Machine Learning Based, Non-invasive Beam Diagnostics

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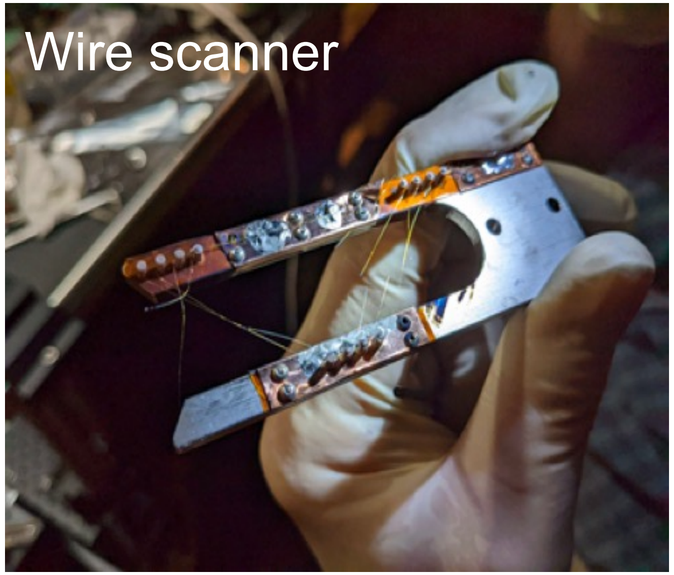
- Why edge radiation is ideal for non-invasive beam diagnostics
- Diagnostic setup at FACET-II
- Using a computer vision model to infer beam size
- Extract more information using a physics informed loss function

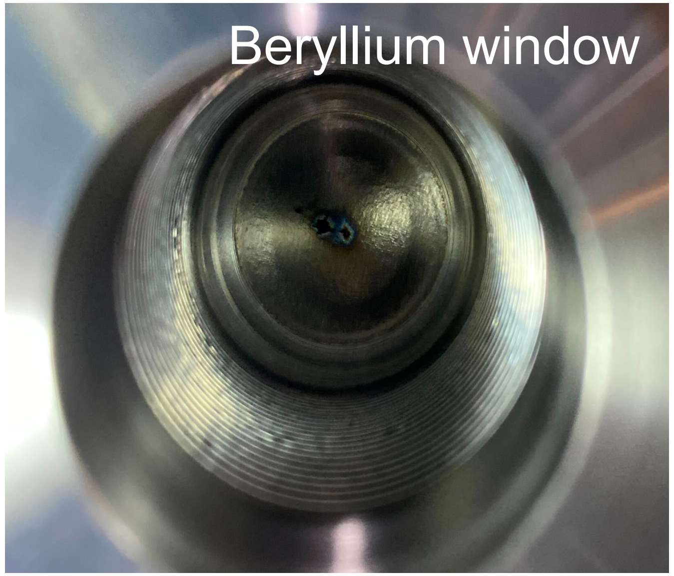
Why are Non-Invasive Beam Diagnostics Important?

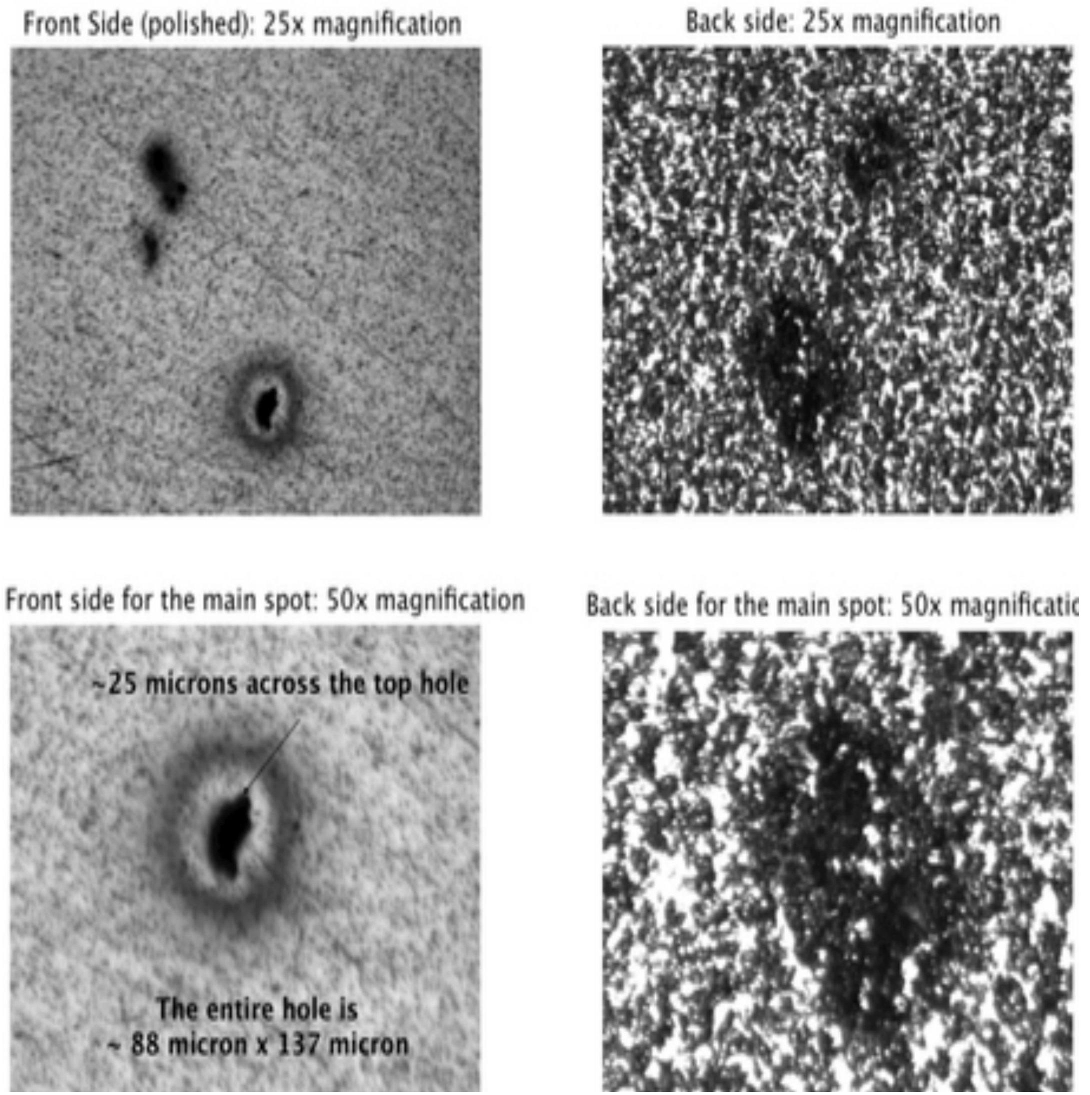
Conventional beam diagnostics have two main drawbacks:

- Material in the beam path destroys the downstream quality
- High intensity beams can destroy the diagnostic making it expensive to operate

Non intercepting diagnostics fix both issues!







Edge Radiation for Non-Invasive Diagnostics

Edge radiation is the synchrotron radiation emitted at the edges of dipoles.

