Adaptive Machine Learning for Control and Virtual Diagnostics of Time-Varying Particle Accelerator Systems and Beams

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Los Alamos
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Adaptive Machine Learning (AML) for Time-Varying Systems

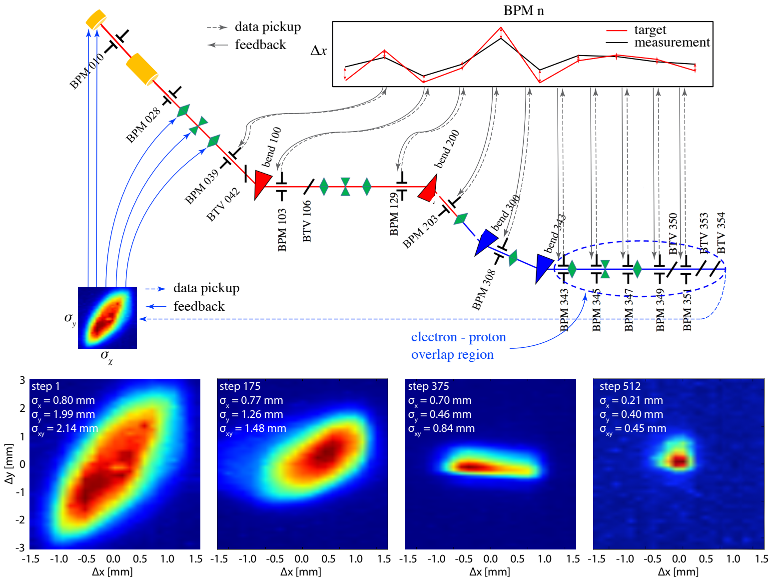
Adaptive Feedback for Particle Accelerators

- Model-independent
- Time-varying systems
- Local minima

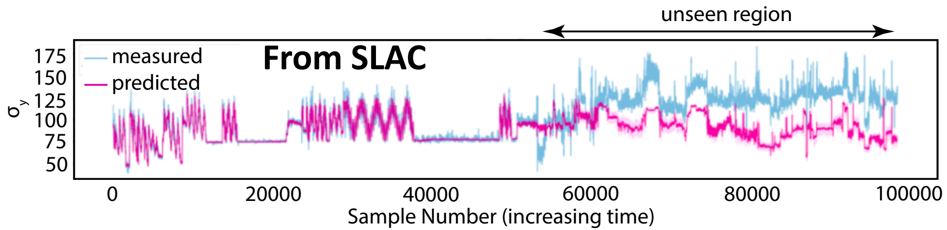
Machine Learning for Particle Accelerators

- Learn directly from data
- Global understanding of large systems
- Time-varying systems

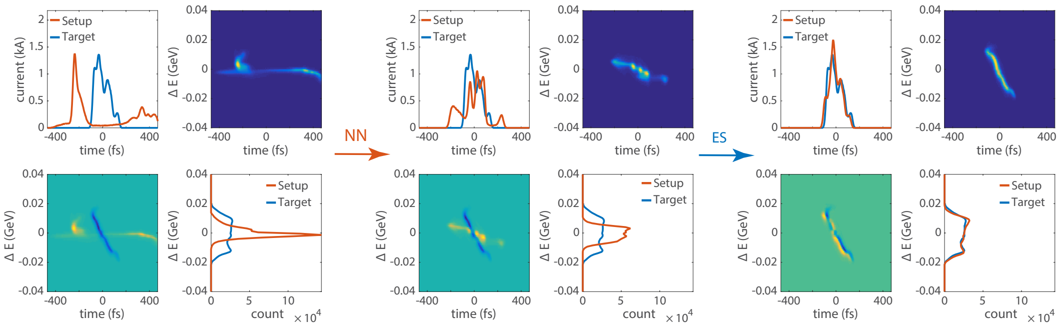
Real-time multi-objective optimization at AWAKE



A. Scheinker, et al. "Online Mulit-Objective Particle Accelerator Optimization of the AWAKE Electron Beam Line for Simultaneous Emittance and Orbit Control." *AIP Advances* 10.5 (2020): 055320 https://doi.org/10.1063/5.0003423



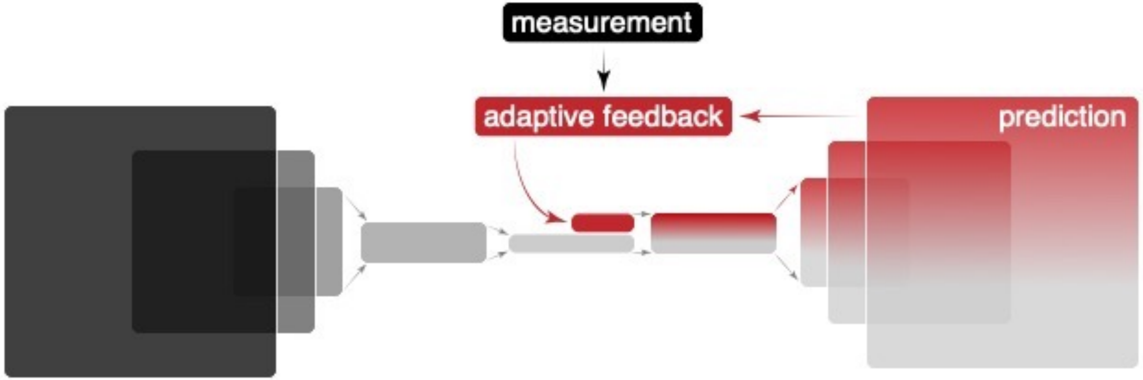
Real-time control of longitudinal phase space at LCLS



A. Scheinker, et al. "Demonstration of model-independent control of the longitudinal phase space of electron beams in the Linac-coherent light source with Femtosecond resolution." Physical Review Letters, 121.4, 044801, 2018. https://doi.org/10.1103/PhysRevLett.121.044801

Adaptive Machine Learning (AML) for Time-Varying Systems – Adaptively Tuning the Latent Space

General approach for any complex time-varying system



A. Scheinker. "Adaptive machine learning for time-varying systems: low dimensional latent space tuning." *Journal of Instrumentation* 16.10 (2021): P10008. https://doi.org/10.1088/1748-0221/16/10/P10008

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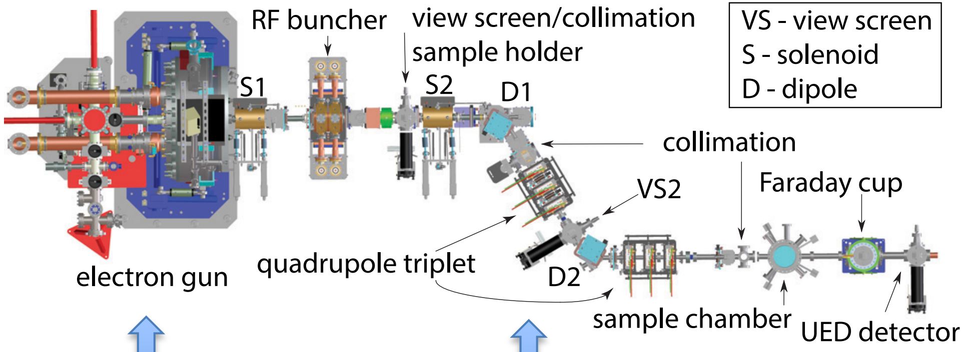
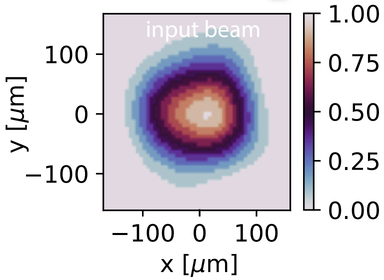
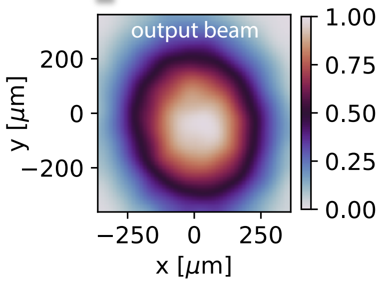
HiRES Ultrafast Electron Diffraction (UED) at LBNL







