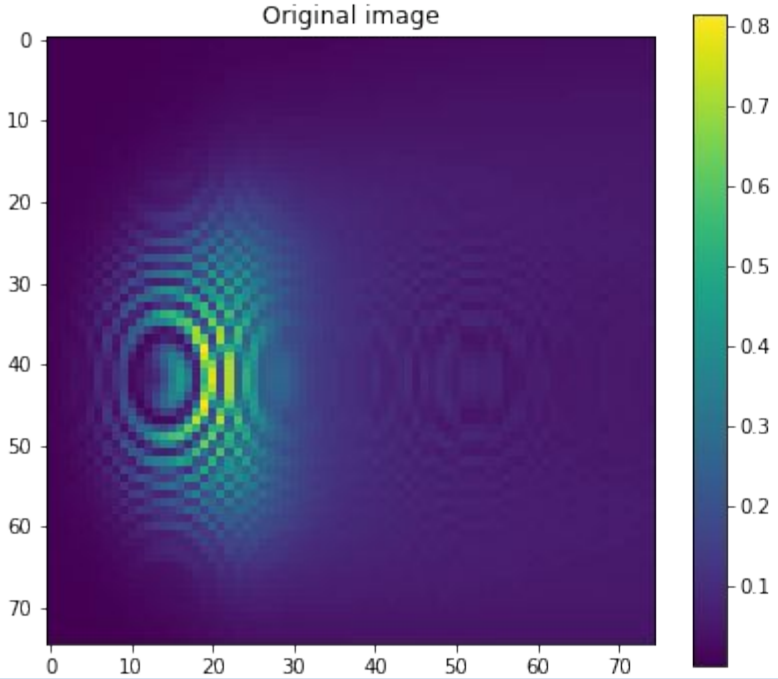
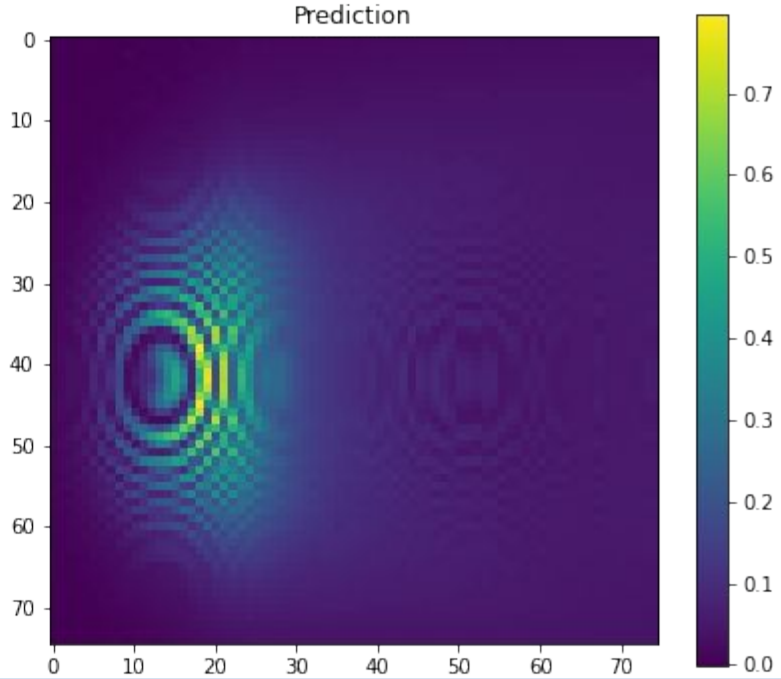
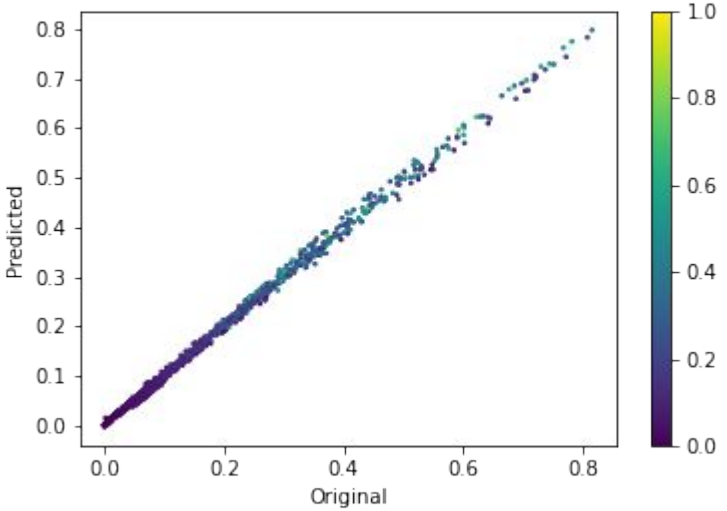