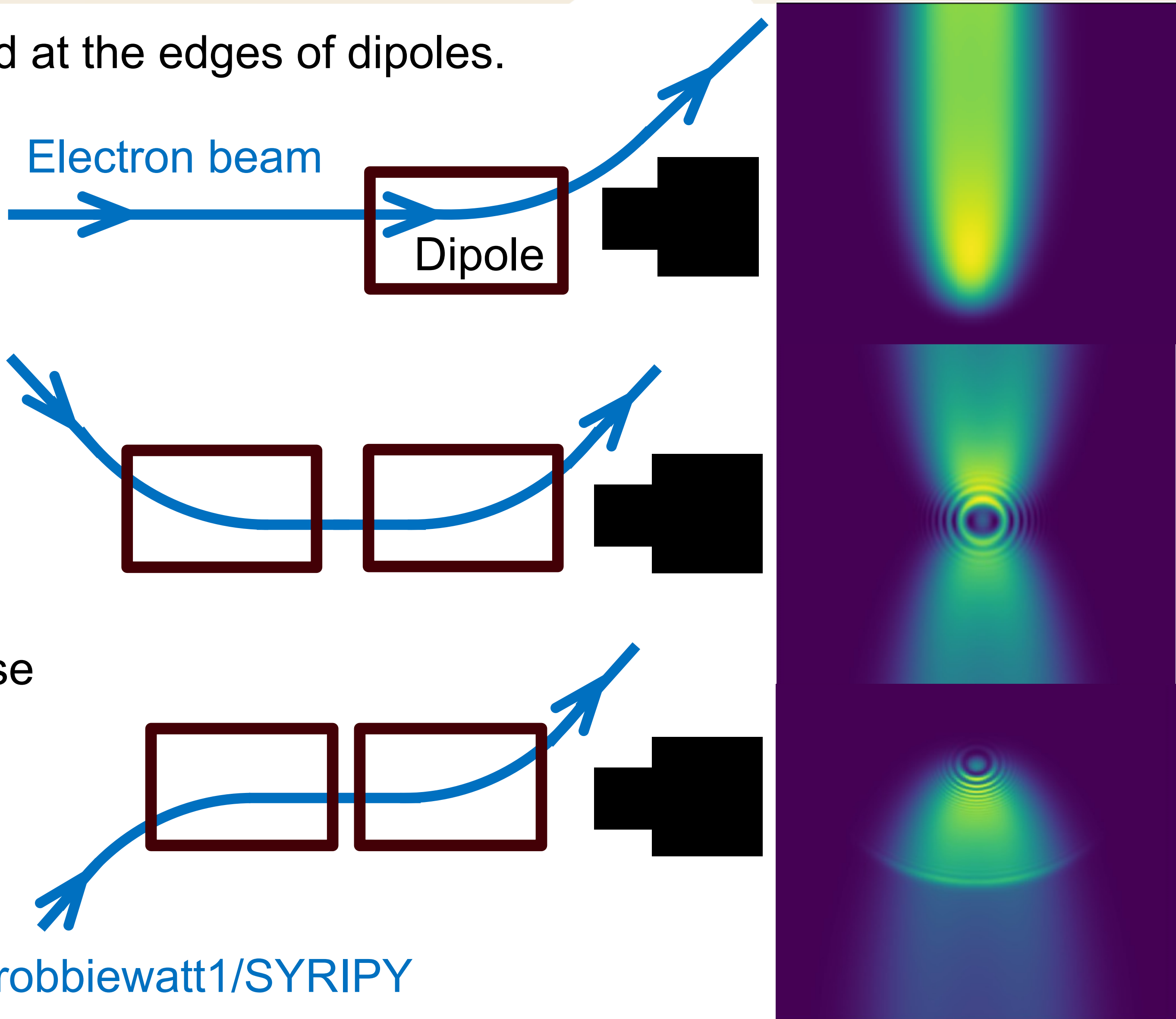
We can model edge radiation by solving the Liénard–Wiechert field:

$$\mathbf{E}_\omega = \frac{ie\omega}{c}\int_{-\infty}^{\infty}\frac{1}{R}\left[\boldsymbol{\beta}-\left(1+\frac{ic}{\omega R}\right)\mathbf{n}\right]e^{i\omega(t+R/c)}\mathrm{d}t$$

Total intensity is obtained by convolving beam distribution over single electron field:

$$I(\mathbf{x}) = \left|\int \mathbf{E}(\mathbf{x}-\mathbf{x}')\rho(\mathbf{x})d\mathbf{x}\right|^2$$

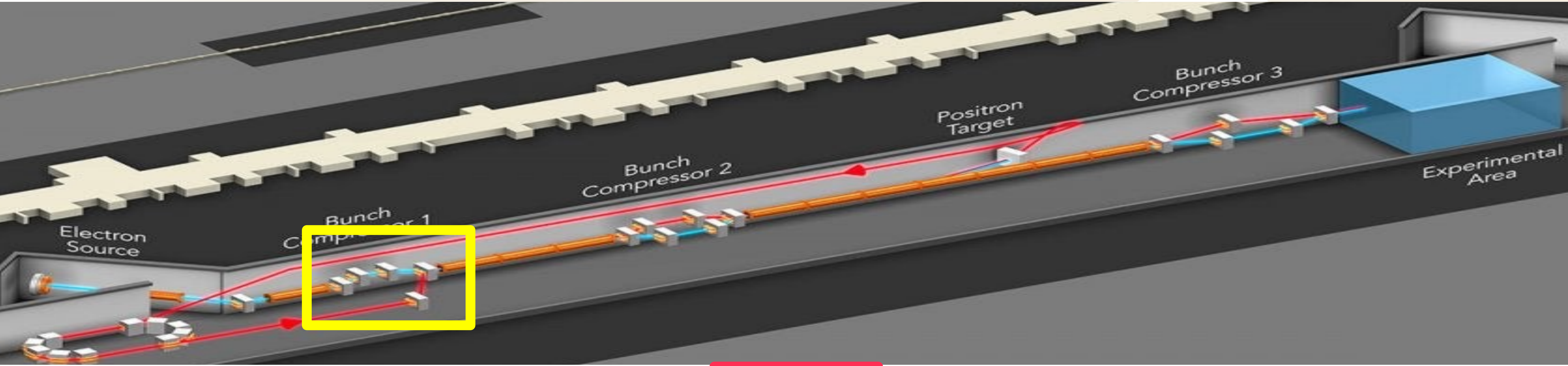
The intensity fringes are sensitive to the transverse beam parameters (size, divergence, correlation)