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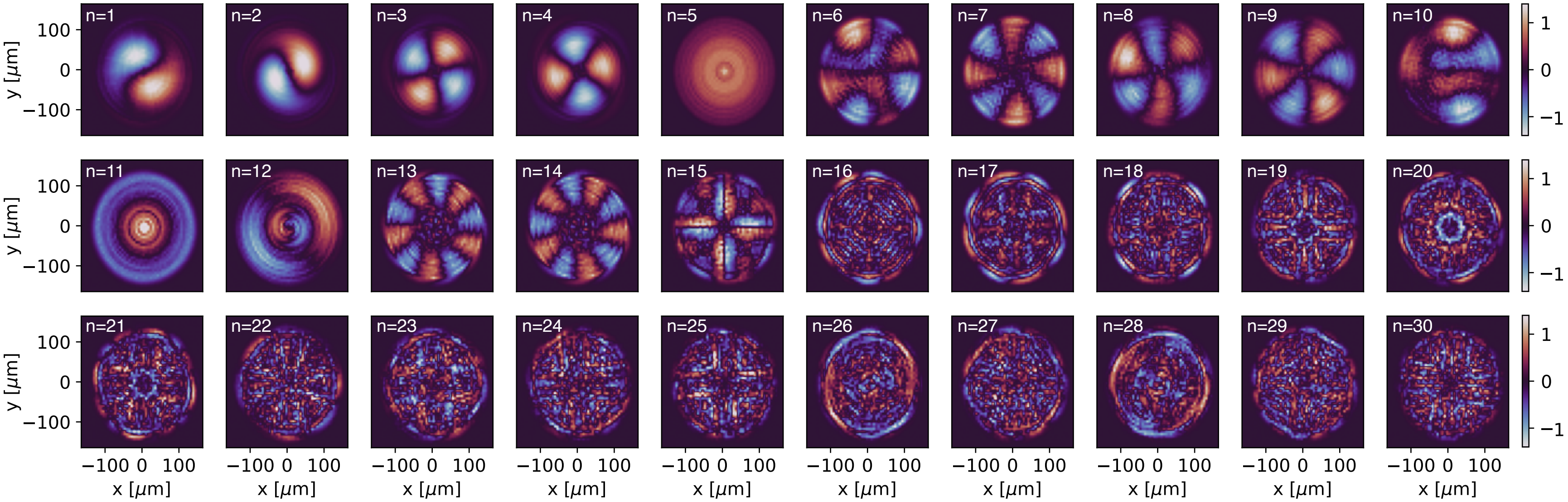
PCA basis for electron beam at HiRES



$$I_{i,N_{pca}} = \sum_{n=1}^{N_{pca}} \alpha_{i,n} \times \mathrm{PC}_n.$$

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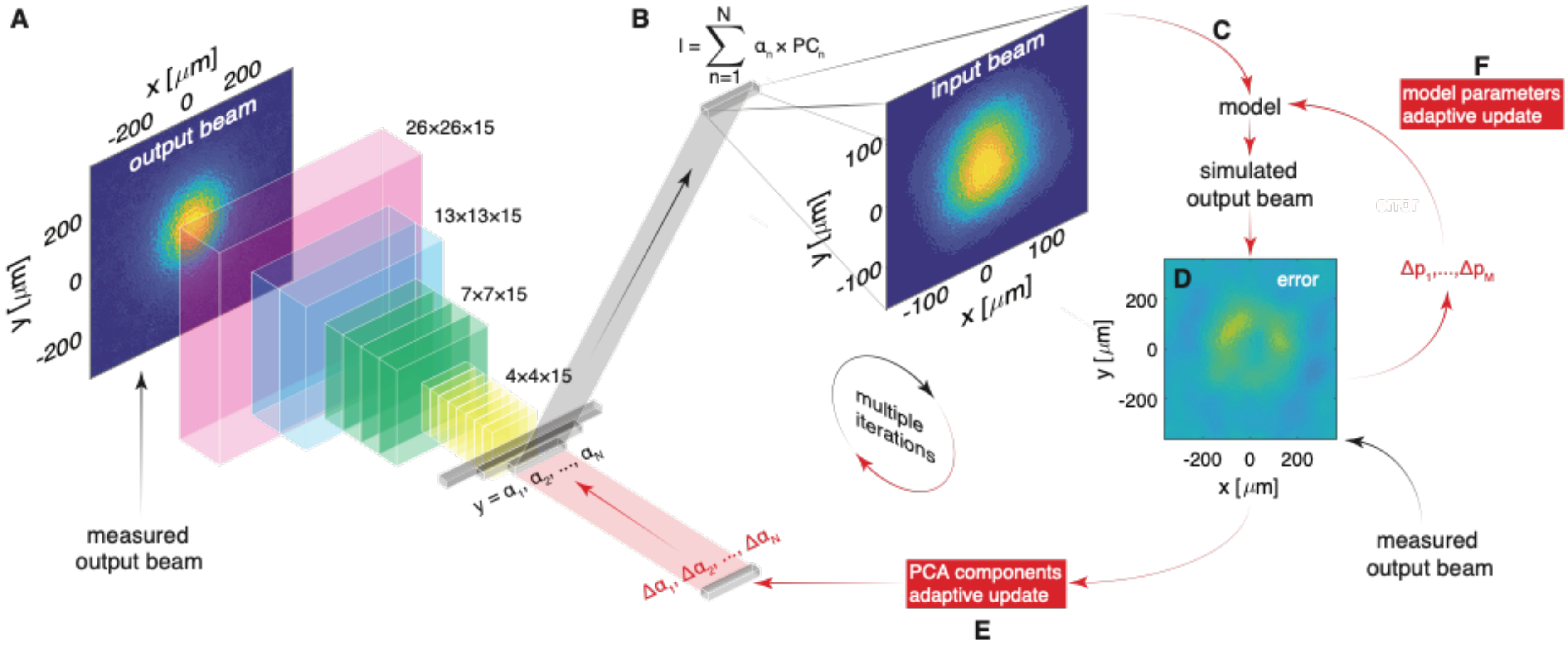
AML for adaptive HiRES inverse physics model



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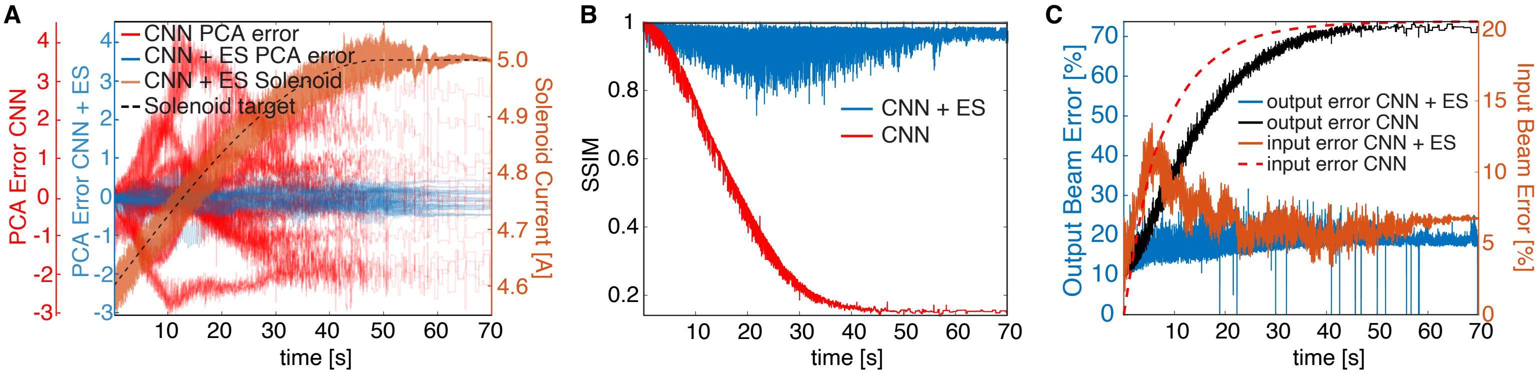

