A Roadmap Towards Direct Imaging of Plasma Targets Using Computational ~~X-Ray Holography~~ Imaging

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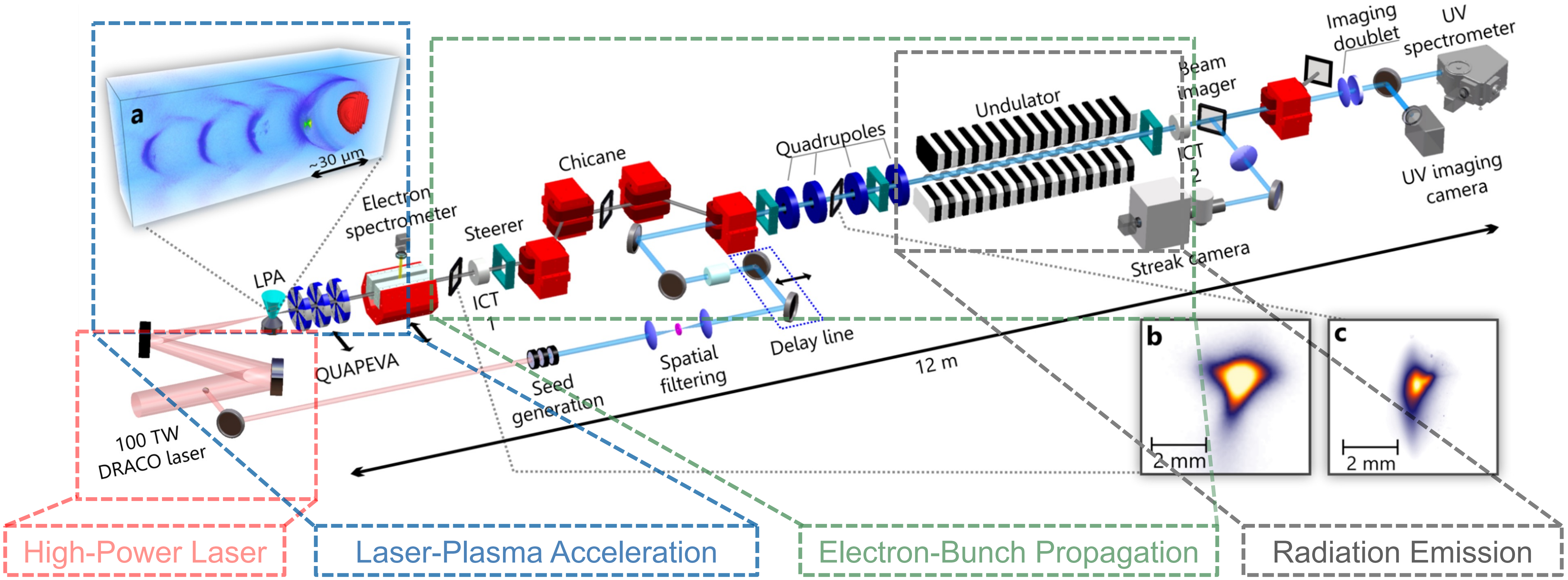
7th European Advanced Accelerator Conference

Sep 21 – 27, 2025

Hotel Hermitage, La Biodola Bay, Isola d'Elba, Italy

Laser-Plasma Accelerator-Driven Free Electron Laser

Goal: Find the optimal input parameters to produce desired radiation.



Challenges: large parameter space, indirect measurement modalities, cost of experiments/simulations

Labat, M., *Nat. Photon.* **17**, 150–156 (2023).

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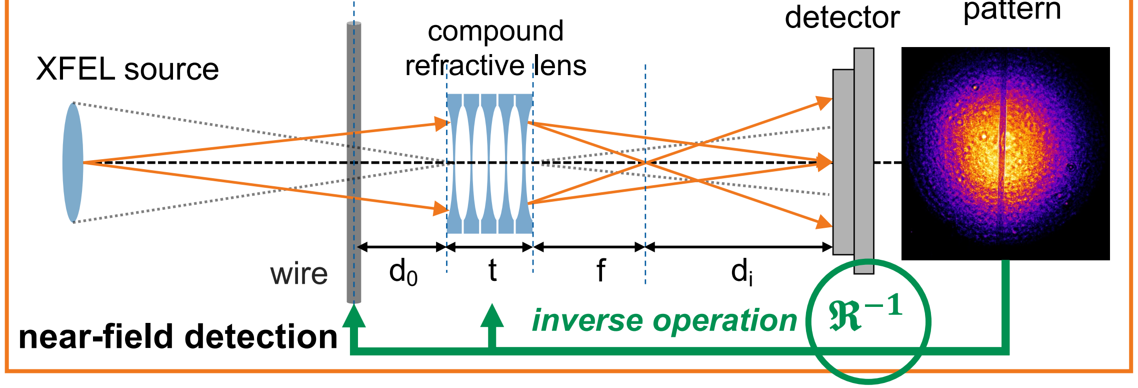
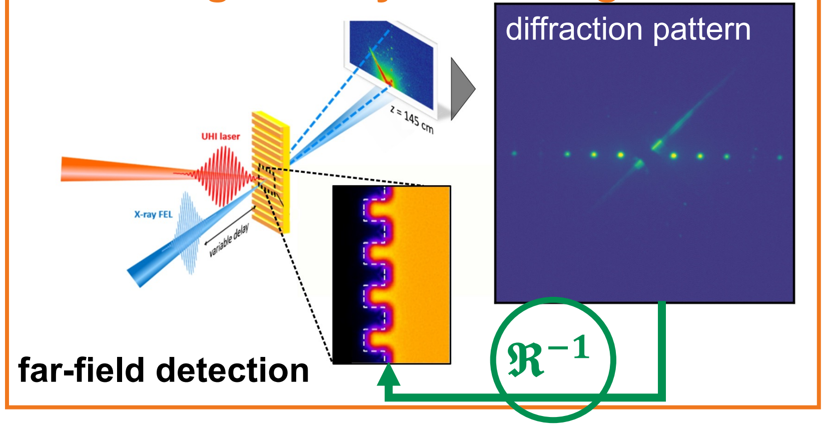
Inverse Problems in Photon Science

Computational X-Ray Holography



Small-Angle X-Ray Scattering



Understanding the plasma dynamics

diffraction patterns

↓

phase maps, structure factor

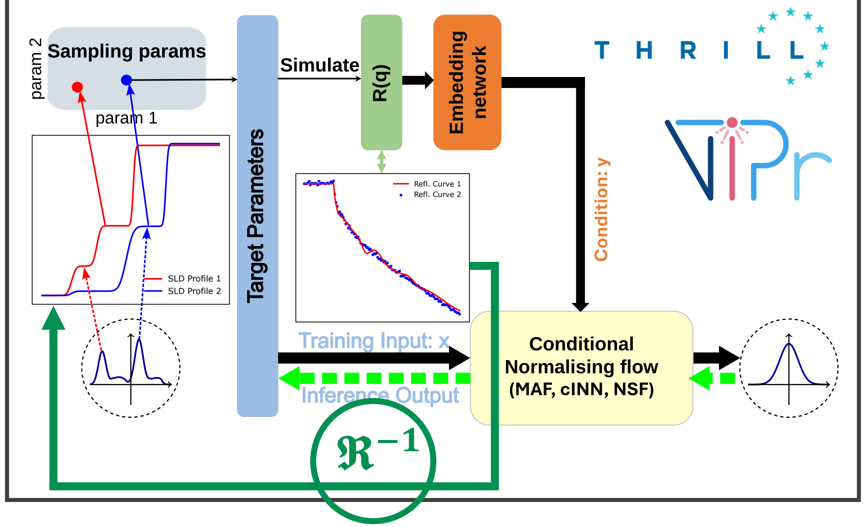
$\mathfrak{R}$

?