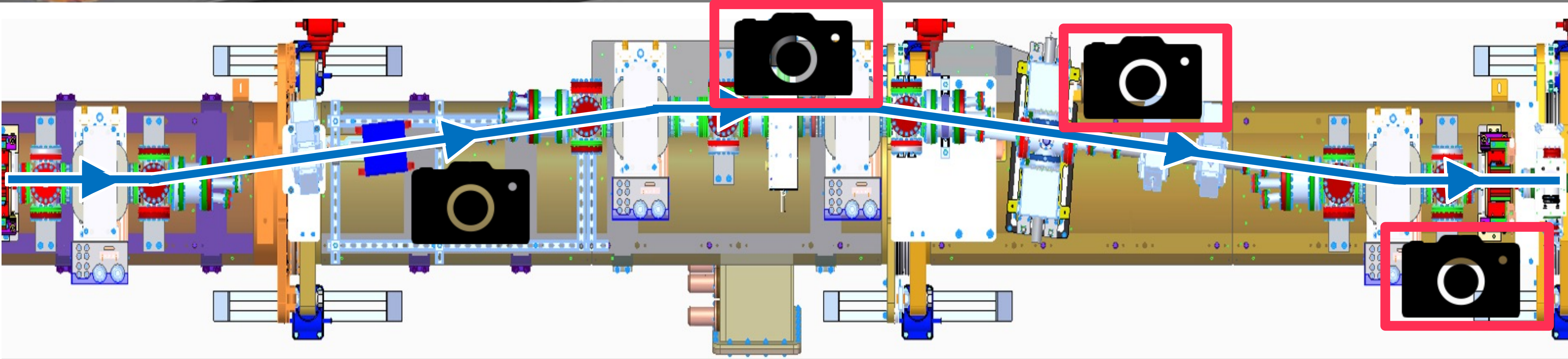


Edge-Radiation is ideal for non-invasive single shot diagnostics

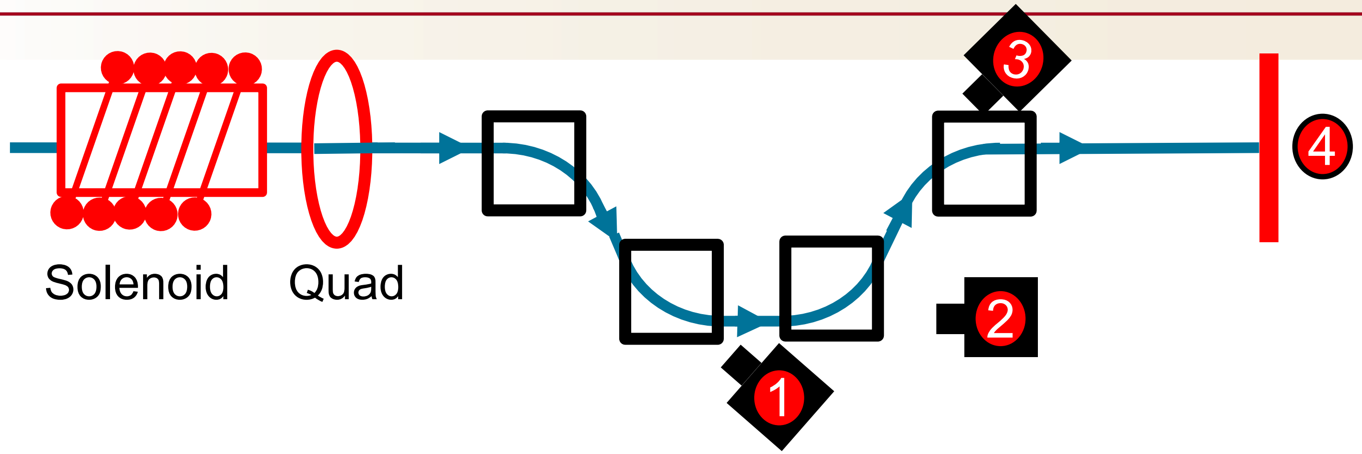
Simulation with SyRiPy: https://github.com/robbiewatt1/SYRIPY