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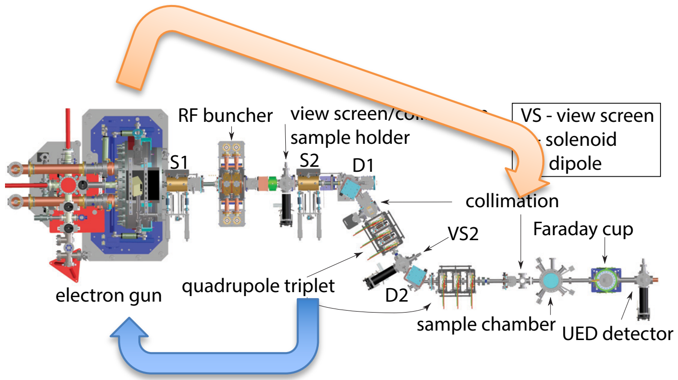

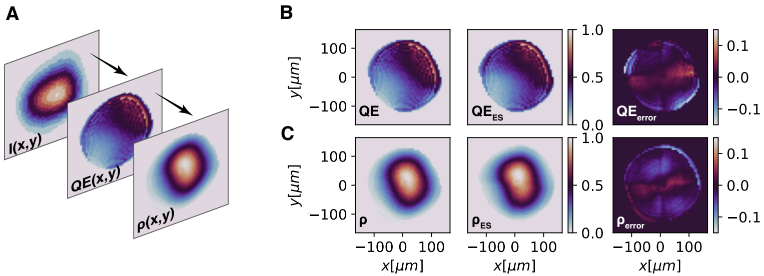

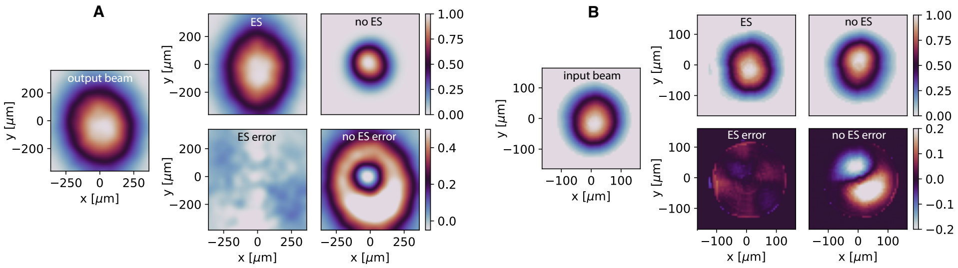

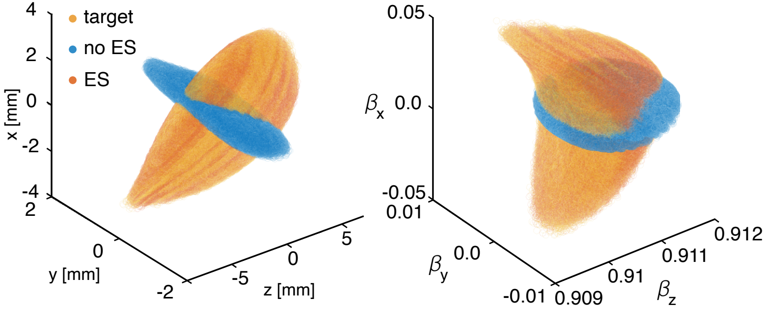

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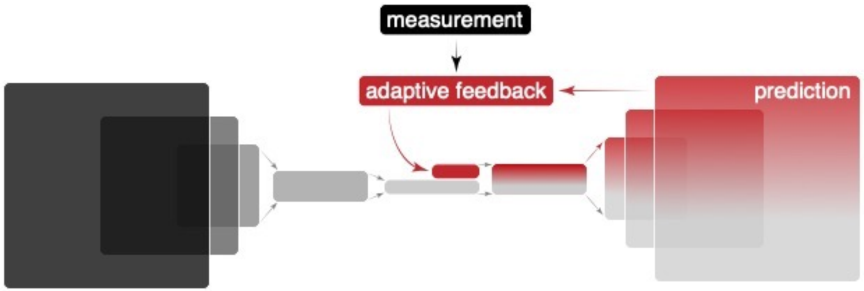
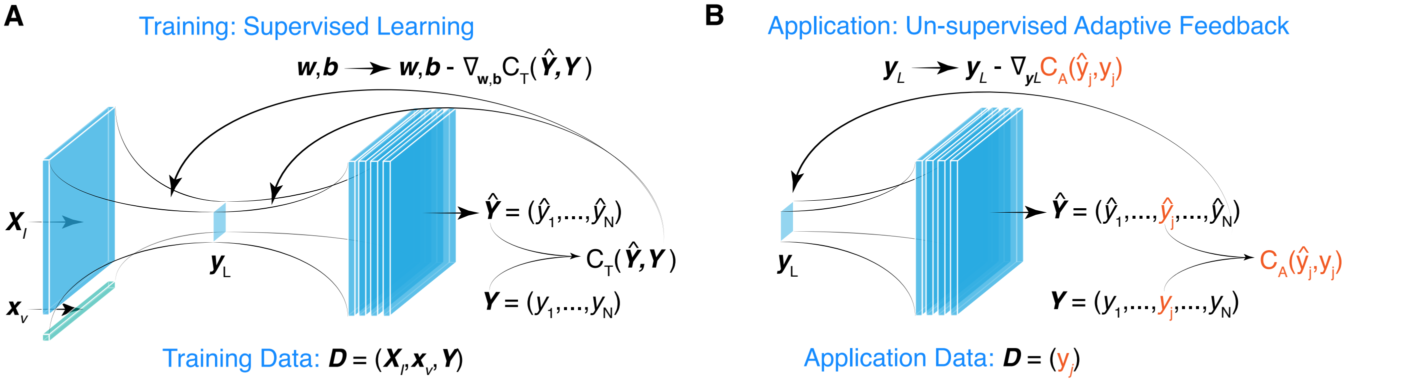
Encoder-decoder generative CNN for nonlinear data compression: Low-dimensional latent space tuning





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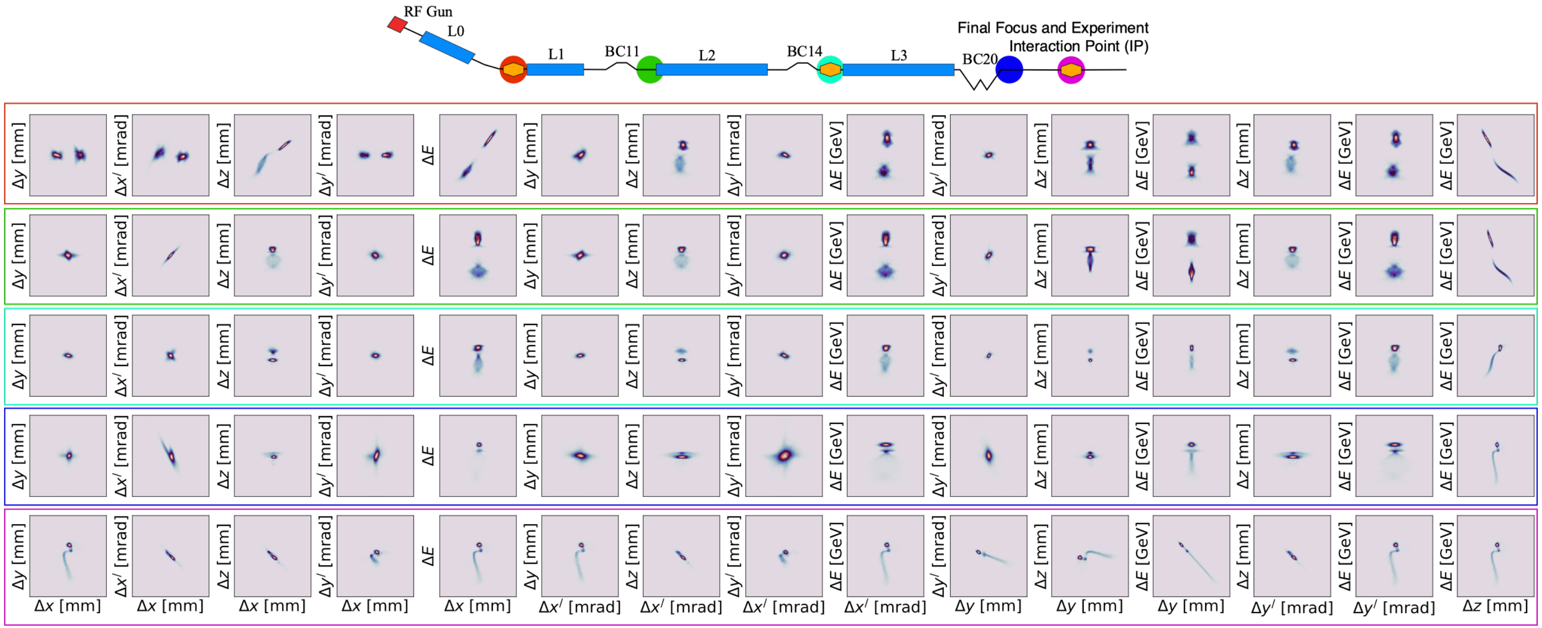
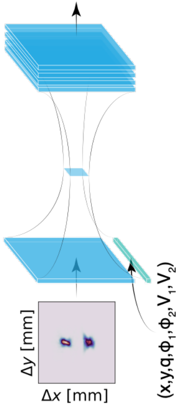