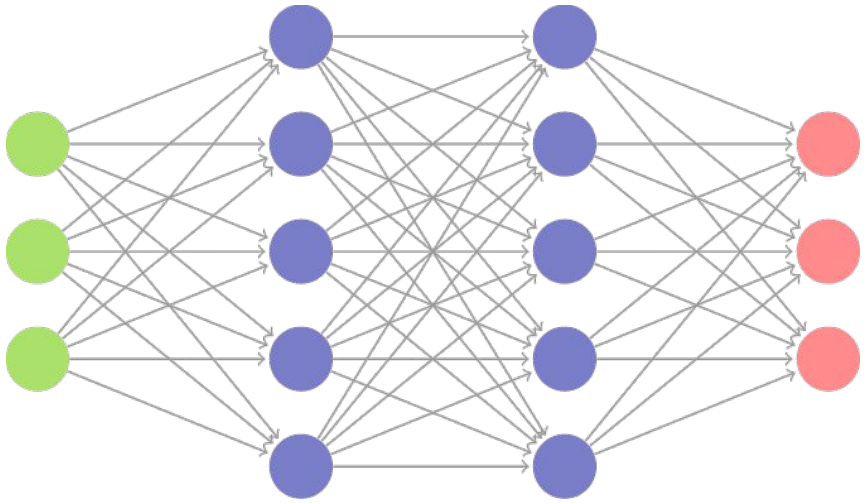






Expanding to Latent Prediction

- Feedforward GNN
  - First bending image is fed through to then reconstruct second bending image
  - Can be any pair of images as long as the latter is downstream
- Autoencoder with Latent Space
  - Representation of inherent physics of the system
  - Force conservation of divergence