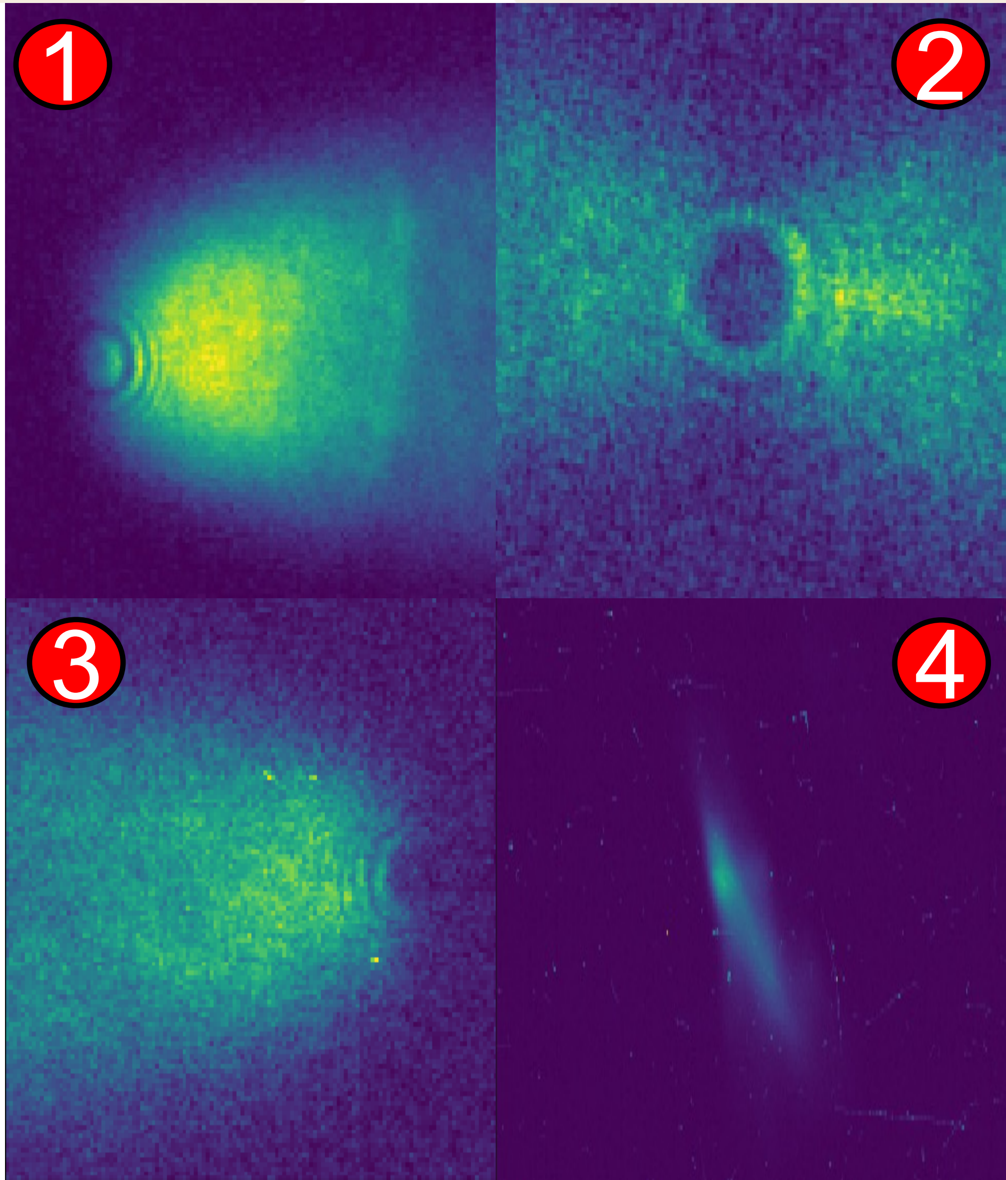
Edge Radiation Diagnostics at FACET II





BC11 Dataset





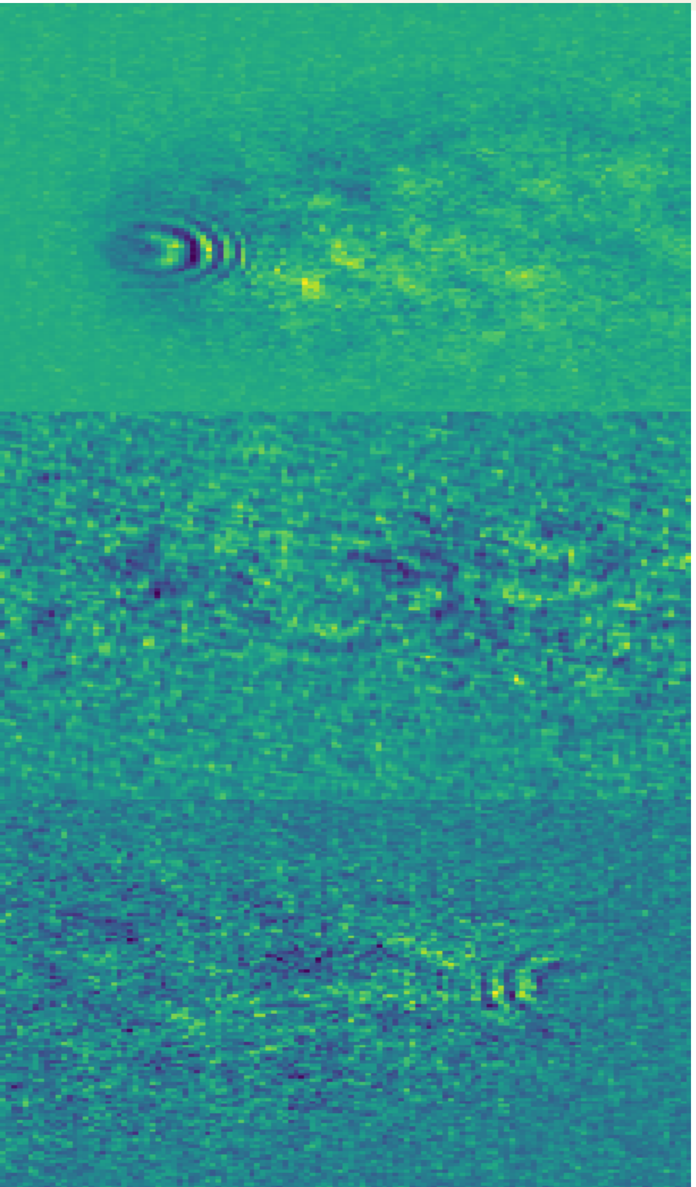
Aim: Build a model to predict beam parameters from radiation

Require: A dataset of images for a verity of beam conditions

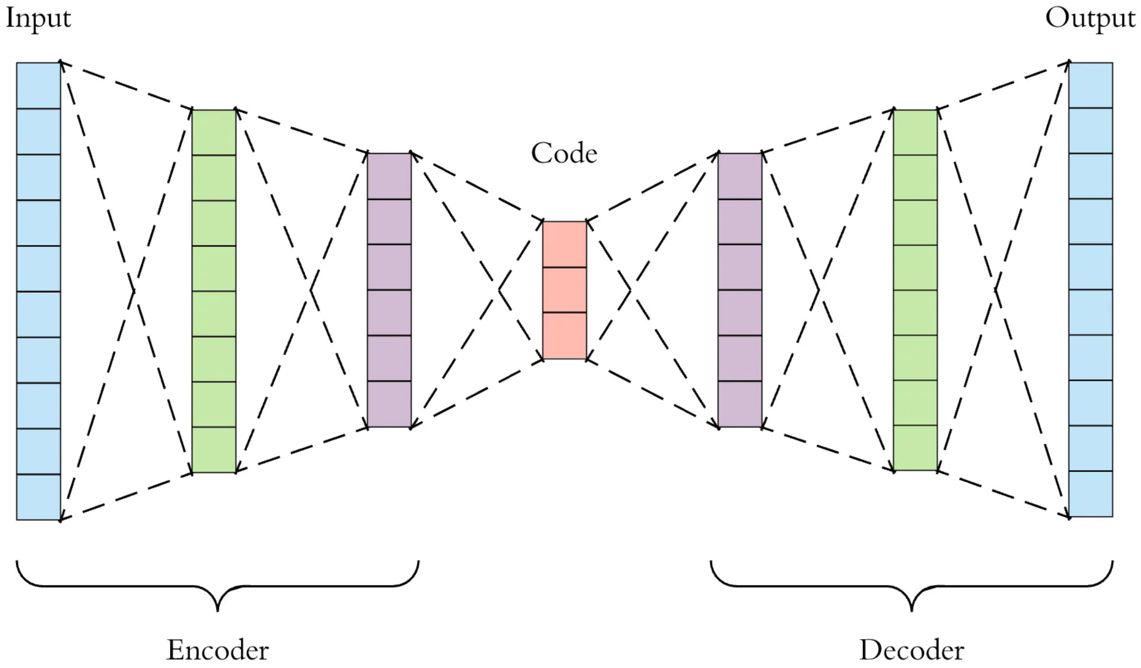
- Solenoid varied to change beam emittance.
- Quad varied to change beam parameters and measure emittance.

Main dataset
6 soln steps (9μm to 14μm)
40 quad field steps
40 shots per configuration
9600 total shots

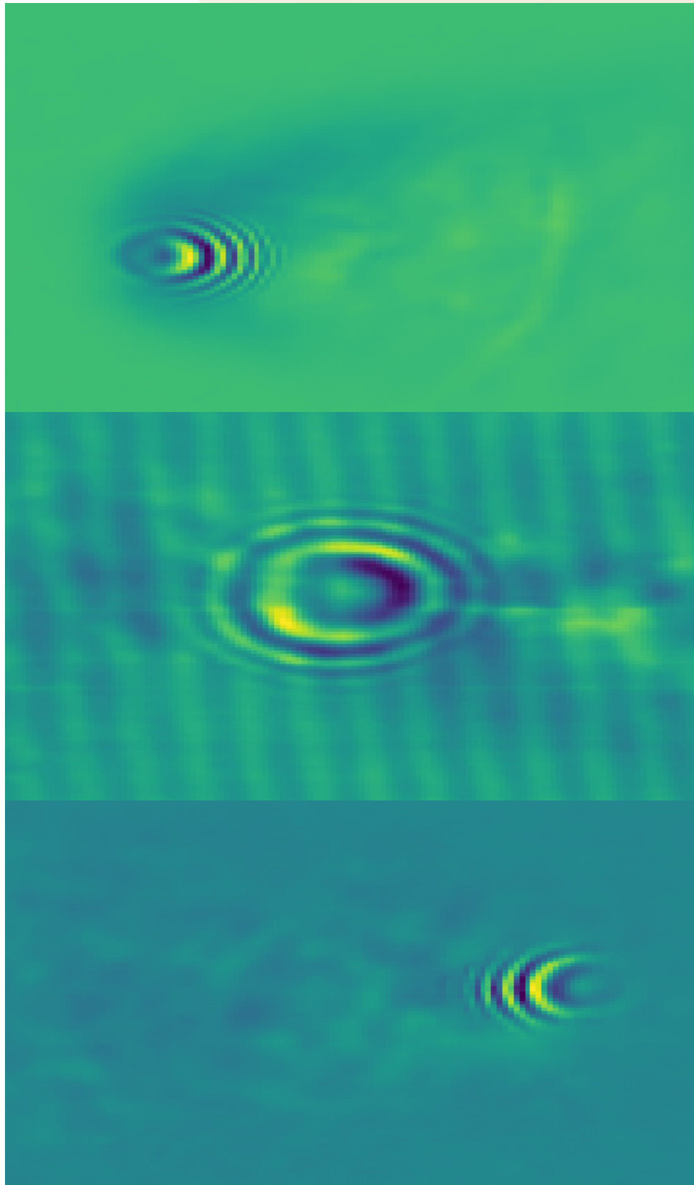
Latent Representation of Images



We have lots more unmatched data. Images are high dimensional objects that are hard to work with. An autoencoder can help!