Predicting all 2D projections of 6D phase space at FACET-II at 5 different locations



6D (x, y, z, x', y', E)

2D projections

$(x, y), (x, z), (x, x'), (x, y'), (x, E)$

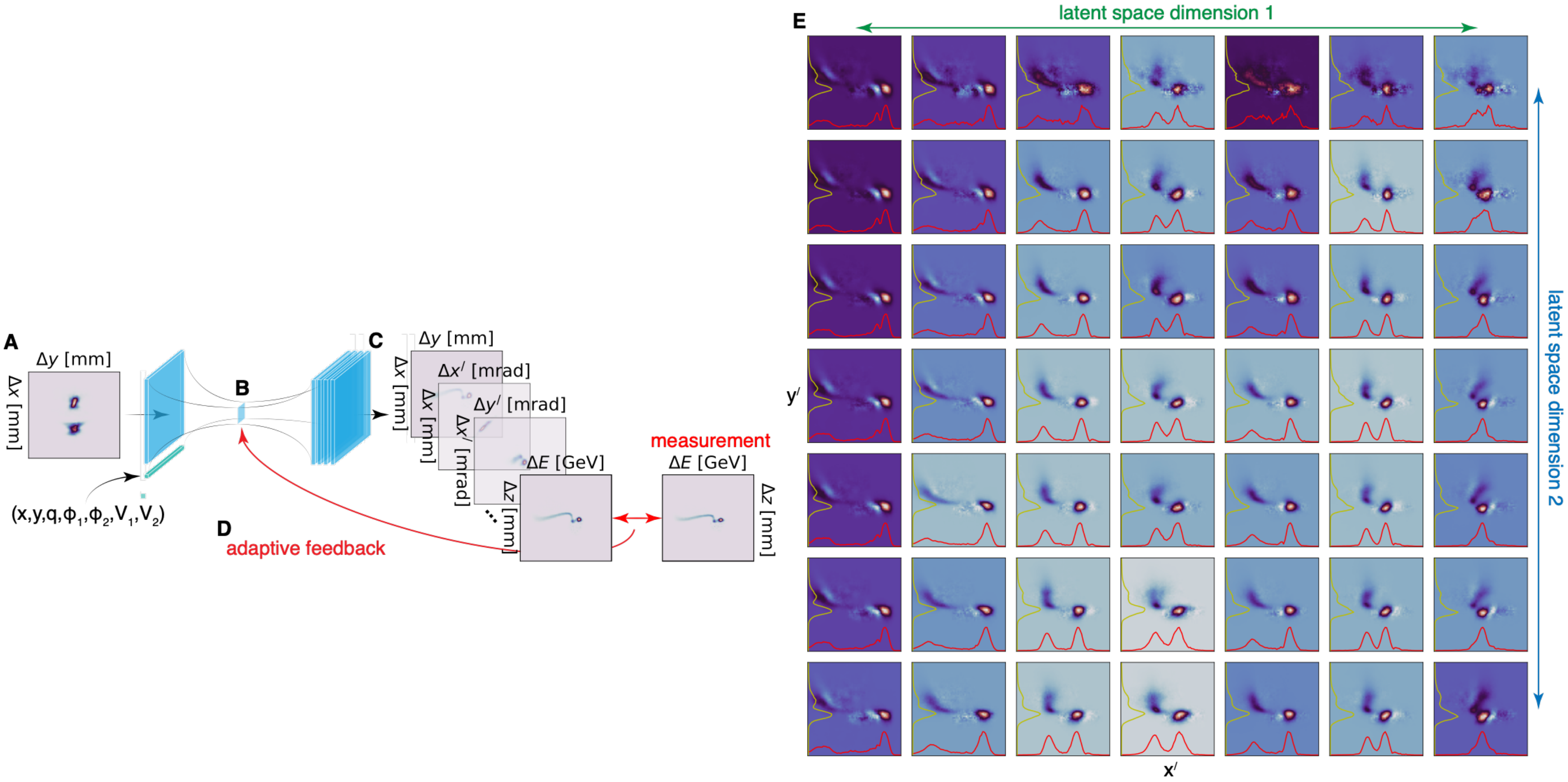
$(x', y), (x', z), (x', y'), (x', E)$

$(y, z), (y, y'), (y, E)$

$(y', z), (y', E)$

(z, E)

Looking at only (z,E) to predict other phase space projections



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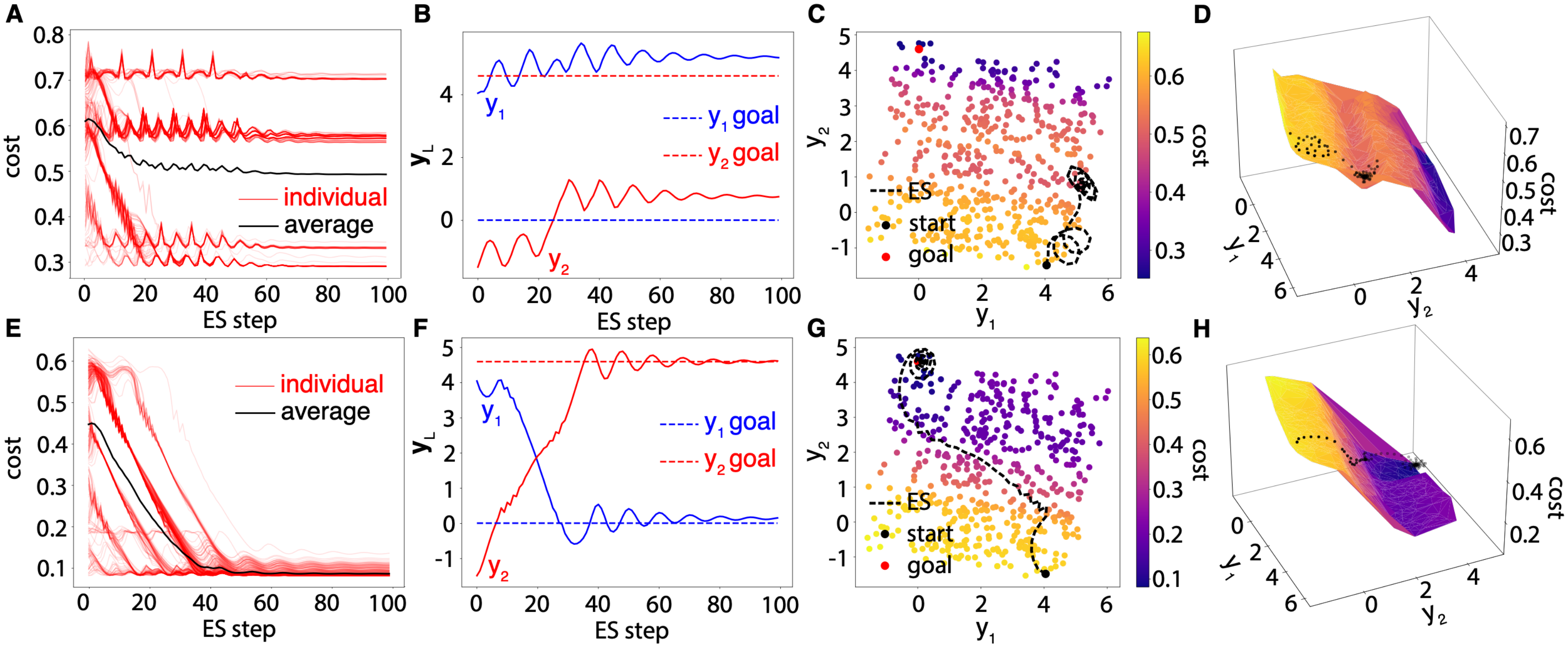
Latent space-informed diagnostics choice can give convex cost functions for unique reconstructions