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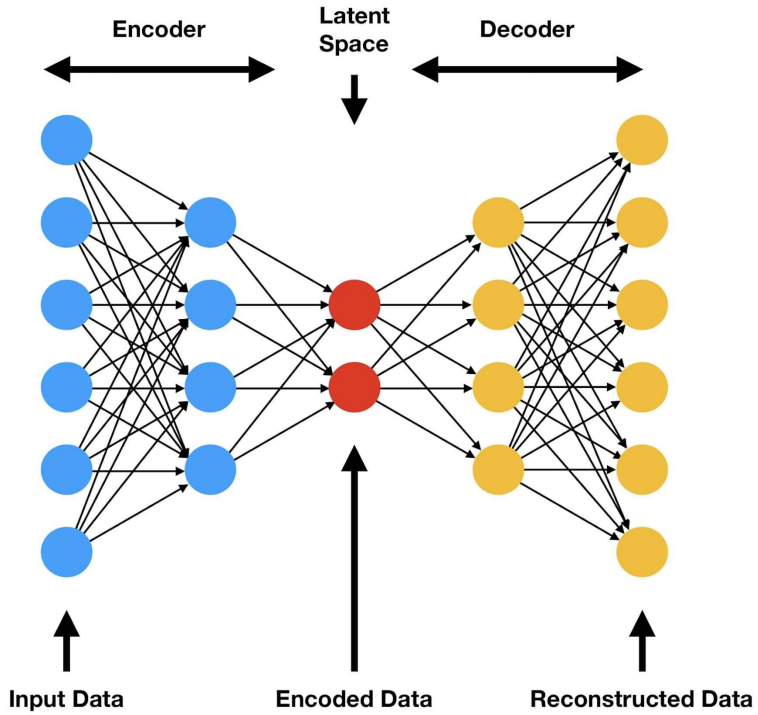
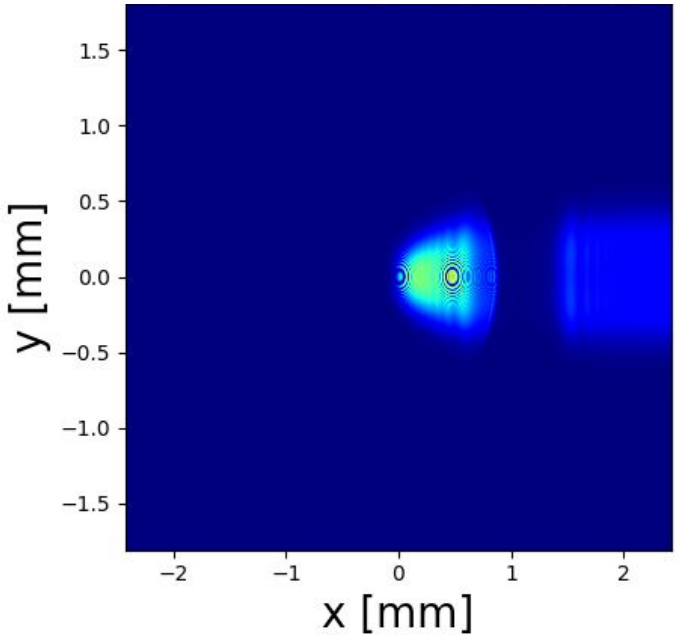
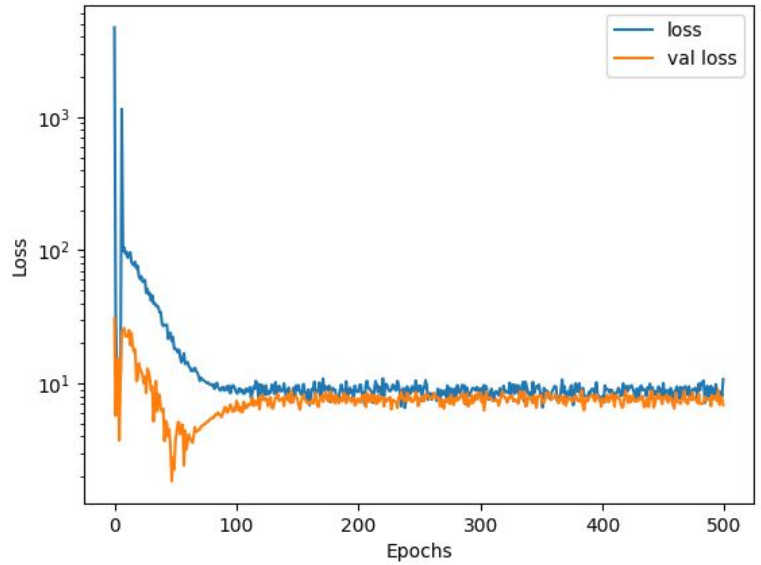
https://www.baeldung.com/cs/latent-vs-embedding-space