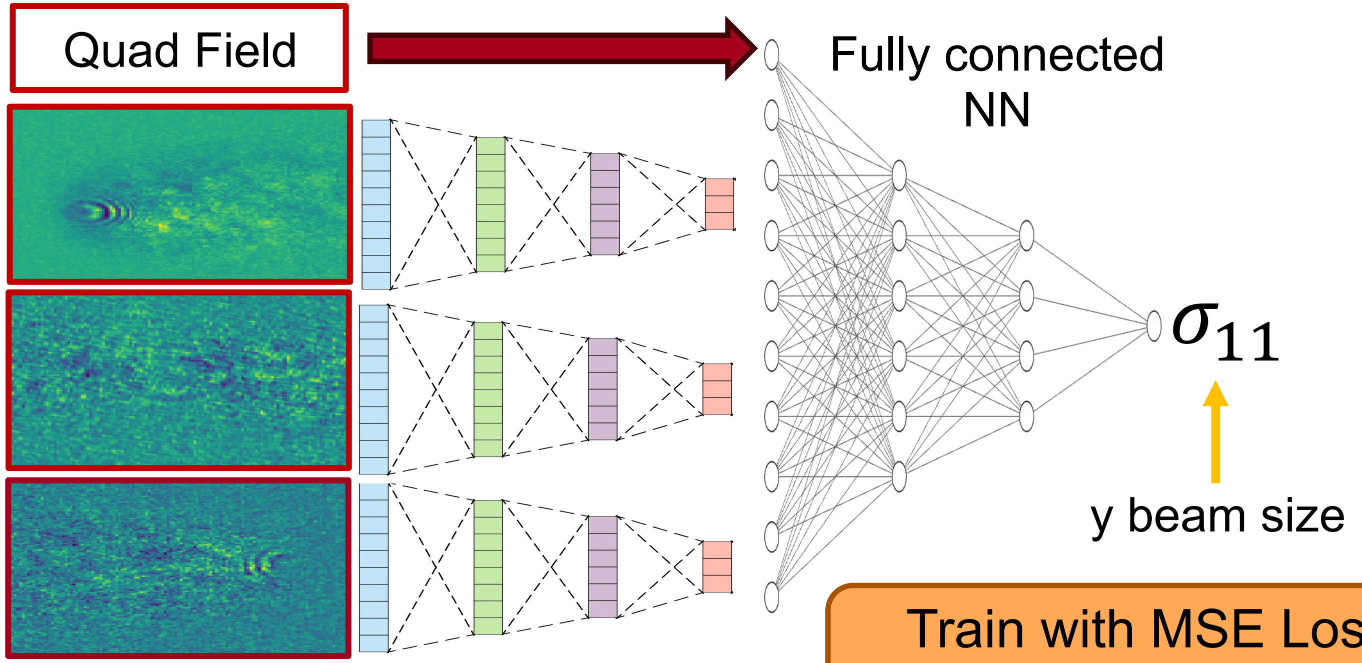


Each image is well represented by only 5 latent parameters.



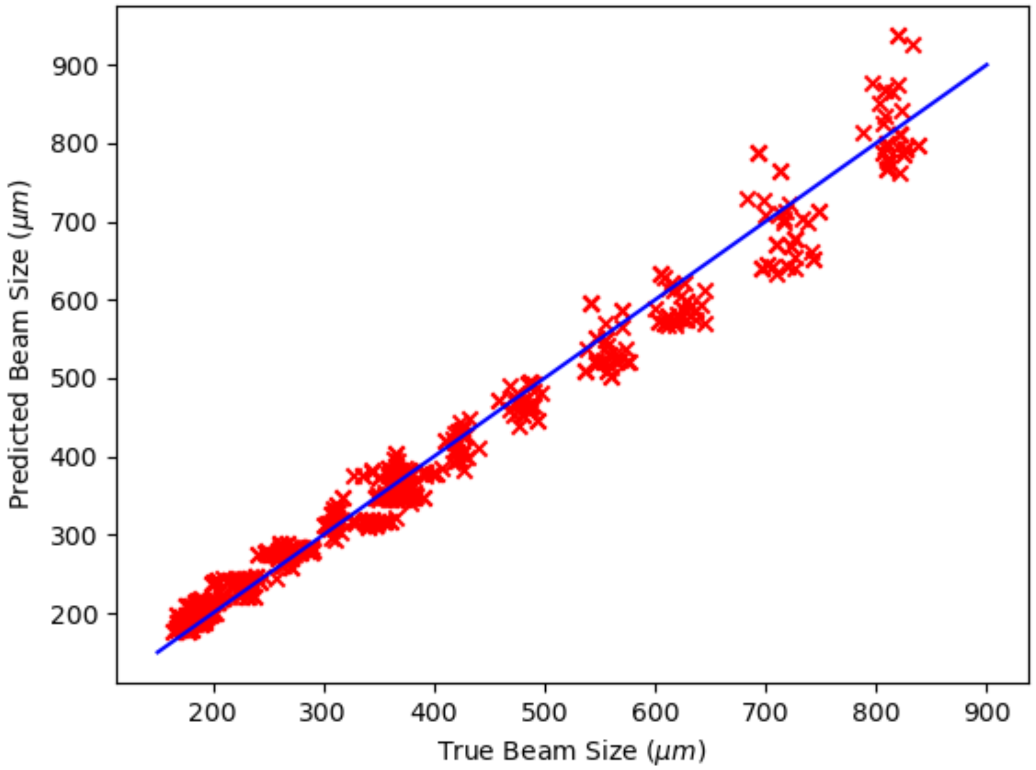
Predicting Downstream Beam Size

We have a latent representation of images and the corresponding downstream beam size. Therefore, We can train a virtual diagnostic for the beam size using supervised learning.



Train with MSE Loss:
$L = \mathbb{E}[(\sigma_{11}{}^{t} - \sigma_{11}{}^{NN})^2]$

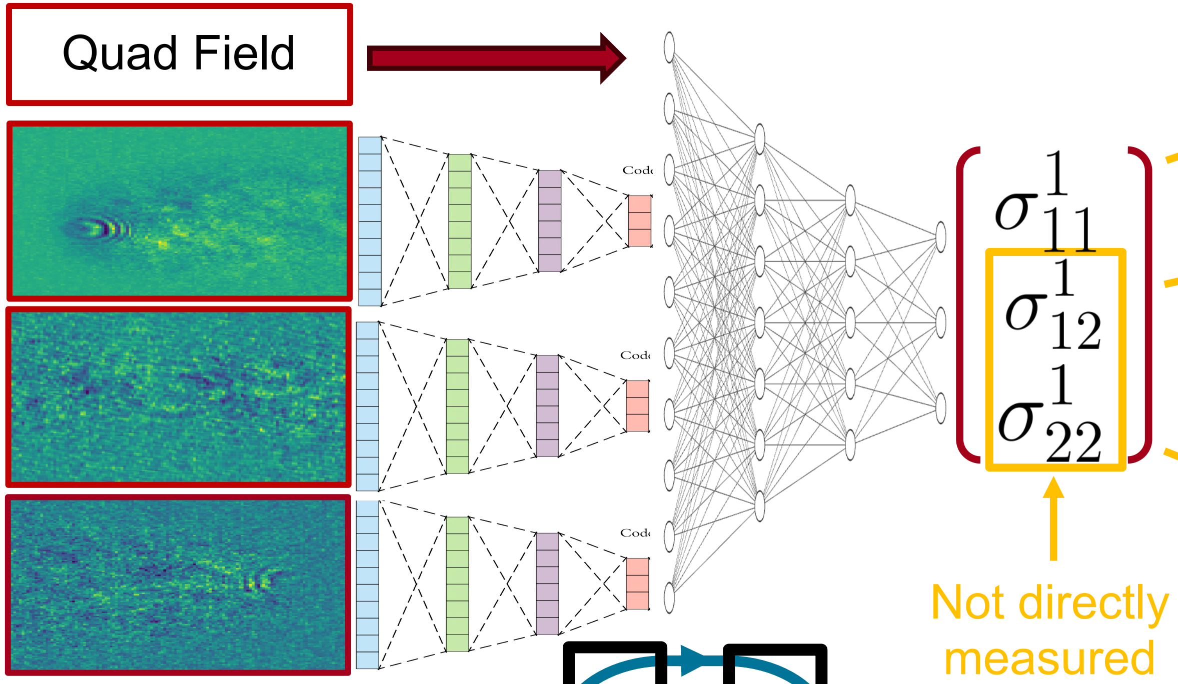
True vs predicted beam size



This model gives us a non-invasive, single shot measurement of the beam size!