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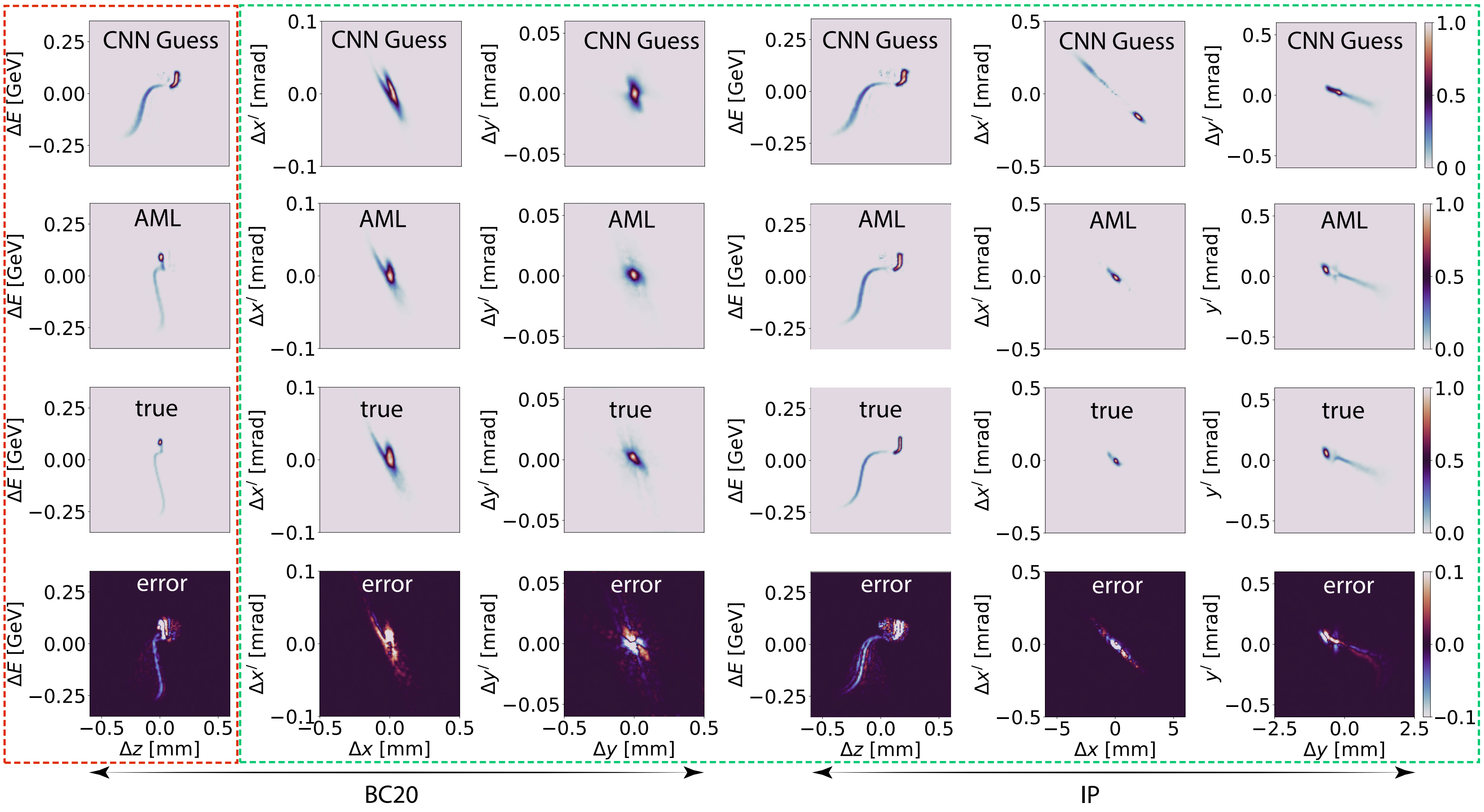
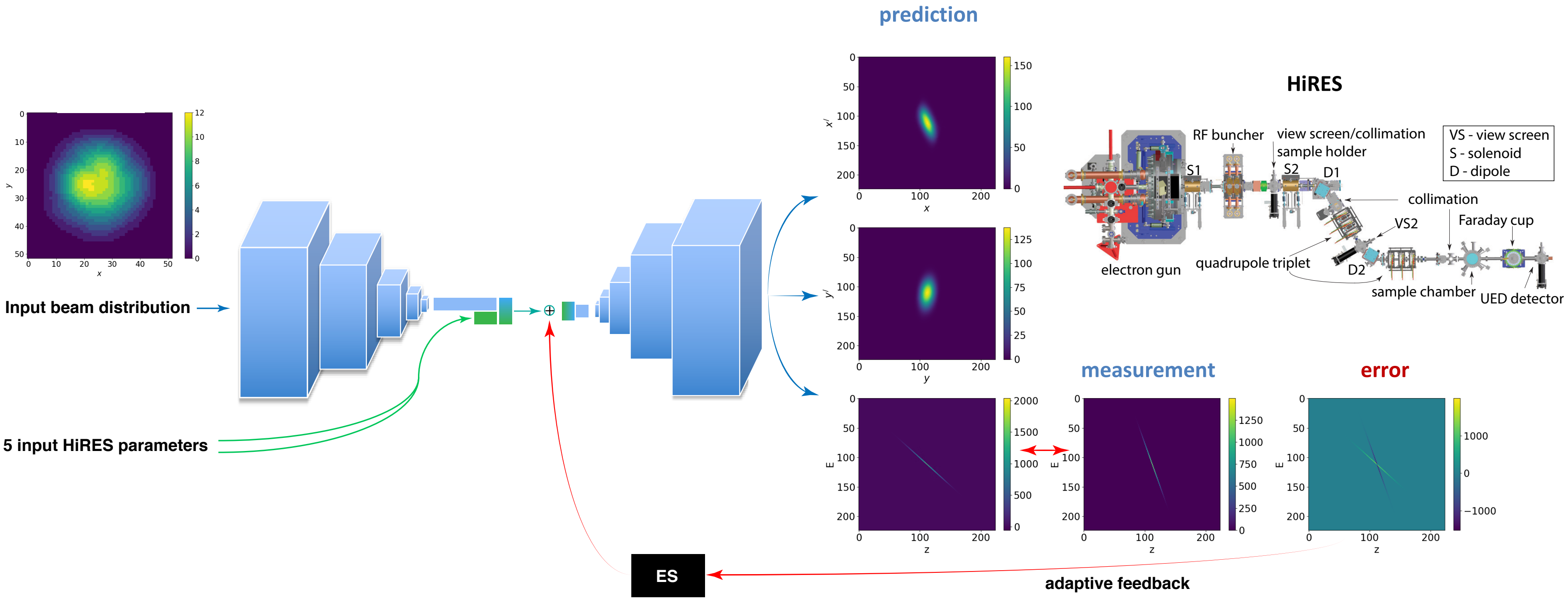
Looking at only (z,E) to predict other phase space projections