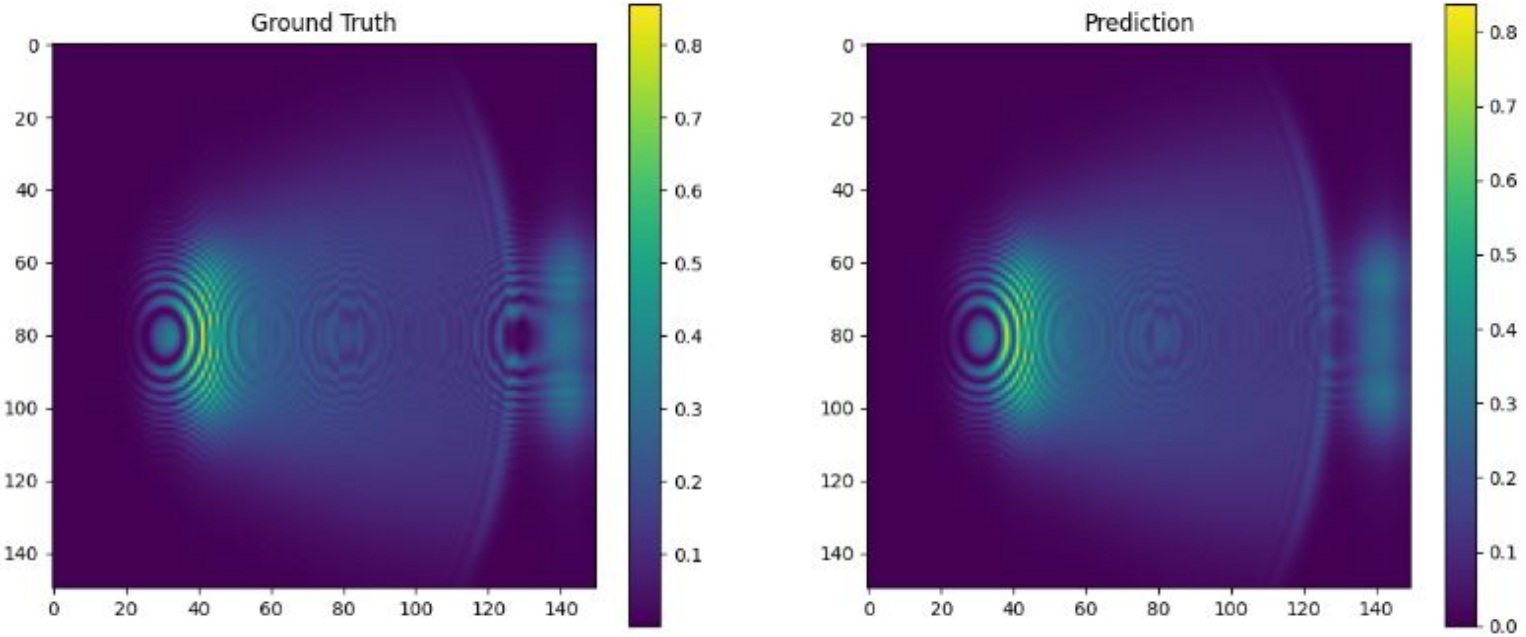


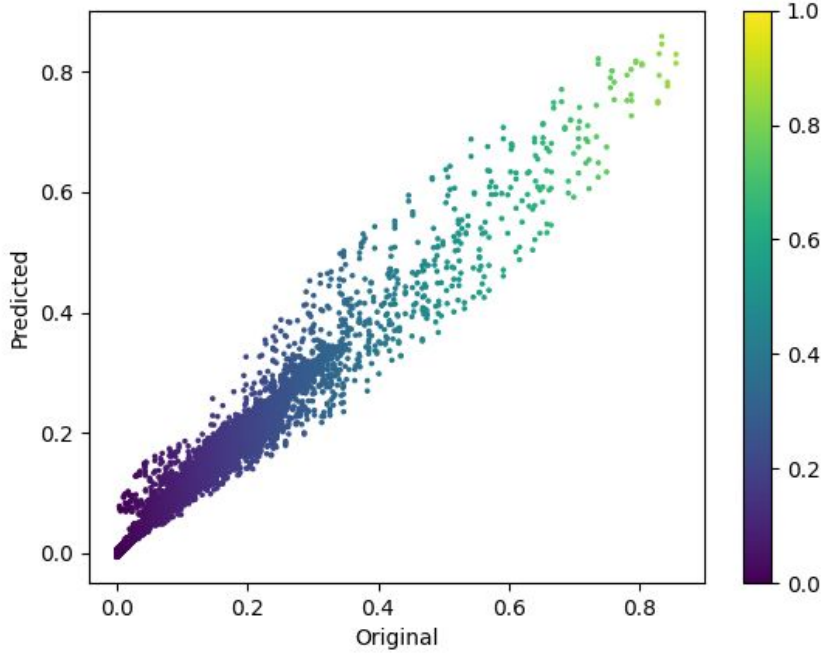


Training and Reconstruction

- GNN with Latent space
  - Model is able to accurately reconstruct downstream radiation