$\approx \mathfrak{R}^{-1}$

Measuring material interface properties

X-Ray and Neutron Reflectometry



reflectivity curves

↓

material properties

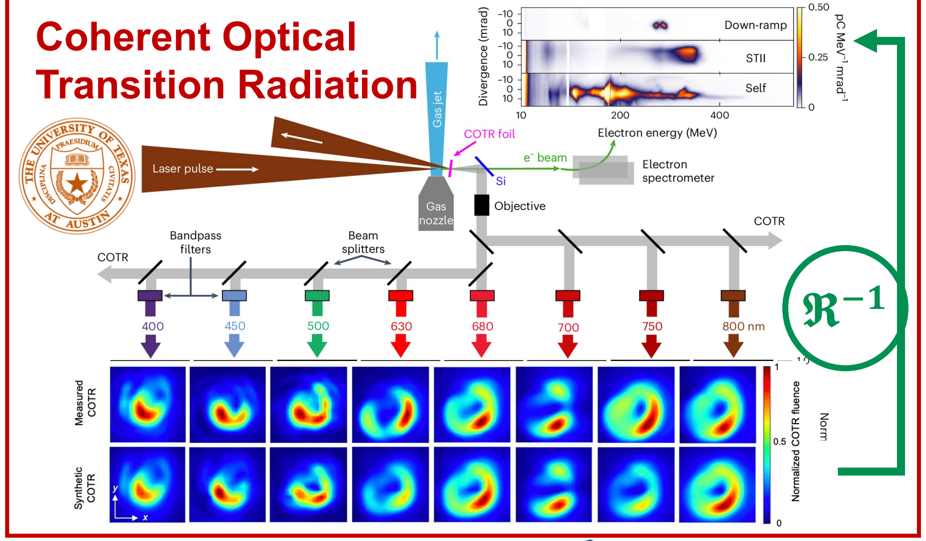
Characterizing laser-plasma accelerators

transition radiation images

↓

electron bunch

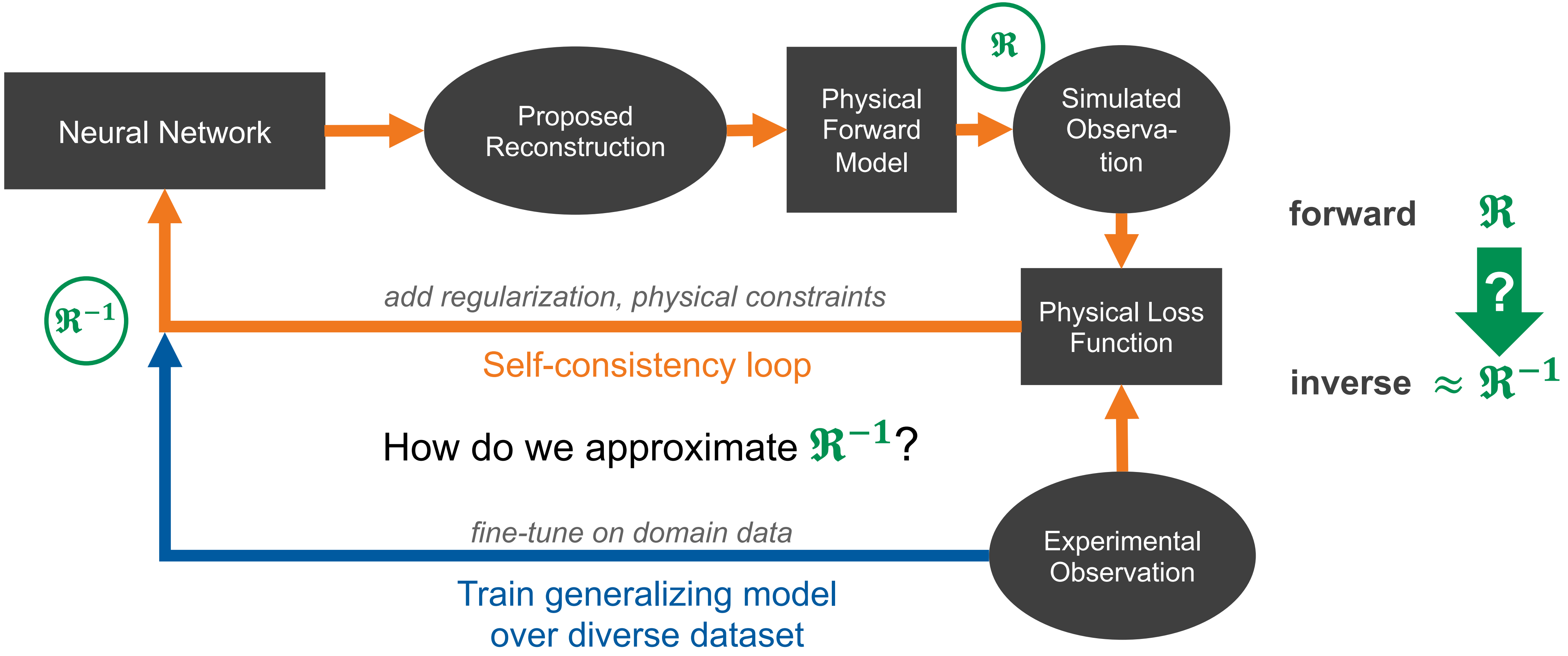
Coherent Optical Transition Radiation



LaBerge et al., *Nat. Photon.* **18**, 952–959 (2024)