Getting More with a Physics Based Loss

We want a single shot beam emittance measurement. Therefore, the network should return the beam size σ_{11}, divergence σ_{22} and correlation σ_{12}.

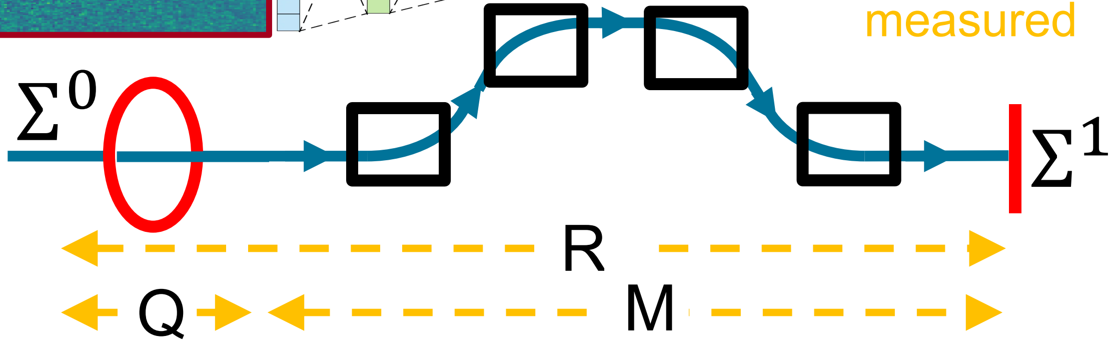


$$\Sigma^1 = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix} \qquad \mathbf{\Sigma}^1 = \mathbf{R} \cdot \mathbf{\Sigma}^0 \cdot \mathbf{R}^T$$

$$\sigma^1_{11} = R^2_{11}\,\sigma^0_{11} + 2R_{11}R_{12}\,\sigma^0_{12} + R^2_{12}\,\sigma^0_{22}$$

$$\sigma^1_{12} = R_{11}R_{21}\,\sigma^0_{11} + R_{12}R_{21}\sigma^0_{12} + R_{11}R_{22}\,\sigma^0_{12} + R_{12}R_{22}\,\sigma^0_{22}$$

$$\sigma^1_{22} = R^2_{21}\,\sigma^0_{11} + 2R_{21}R_{22}\,\sigma^0_{12} + R^2_{22}\,\sigma^0_{22}$$

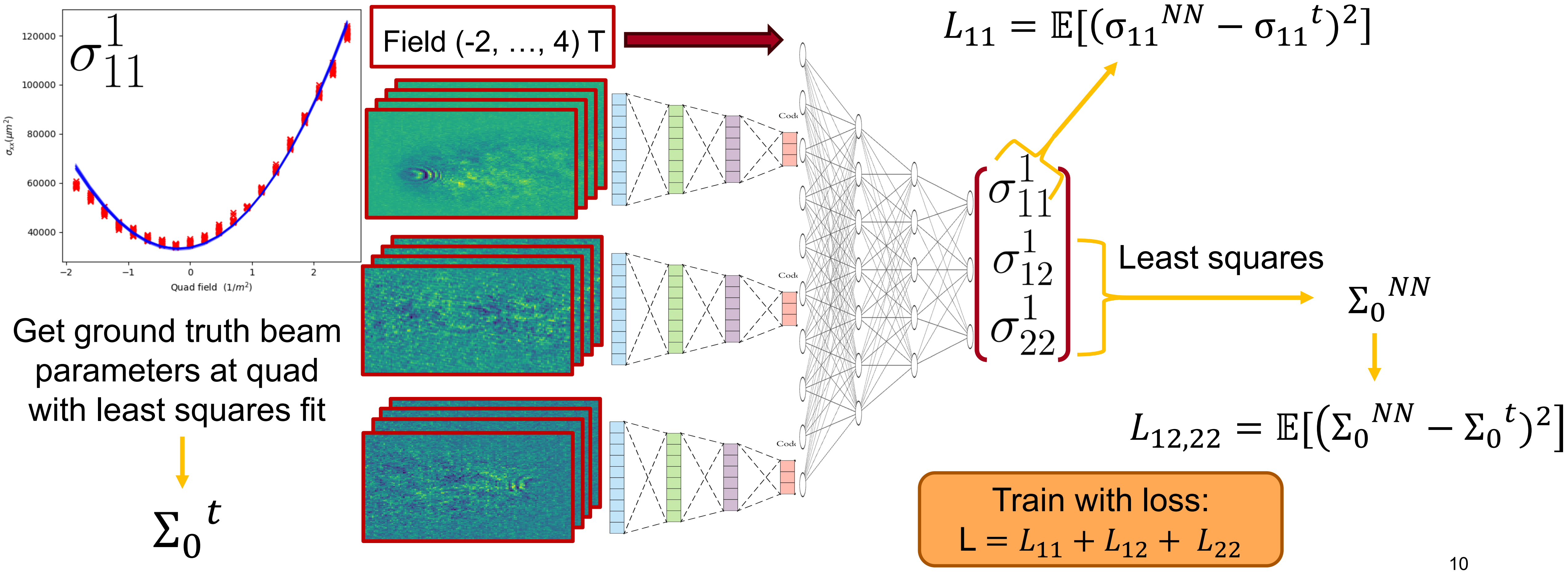


$$R = M \cdot Q \qquad Q = \begin{pmatrix} \cos\sqrt{kl} & \frac{1}{\sqrt{k}}\sin\sqrt{kl} \\ -\sqrt{k}\sin\sqrt{kl} & \cos\sqrt{kl} \end{pmatrix}$$

Each equation has 3 unknowns. They can be solved with >3 data points at different field values (k).

Getting More with a Physics Based Loss

We can perform a quad scan with the beam size measurements to obtain the beam parameters at the upstream quad. This is then used to constrain the unmeasured model outputs (divergence and correlation).