Adaptive Machine Learning (AML) for Time-Varying Systems – Adaptively Tuning the Latent Space



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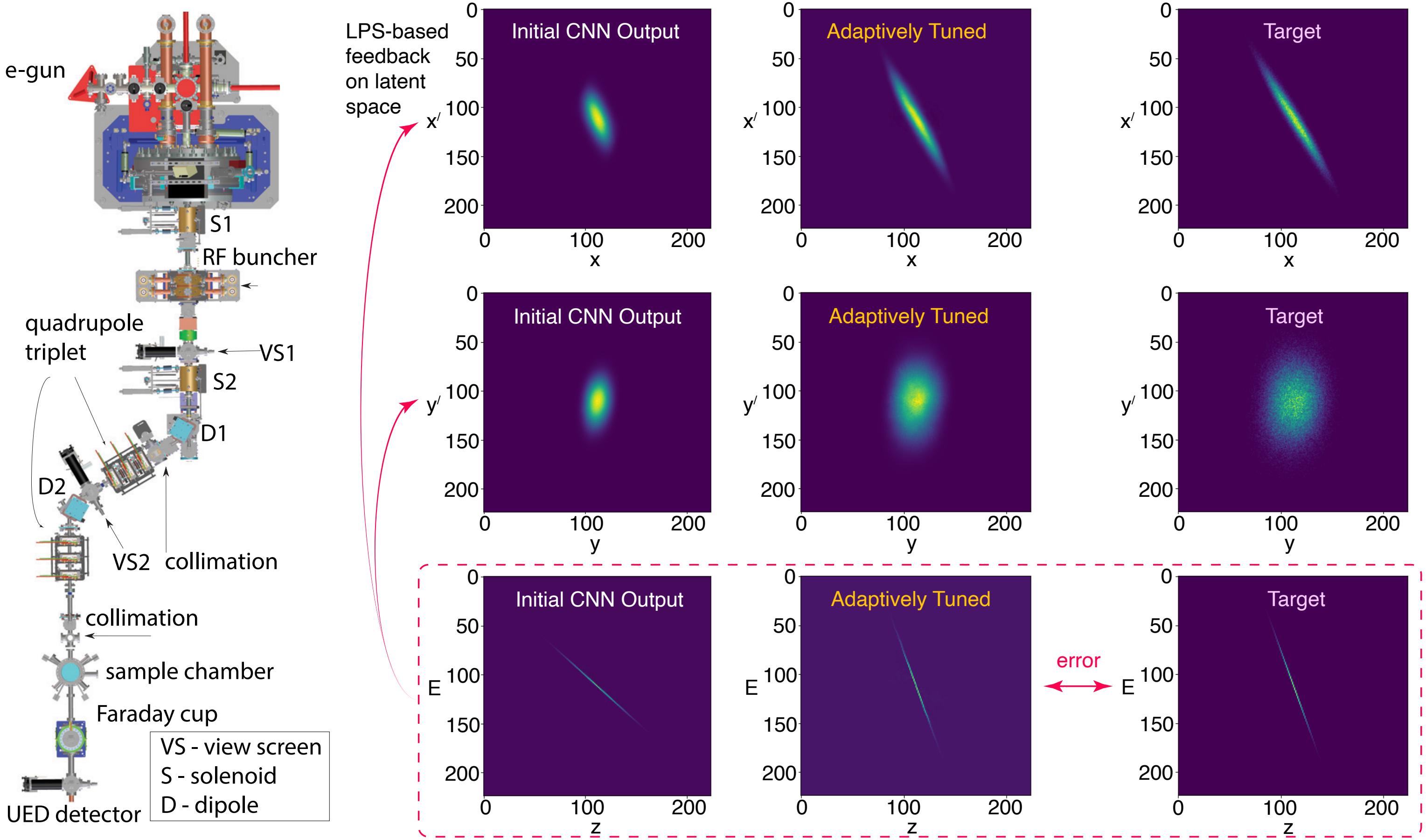
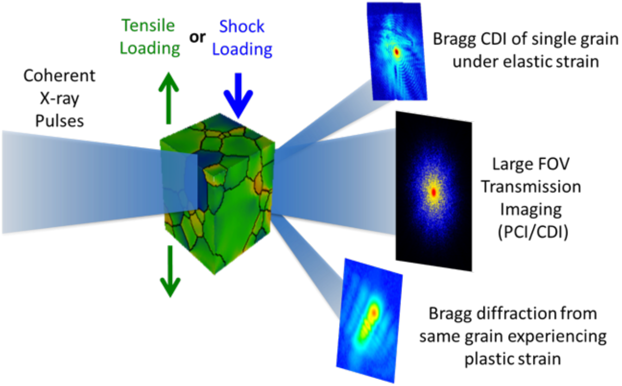


Scheinker, A., Cropp, F., Paiagua, S., & Filippetto, D. (2021). Adaptive deep learning for time-varying systems with hidden parameters: Predicting changing input beam distributions of compact particle accelerators. *arXiv preprint arXiv:2102.10510*.

Coherent Diffraction Imaging

Bragg coherent diffractive imaging enables us to view the atomic disorder and defects within a single crystal



Sayre, Acta Cryst 5, 843 (1952)
Miao et al., Nature 400, 342 (1999)
Miao and Sayre, Act Cryst A56, 596 (2000)

- ❖ **BCDI employs coherent beam to image incoherent domains in a crystal with atomic resolution**

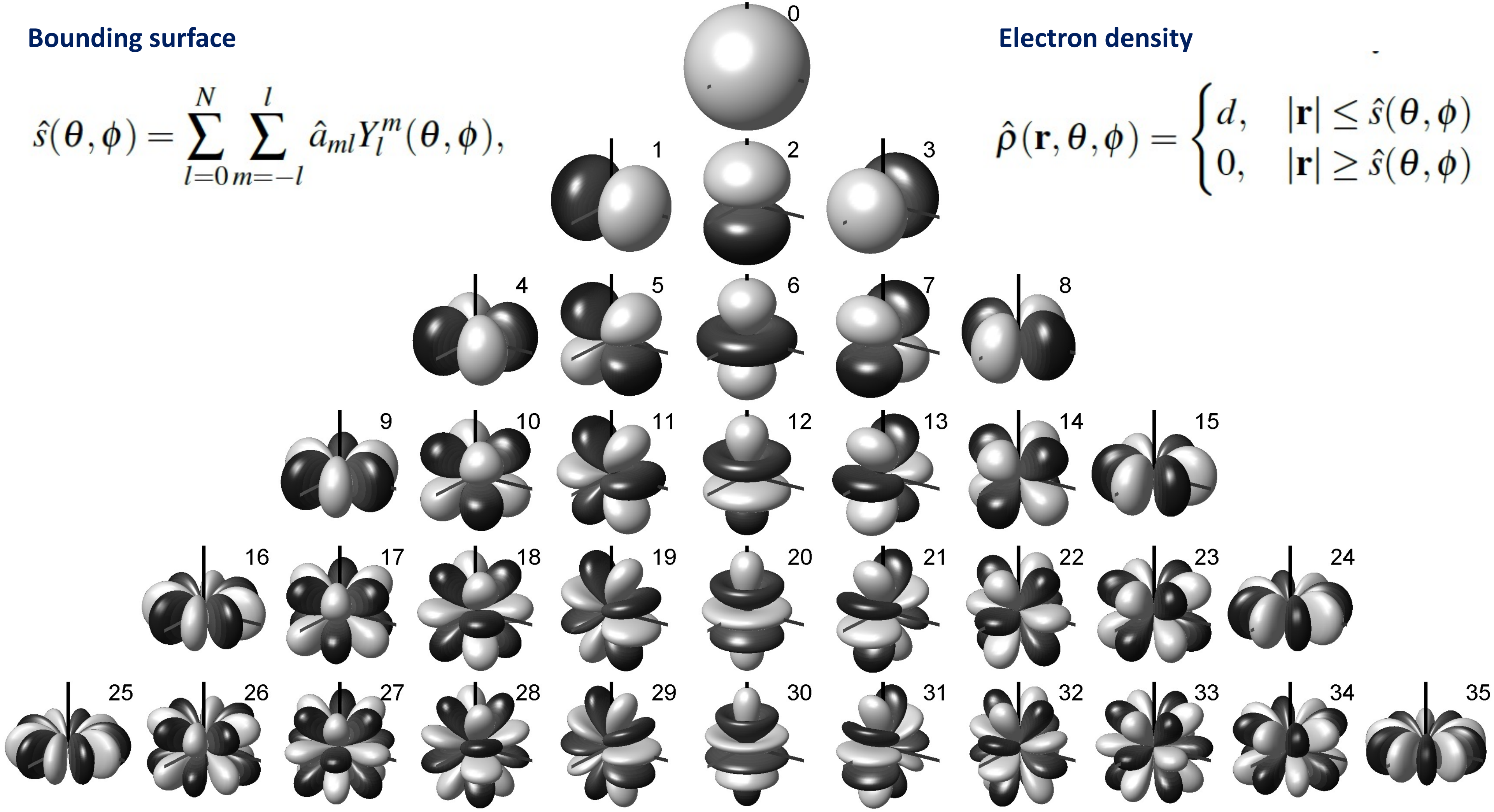
$$
\begin{aligned}
I(\mathbf{w}) &= \iint \rho(\mathbf{r}_1)\rho^\star(\mathbf{r}_2)\exp\left[i\mathbf{q}\left(\mathbf{r}_1-\mathbf{r}_2\right)\right]d\mathbf{r}_1 d\mathbf{r}_2 \\
&= \psi(\mathbf{w})\psi^\star(\mathbf{w}) \\
&= |\psi(\mathbf{w})|^2 \exp\left[i\phi(\mathbf{w})\right]\exp\left[-i\phi(\mathbf{w})\right] \\
&= |\psi(\mathbf{w})|^2,
\end{aligned}
$$