Physics-informed Machine Learning + Data-Driven Approaches

A general overview



Inference time:
minutes to seconds

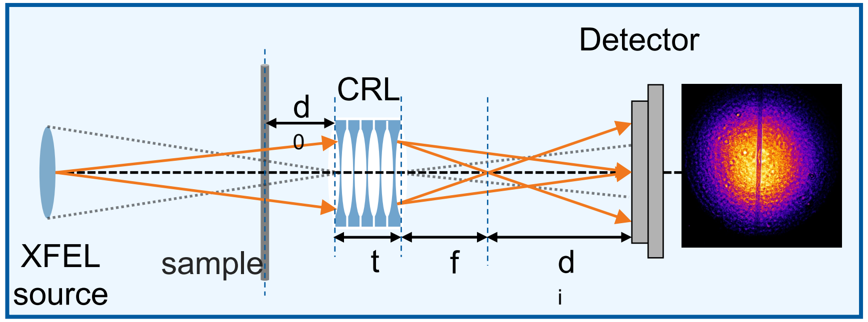
Use Case: Computational X-Ray Holography/Phase-Contrast Imaging

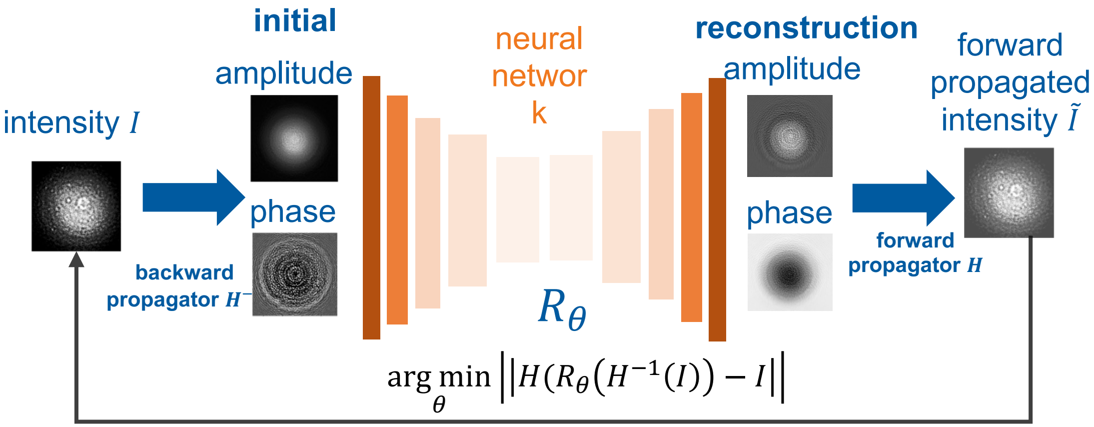
- **Physical forward model: Fresnel free-space propagator**

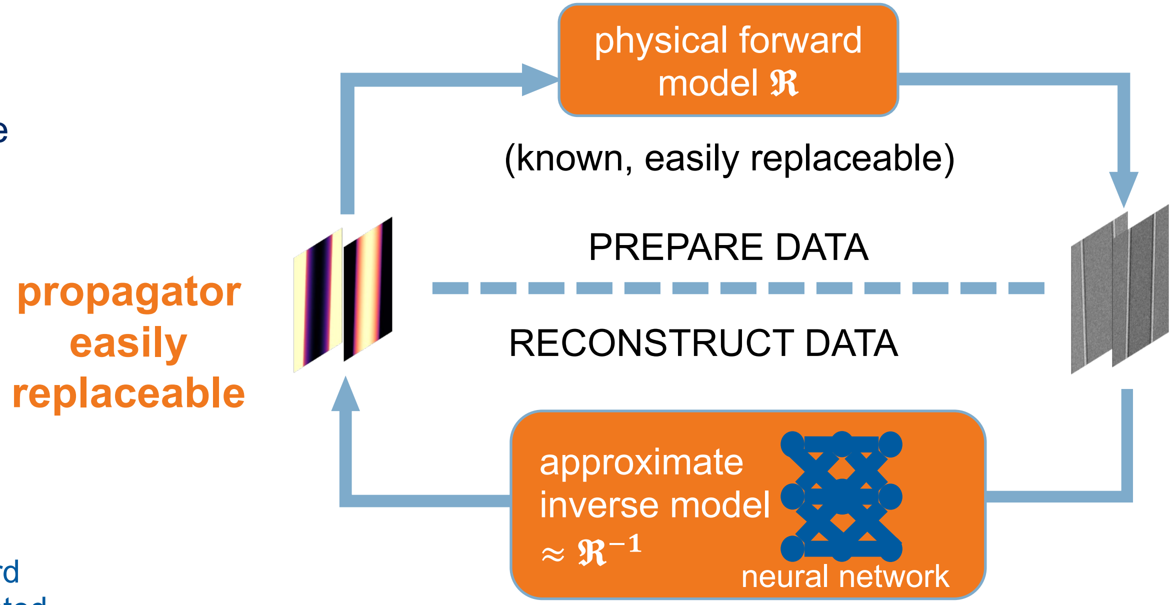
$$\mathcal{D}_{\mathrm{Fr}}(\Psi) = \mathcal{F}^{-1}\{\exp((-i\pi)/(2\,\mathrm{Fr})(\varepsilon^2+\eta^2))\mathcal{F}[\Psi]\}$$

Ψ: complex wavefield ($\Psi = A\exp(i\phi)$)
ε, η: inverse space coordinates
Fr: Fresnel number ($\mathrm{Fr} = \Delta x^2/\lambda z$)