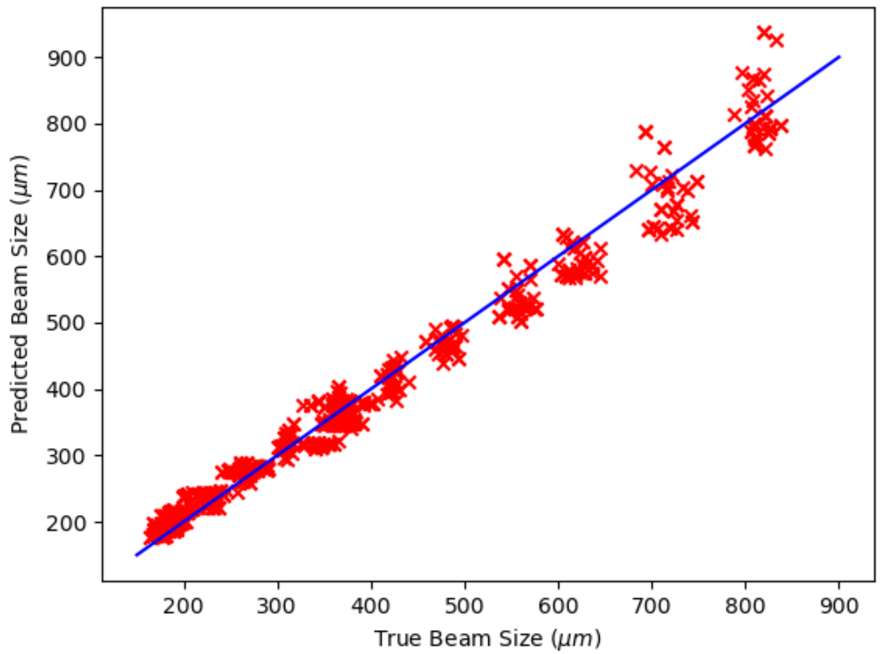


Model Results

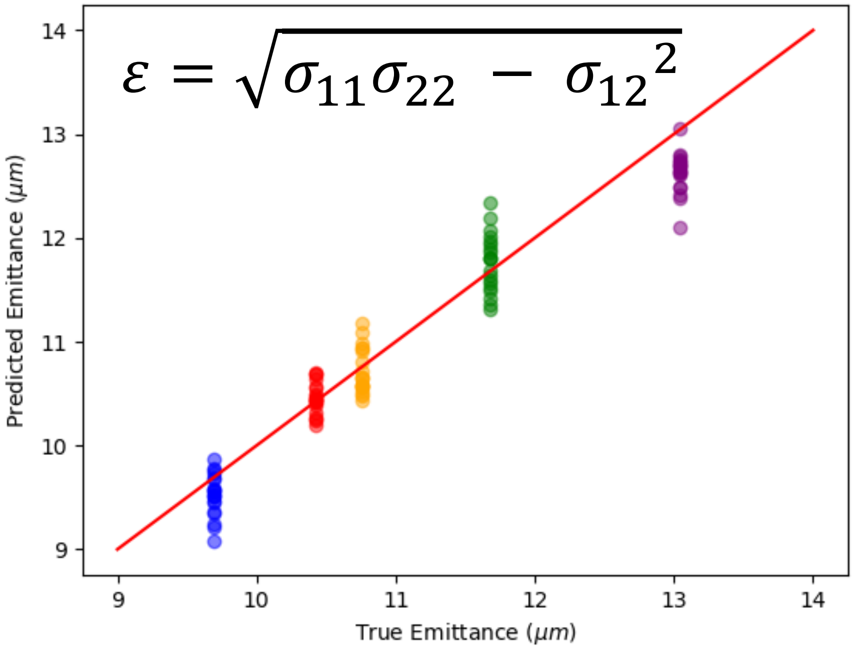
Model performs well on test set:

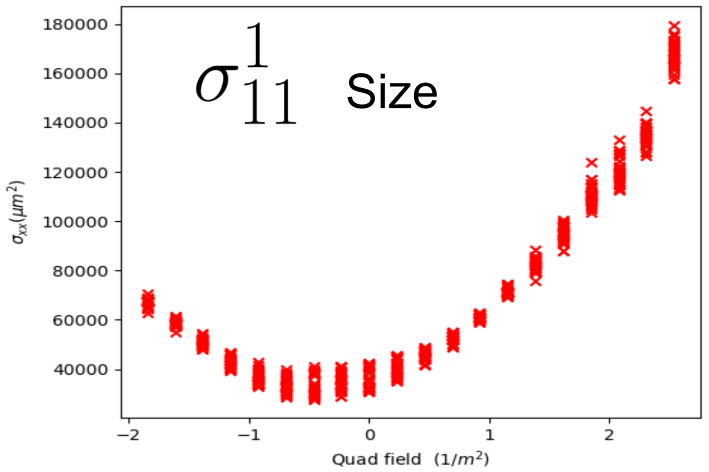
- Predicted beam size is highly correlated with true beam size
- Size, correlation and divergence vary approximately quadratically against field strength
- The predicted emittance is highly correlated with the true emittance

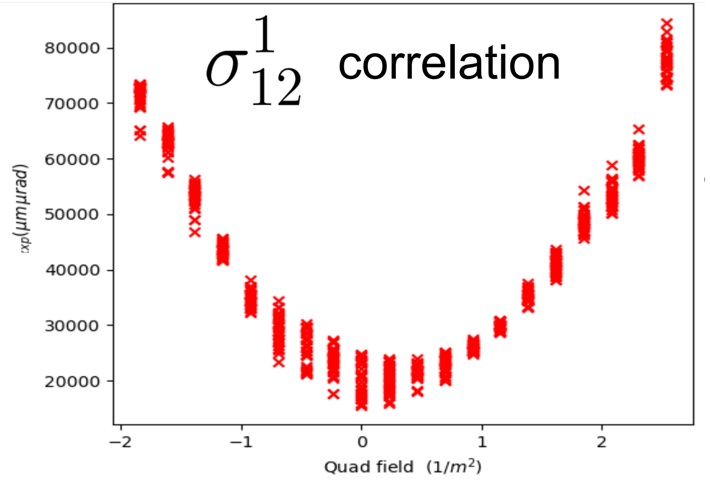
True vs predicted beam size

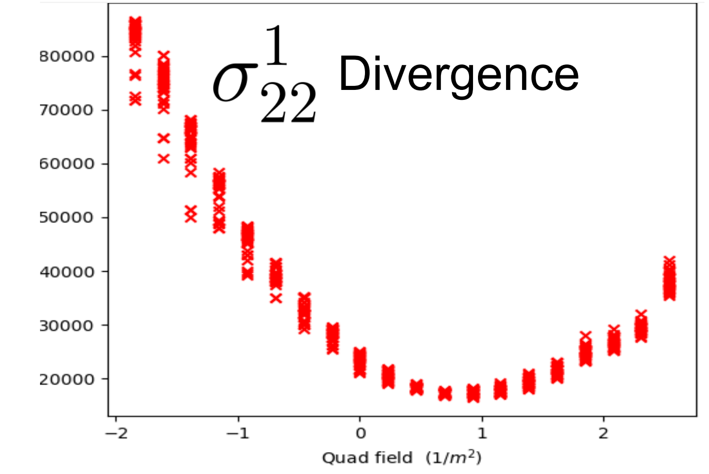


True vs predicted emittance







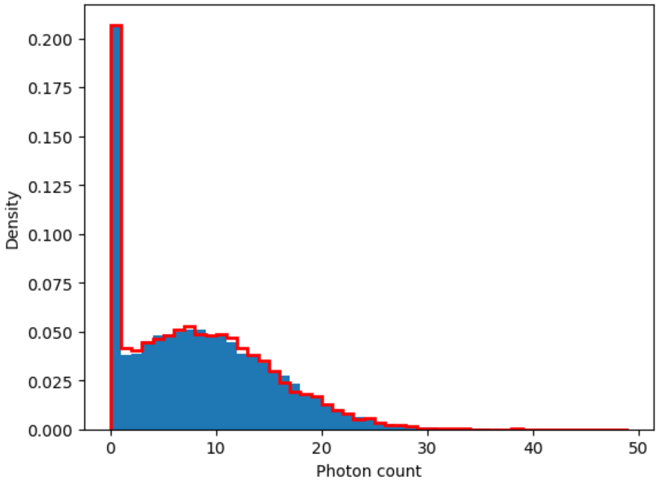


Summary

- Non-invasive diagnostics prevent the mutual destruction of diagnostics and downstream quality
- Edge radiation is non-invasive and sensitive to beam parameters, making it ideal for diagnostics
- We have developed a virtual diagnostic of the beam size using a computer vision model
- More information (including the emittance) can be extracted by constraining the loss with physics