- Latent Space
  - Train latent space to conserve beam divergence
  - Seems to recover the average divergence







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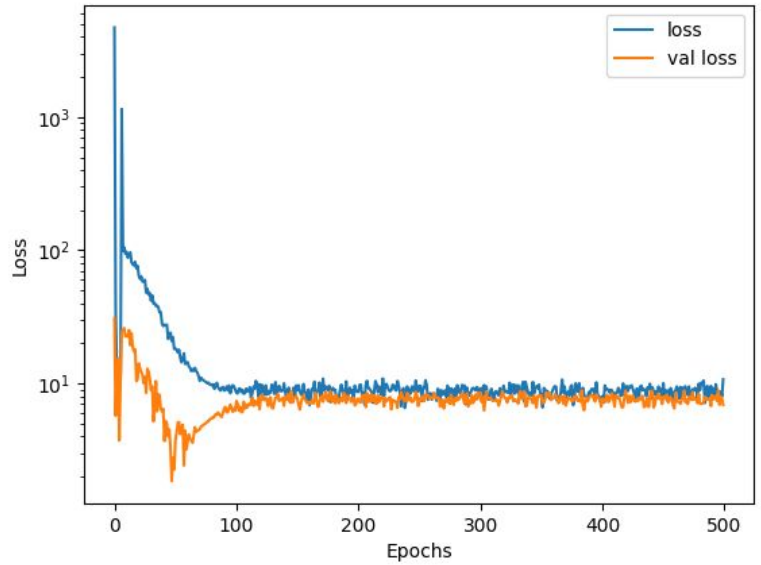
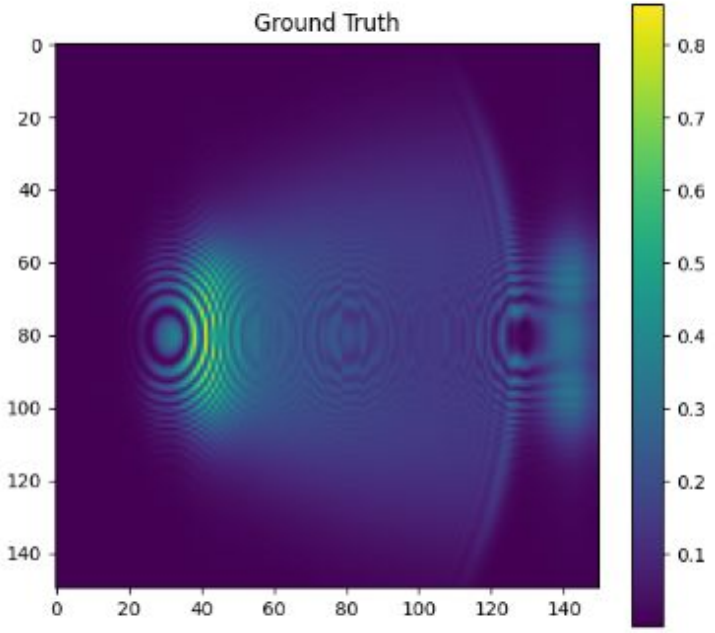
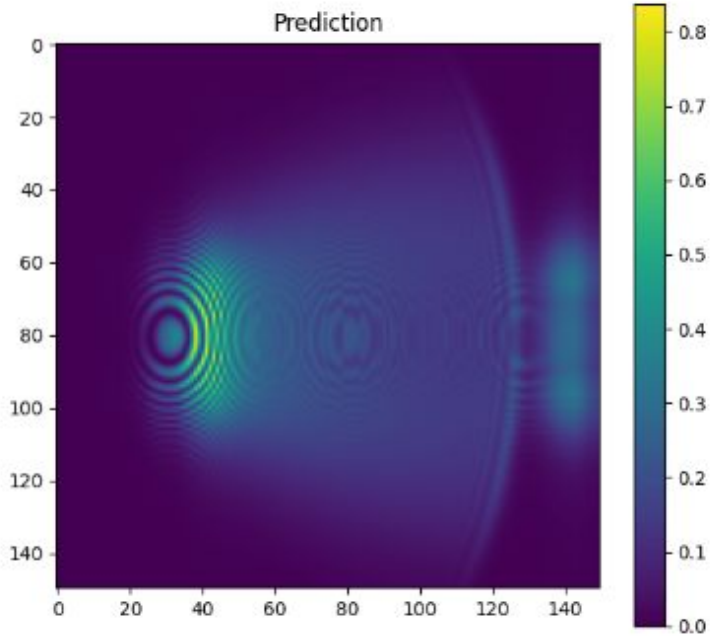
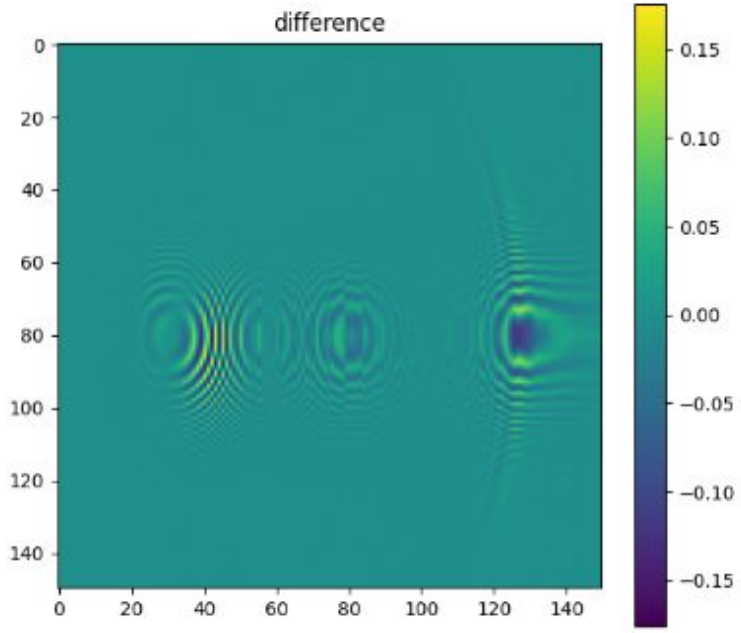