Δx: detector pixel size
λ: source wavelength
z: propagation distance



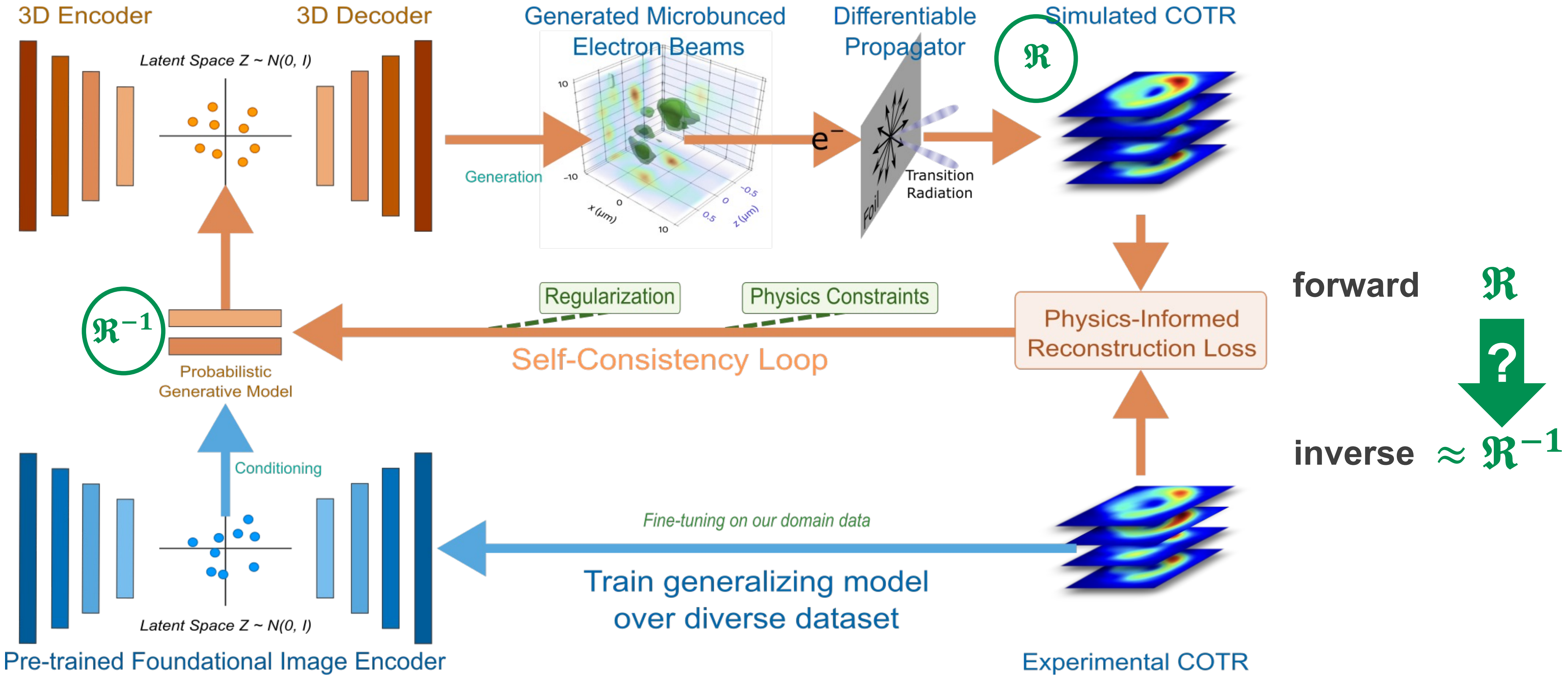




Sample physics-informed machine learning framework:
- Target is the Compound Refractive Lens (CRL)
- Network reconstructs the phase and amplitude of the CRL

Physics-informed Machine Learning + Data-Driven Approaches

Use Case: Multiwavelength Coherent Optical Transition Radiation (COTR)



Inference time:
minutes to seconds

LaBerge et al., *Nat. Photon.* **18**, 952–959 (2024)

Normalizing flow model: a probabilistic generative model

Yunfan Zhang, Master's Thesis, HZDR (2023).
Now a PhD student @ TU Delft

Training

Input x: decomposed by a **Haar wavelet transform**.

Coupling layers learn the conditional distribution of the details.

Hologram: conditional input from which features are extracted from.

Model is trained on **bits-per-dimension (BPD)**:

$$\text{BPD} = \frac{-\log \mathcal{L}(\theta)}{H \cdot W \cdot C \cdot \log 2}$$

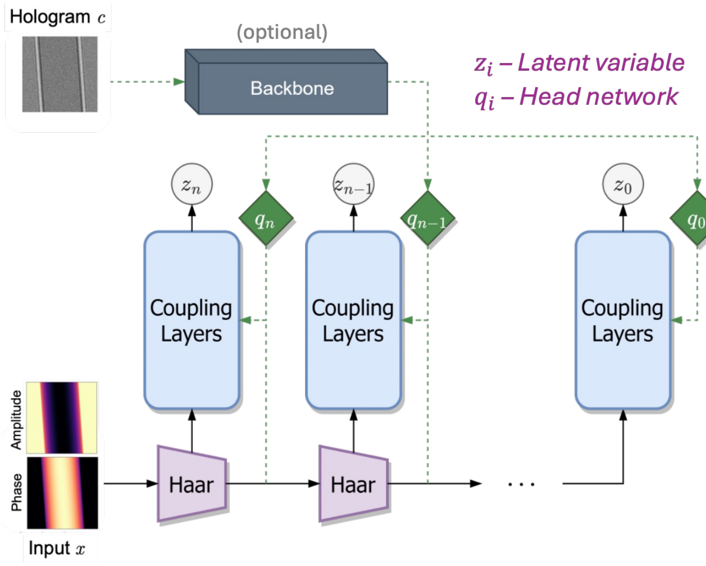
Negative log-likelihood:
$\mathcal{L}(\theta) = p_\theta(x|c)$
θ: model parameters
H, W, C: height, width, channel

Has tractable density estimation.

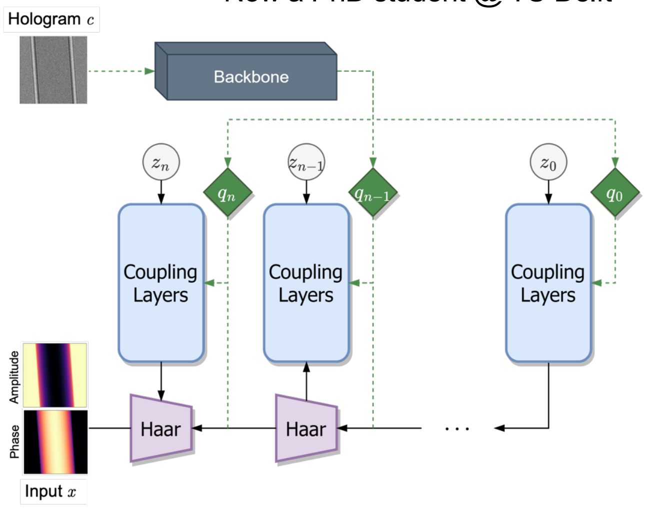
Sampling

To reconstruct images with the trained model, **the "flow"** is simply reversed (from z to x).

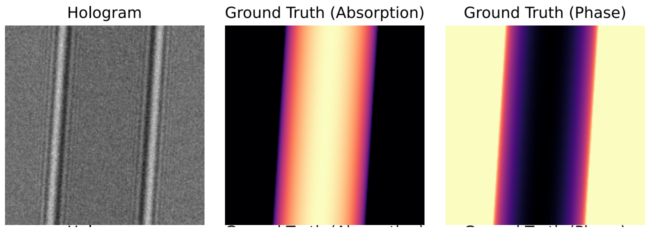
The **path of the hologram** is the same.



Training path of Conditional Wavelet Flow (cWF).

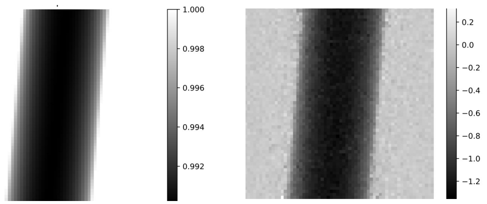


Sampling path of cWF.