Removing Noise with a UNet

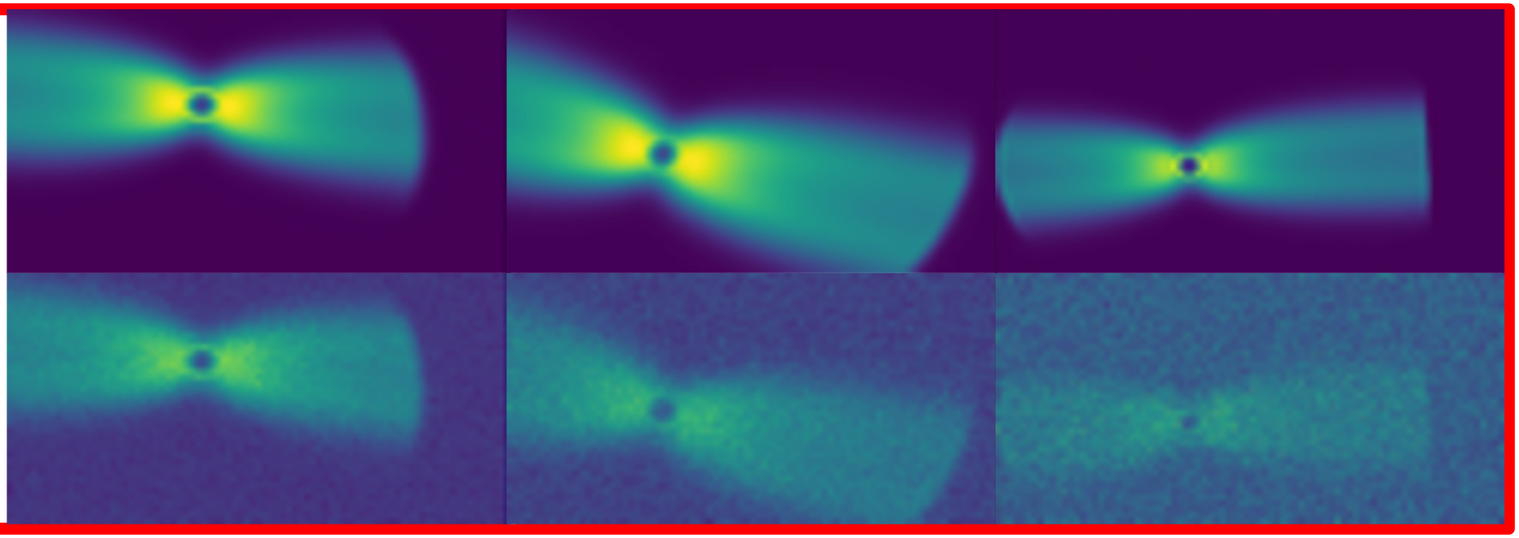
Can we use simulations and deep learning to do a better job?

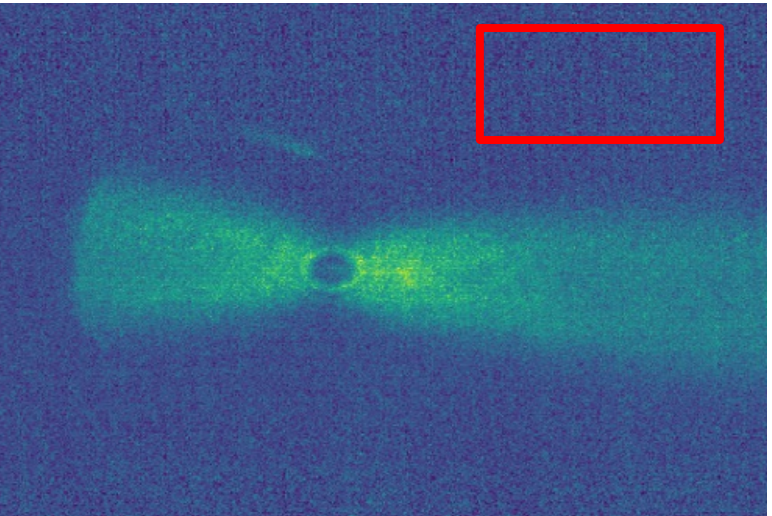


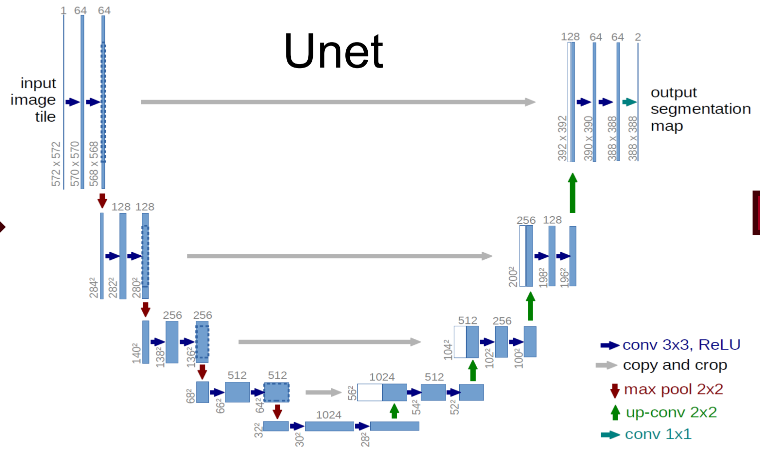
Training dataset

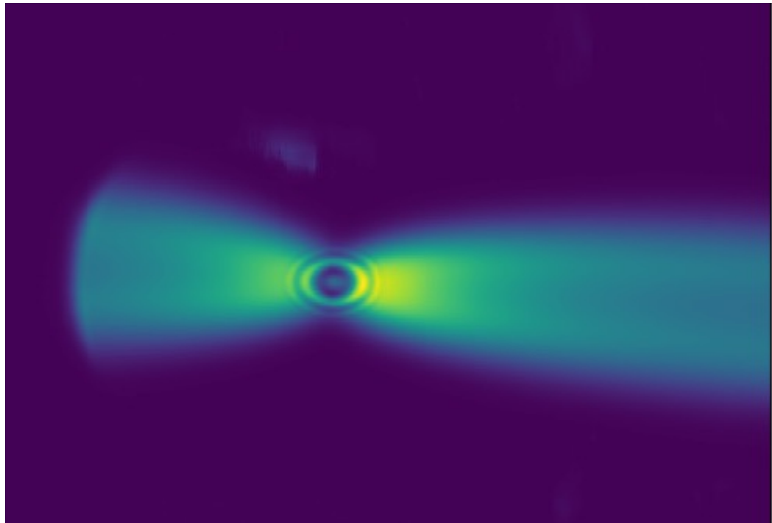
Target:

Input:









MLE Inference of Beam Parameters

Inferring beam parameters using simulations is an inverse problem:

α → $f(\alpha)$ → I

What we want — What we have

α: Beam parameters
$f(\alpha)$: Simulation
I: Intensity image

This problem can be solved in several ways. Here we will use a maximum likelihood estimation (MLE) with gradient ascent:

$$\alpha_{MLE} = \arg\max_{\alpha} l(\alpha; I)$$

$$l(\alpha; I) \propto (I - f(\alpha))^2$$

$$\alpha_{n+1} = \alpha_n + \gamma \nabla l(\alpha; I)$$