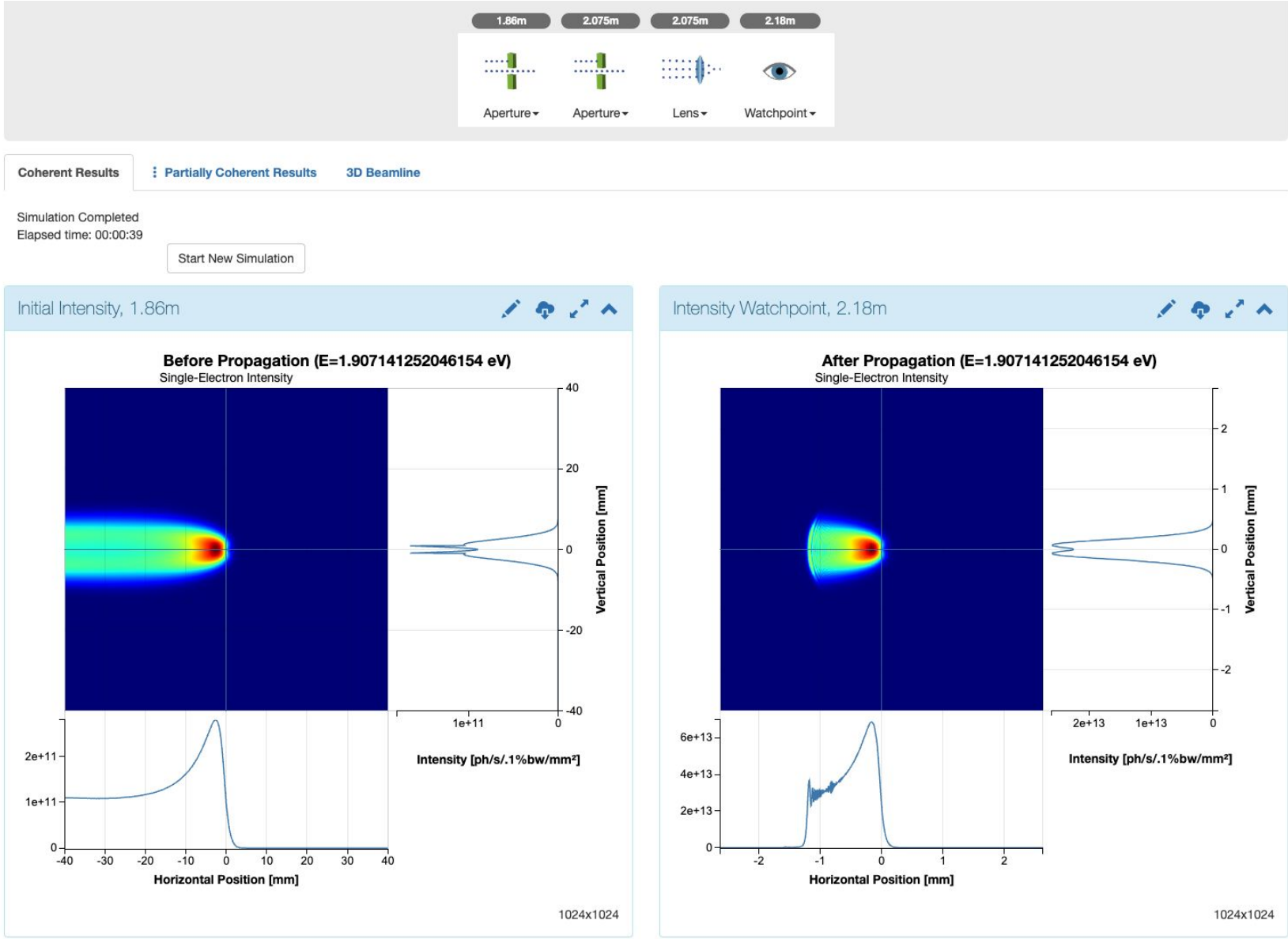






In-Browser SRW Simulation

- Online computing
  - Many processing nodes for faster computation time
  - Interactive edge radiation analysis
- Online model
  - Go from data generation to model training and evaluation
  - Monitoring reconstruction in real time



Future Work

- Project undergoing constant development at a SBIR Phase I project
  - Goals are a proof of concept!
  - Once shown we can move to Phase 2!
- Physics integration
  - Proven simple GNN shows accurate reconstruction of downstream dynamics
  - Incorporate beam physics within GNN latent space
  - Integrate within online computing framework
- Surrogate Modeling
  - Generate new possible beam states due to changes within the beamline
  - Investigate potential forecasting capabilities
- Phase 2 Plans
  - Integration of model training and evaluation within Sirepo
  - Predict an beam state generated with Surrogate models and confirmed on the beamline

THANK YOU!

Acknowledgements

- RadiaSoft Collaborators: Paul Moeller, Boaz Nash

- SLAC Collaborators: Robbie Watt, Brendan O'Shea

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