Sample Simulations

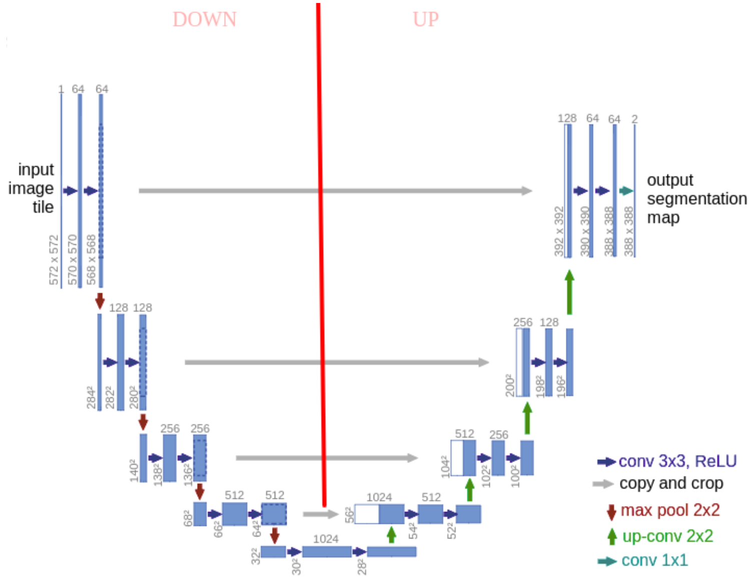
Absorption
Phase



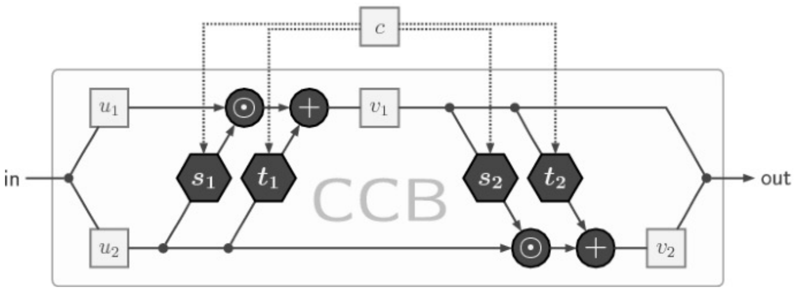
Reconstruction Results

Results: Comparison to other models

↑ **model capacity and complexity,**
↑ **computational resources and time**

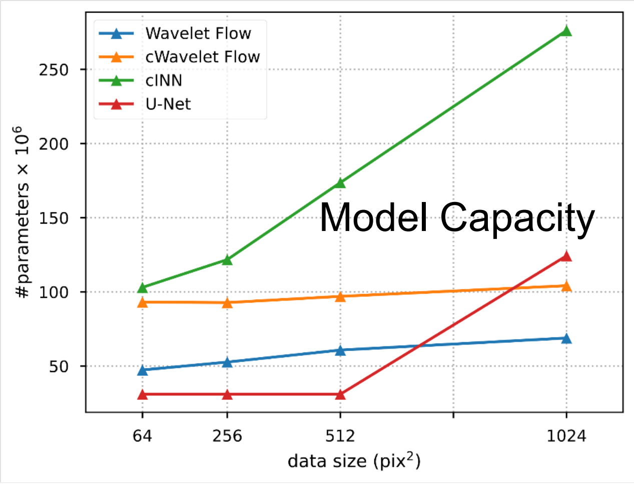


U-Net Architecture

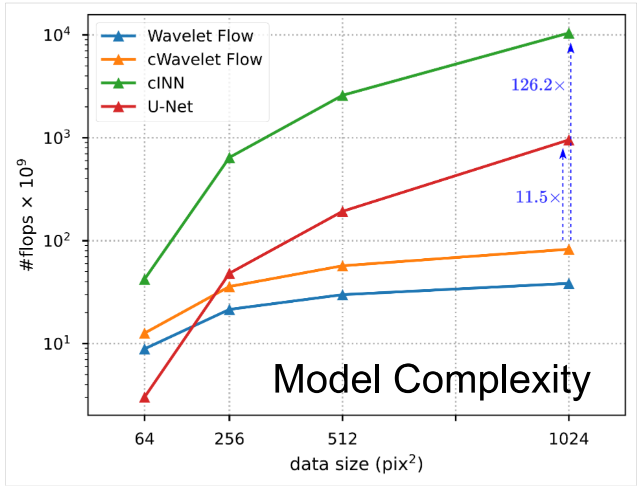


Conditional Invertible Neural Network (cINN) Architecture

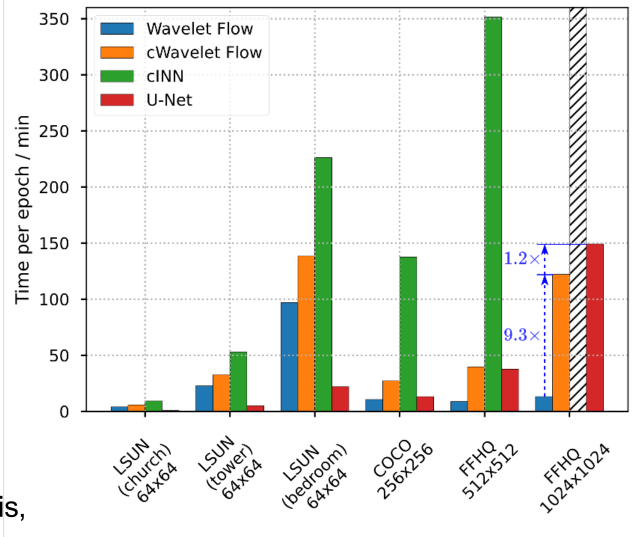
Tested on different open-source standard datasets used in machine learning: LSUN, COCO, FFHQ



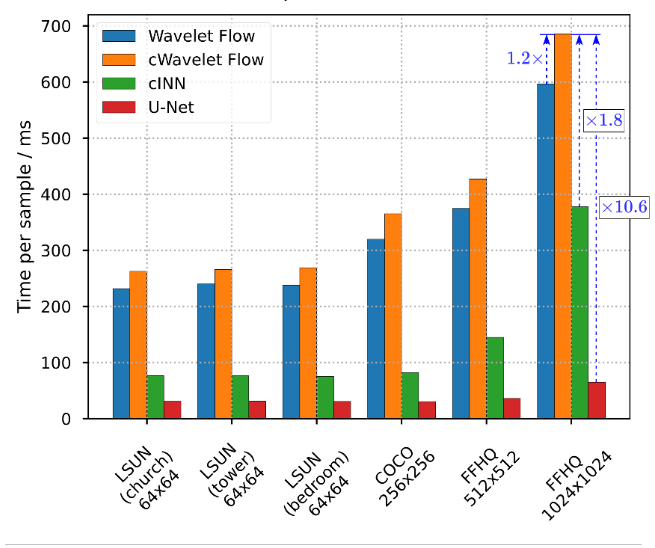
a) Number of parameters



b) FLOPs



a) Training time



b) Inference time

Yunfan Zhang, Master's Thesis, HZDR (2023).
Now a PhD student @ TU Delft

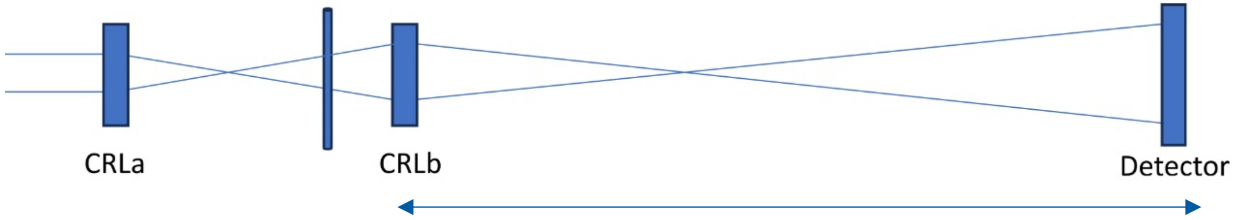
First Steps: Imaging of a Compressed Hydrogen Jet