Bounding surface

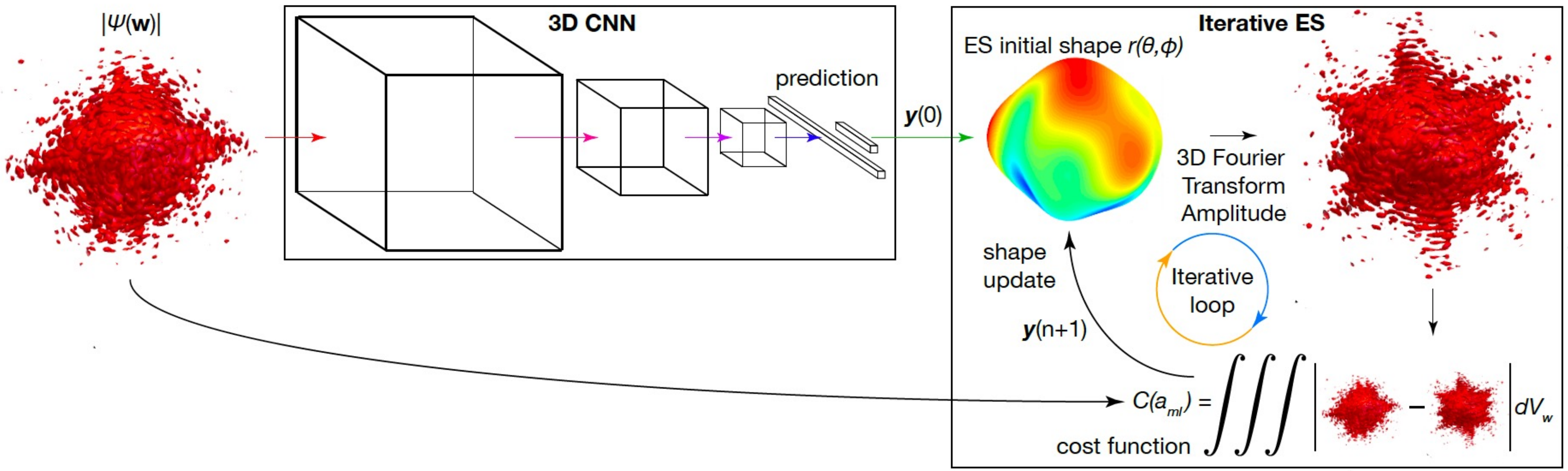
$$\hat{s}(\theta,\phi)=\sum_{l=0}^{N}\sum_{m=-l}^{l}\hat{a}_{ml}Y_l^m(\theta,\phi),$$

Electron density

$$\hat{\rho}(\mathbf{r},\theta,\phi)=\begin{cases} d, & |\mathbf{r}|\leq\hat{s}(\theta,\phi)\\ 0, & |\mathbf{r}|\geq\hat{s}(\theta,\phi)\end{cases}$$



Overview of Adaptive ML Approach



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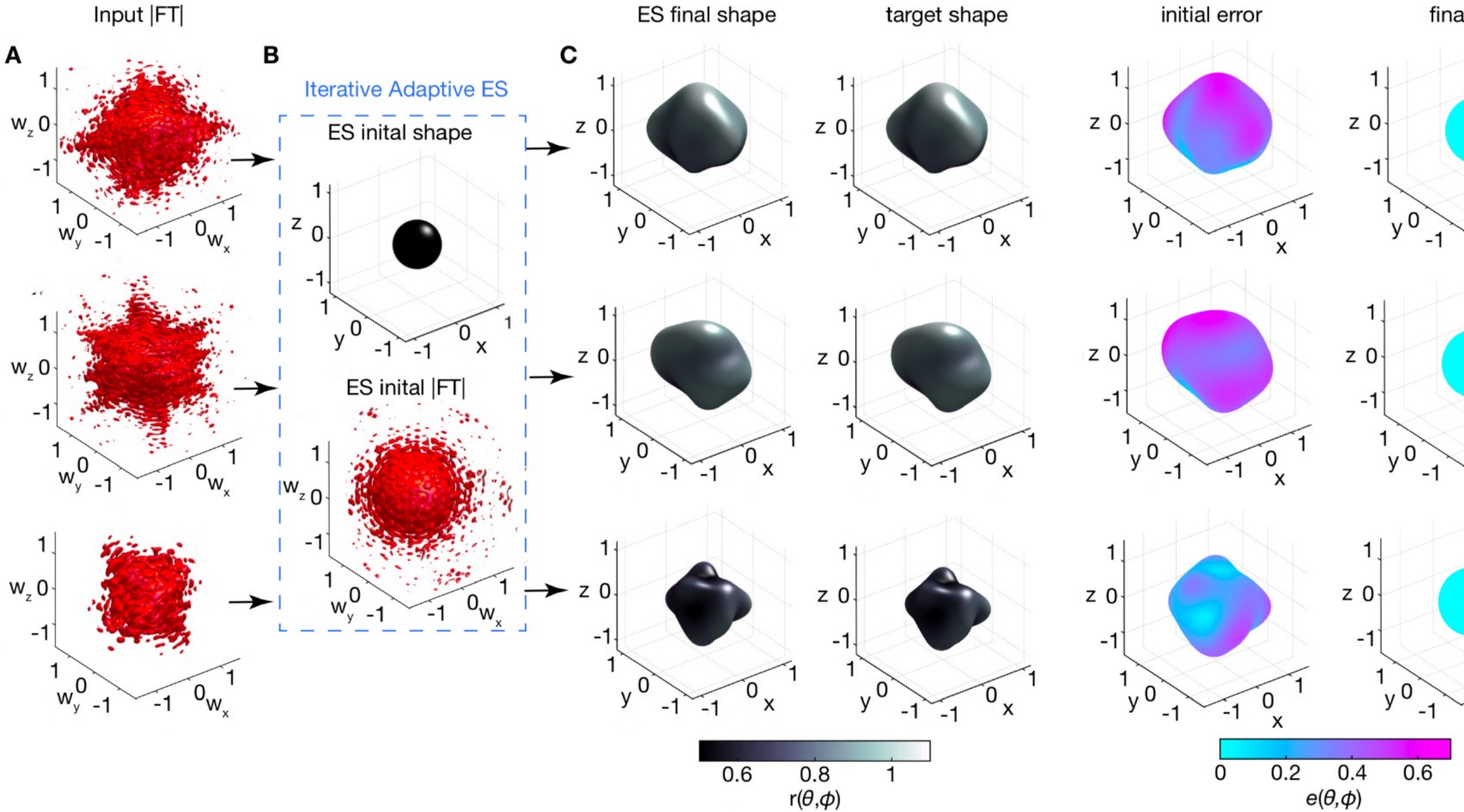
Adaptive Tuning for 3D Shapes