Hydrogenic Imaging at Gbar pressures with XFEL

Ongoing Project…

Schematic of XFEL imaging configration for imaging a hydrogen jet.

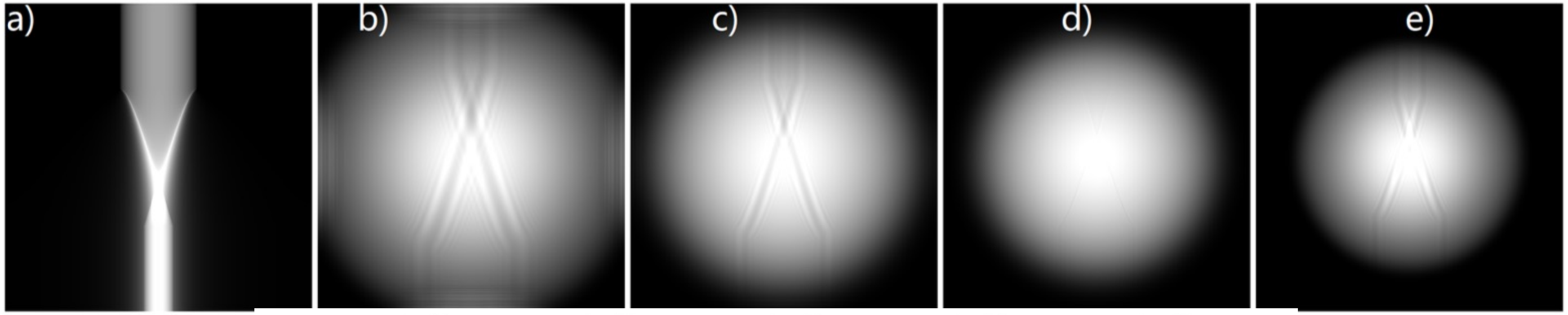
XFEL @
8.13 keV

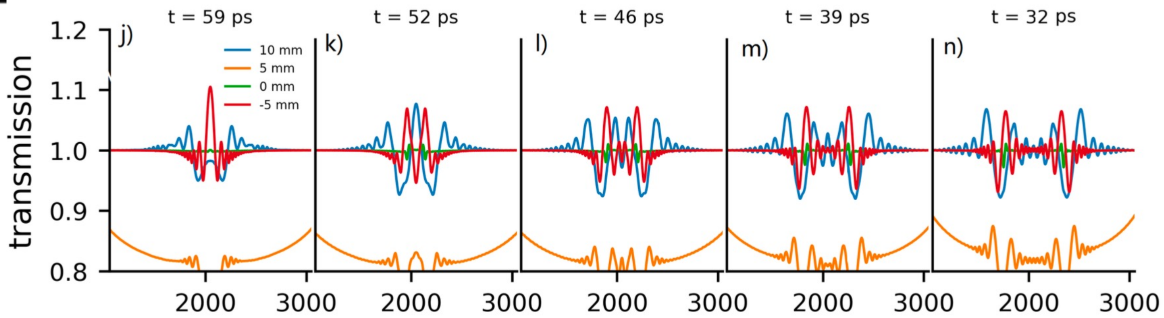


CRL: compound refractive lens

Density Projection

Simulated Phase Contrast Images at Different Distances

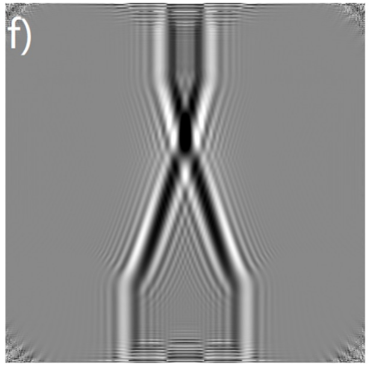


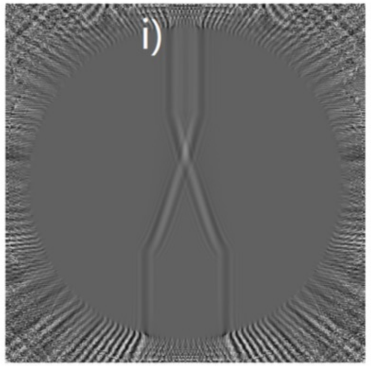


Jet focal spot:
40 microns

Challenge:
- Sampling limits

Sample Phase Contrast Images at (b) and (e)





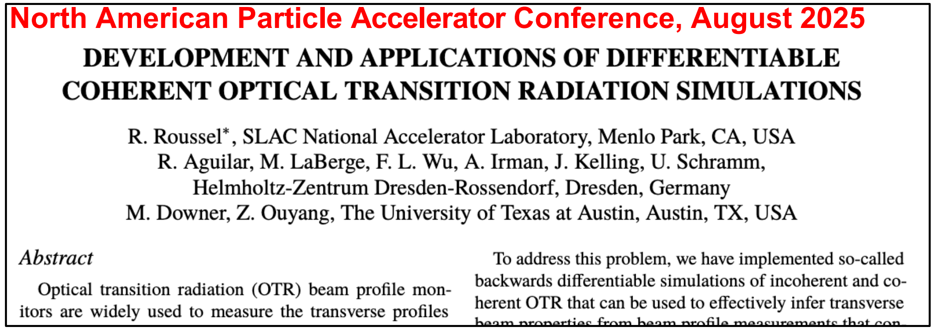
Simulation Credits:

- Long Yang, HZDR
- Thomas Cowan, HZDR

Differentiable Optical Transition Radiation (OTR) Simulations

Incoherent and coherent OTR (**IOTR** and **COTR**) were simulated in a machine learning framework, PyTorch

- Provides **backwards-differentiable** and **GPU-compatible** calculations
- Enables **fast**, **inexpensive gradient calculations** of simulation outputs



North American Particle Accelerator Conference, August 2025

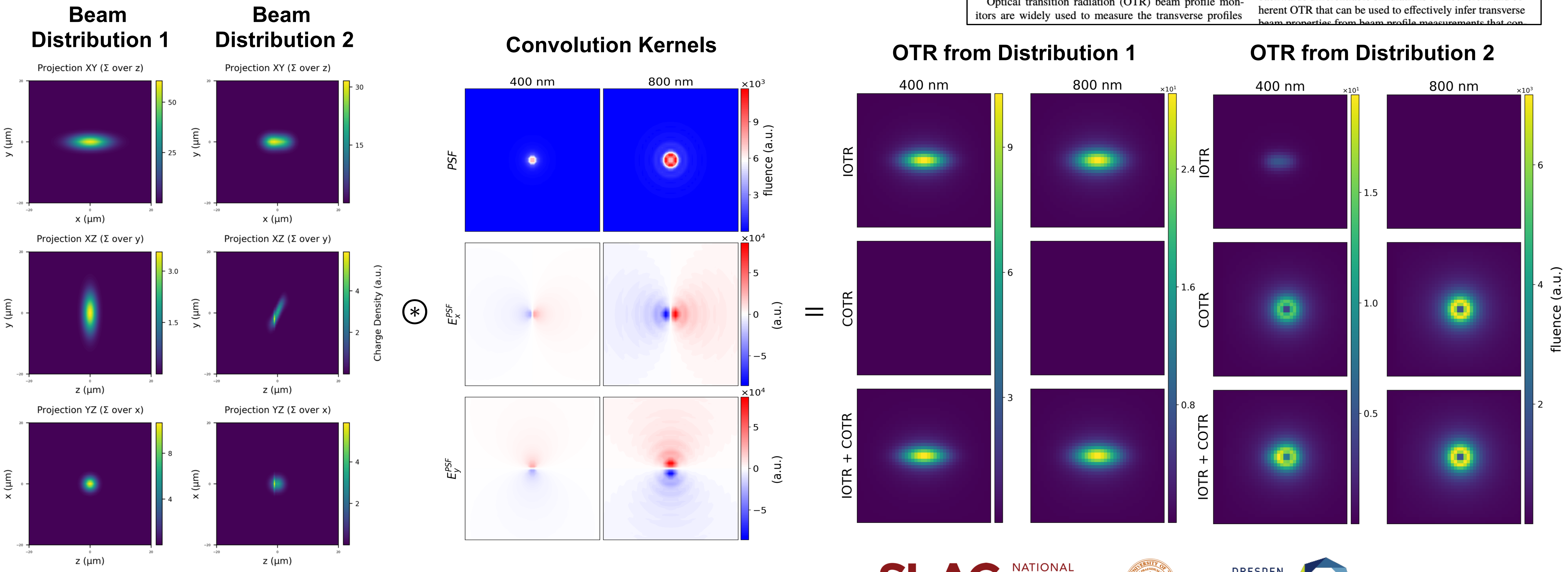
DEVELOPMENT AND APPLICATIONS OF DIFFERENTIABLE COHERENT OPTICAL TRANSITION RADIATION SIMULATIONS

R. Roussel*, SLAC National Accelerator Laboratory, Menlo Park, CA, USA
R. Aguilar, M. LaBerge, F. L. Wu, A. Irman, J. Kelling, U. Schramm, Helmholtz-Zentrum Dresden-Rossendorf, Dresden, Germany
M. Downer, Z. Ouyang, The University of Texas at Austin, Austin, TX, USA

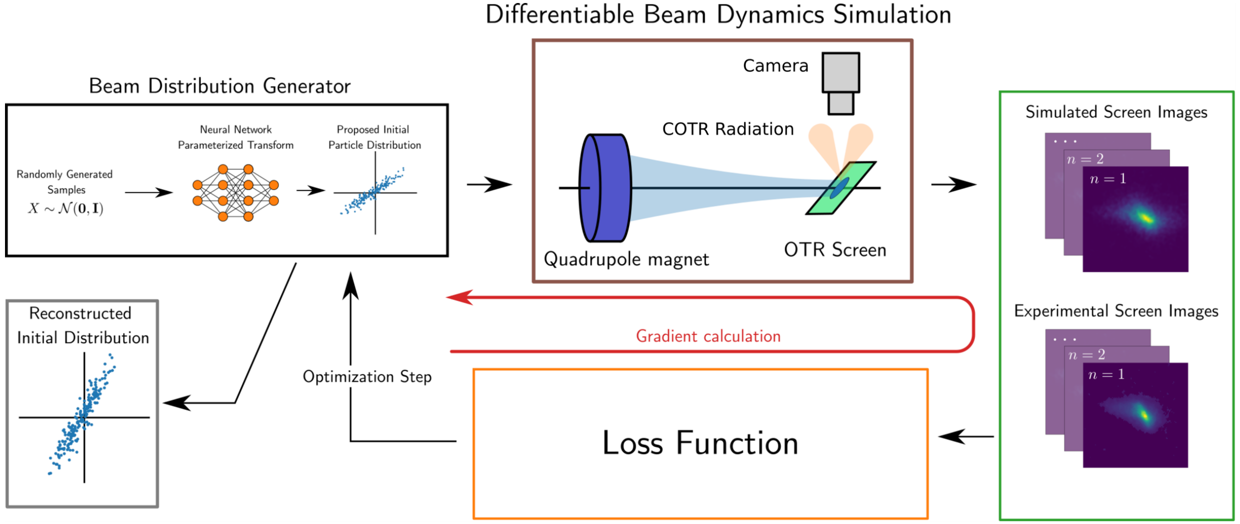
Abstract

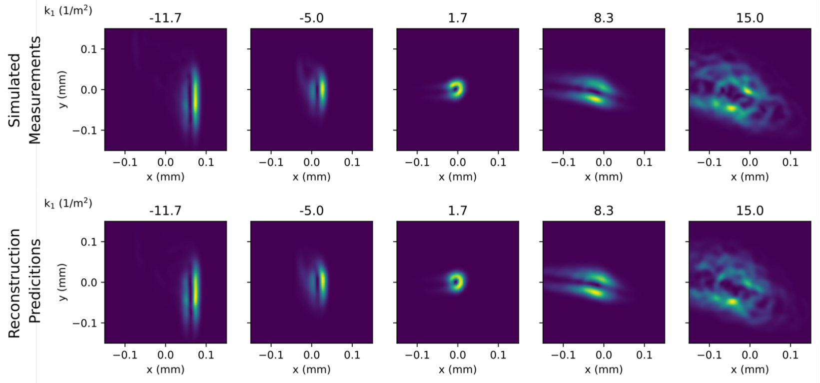
Optical transition radiation (OTR) beam profile monitors are widely used to measure the transverse profiles

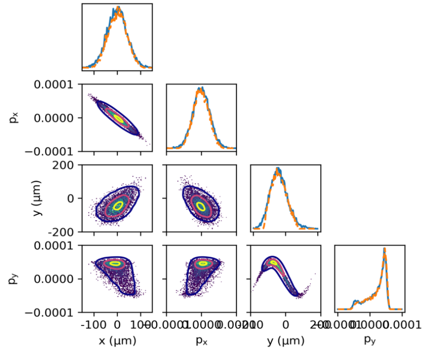
To address this problem, we have implemented so-called backwards differentiable simulations of incoherent and coherent OTR that can be used to effectively infer transverse



Reconstruction of 6D Phase Space Distributions using Coherent Optical Transition Radiation (COTR)







Generative Phase Space Reconstruction (GPSR) of a test distribution that emits COTR from an intercepting foil while an upstream quadrupole is scanned

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To address this problem, we have implemented so-called backwards differentiable simulations of incoherent and coherent OTR that can be used to effectively infer transverse

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- Assumes beam distribution has full transverse coherence at visible wavelengths and beam size is large enough compared to the wavelength
- The physics is incorporated into the beam dynamics simulation
- Enables reconstruction of the beam phase space distribution using GPSR

Loos, H., et al. Materials of Proceedings of FEL08. Gyeongju, Korea (2008): 485
R. Roussel, et al. PRL 130.14 (2023): 145001.

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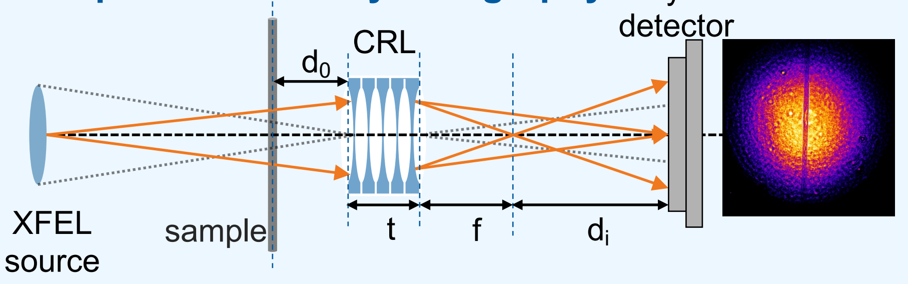
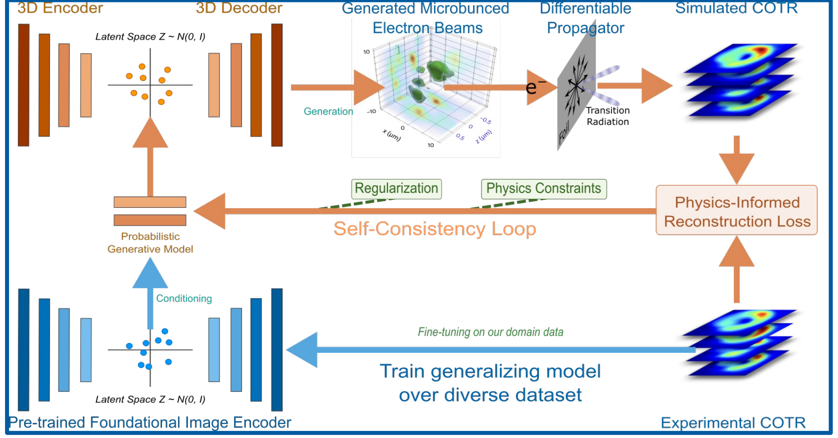
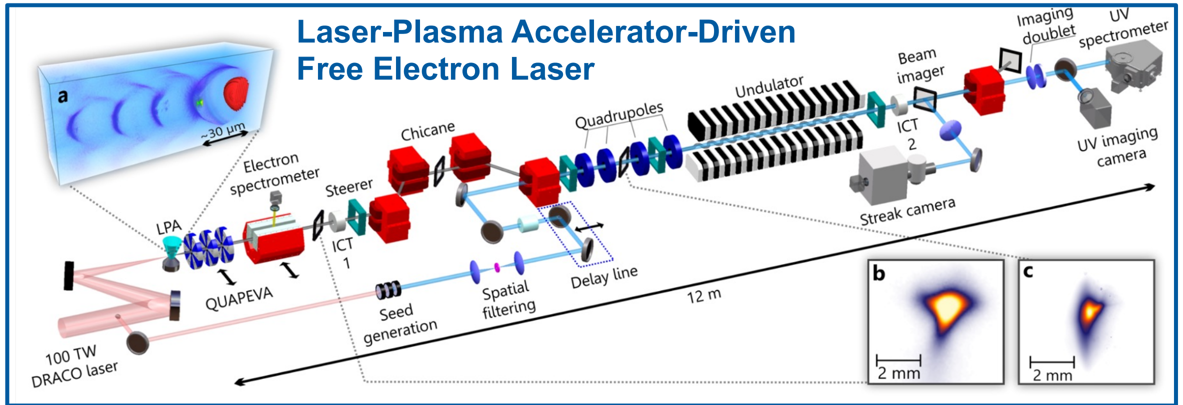
Summary and Future Work

Computational X-Ray Holography





Laser-Plasma Accelerator-Driven Free Electron Laser

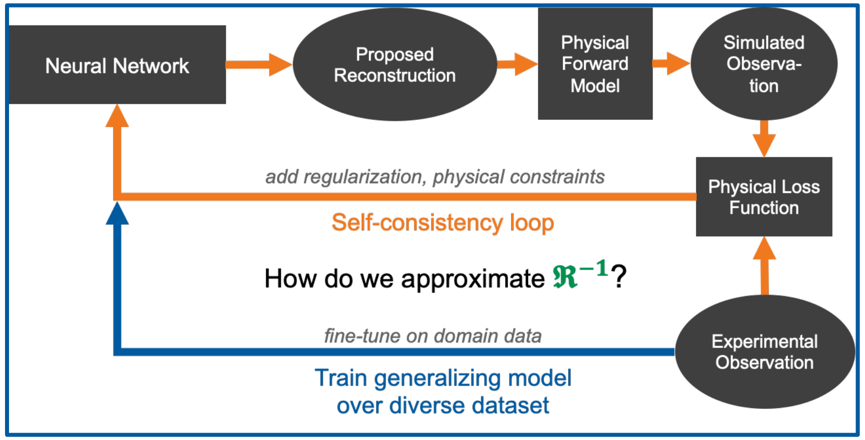


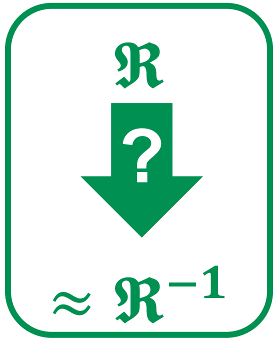
Online diagnostics

- From simulation → beamline experiments

Open-source toolkit

- Share our pipelines with the photon science community





Goal: To develop a unified machine learning framework to solve the inverse problems.

QUESTIONS?

Coherent Optical Transition Radiation