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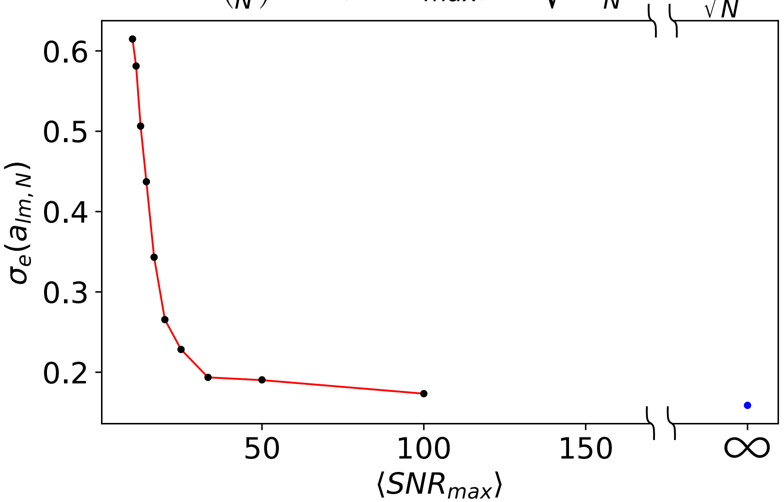
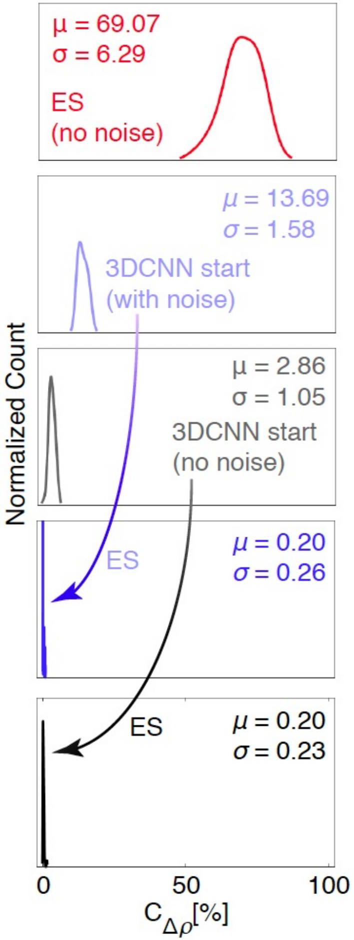
Noisy Data

$$P_{N,\mathbf{w}} \sim \frac{\lambda_{N,\mathbf{w}}^k e^{-\lambda_{N,\mathbf{w}}}}{k!}, \quad \lambda_{N,\mathbf{w}} = \frac{|\psi(\mathbf{w})|}{N}$$

$$\text{SNR} = \sqrt{\frac{10000}{N}} \approx \frac{100}{\sqrt{N}}$$

$$N \times P\left(\frac{\lambda}{N}\right) \Longrightarrow \langle SNR_{max} \rangle = \sqrt{\frac{\langle \lambda_{max} \rangle}{N}} \approx \frac{100}{\sqrt{N}}$$





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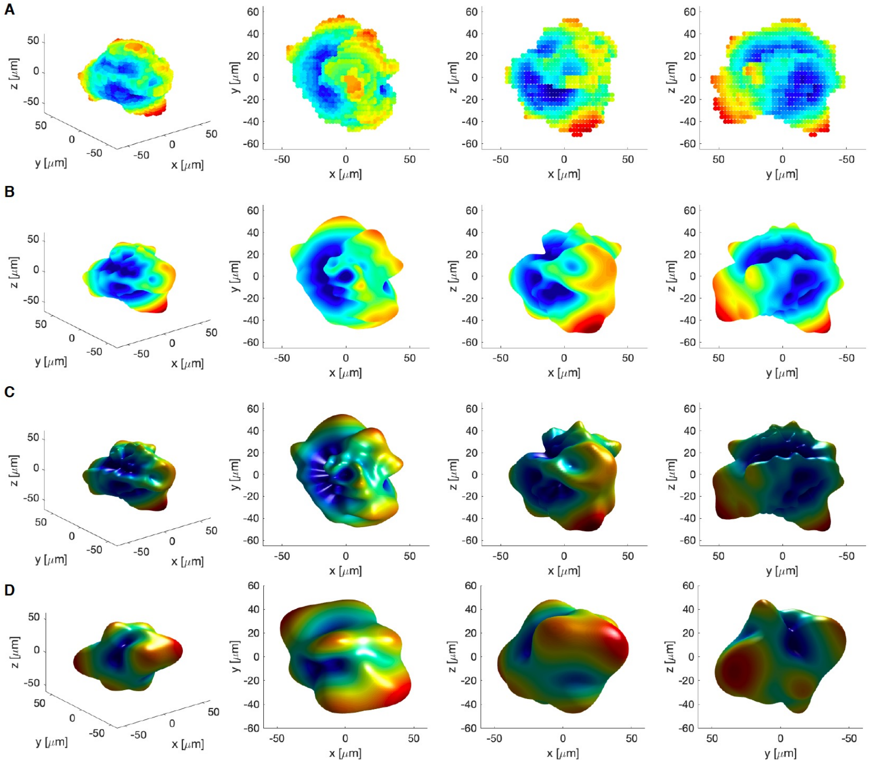
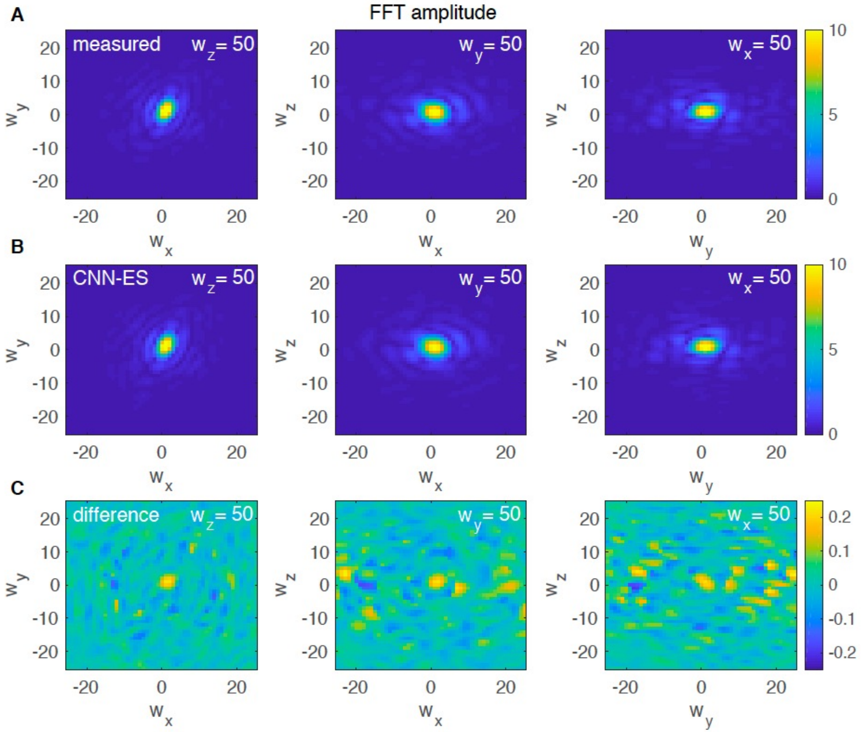
Realistic 3D Structures





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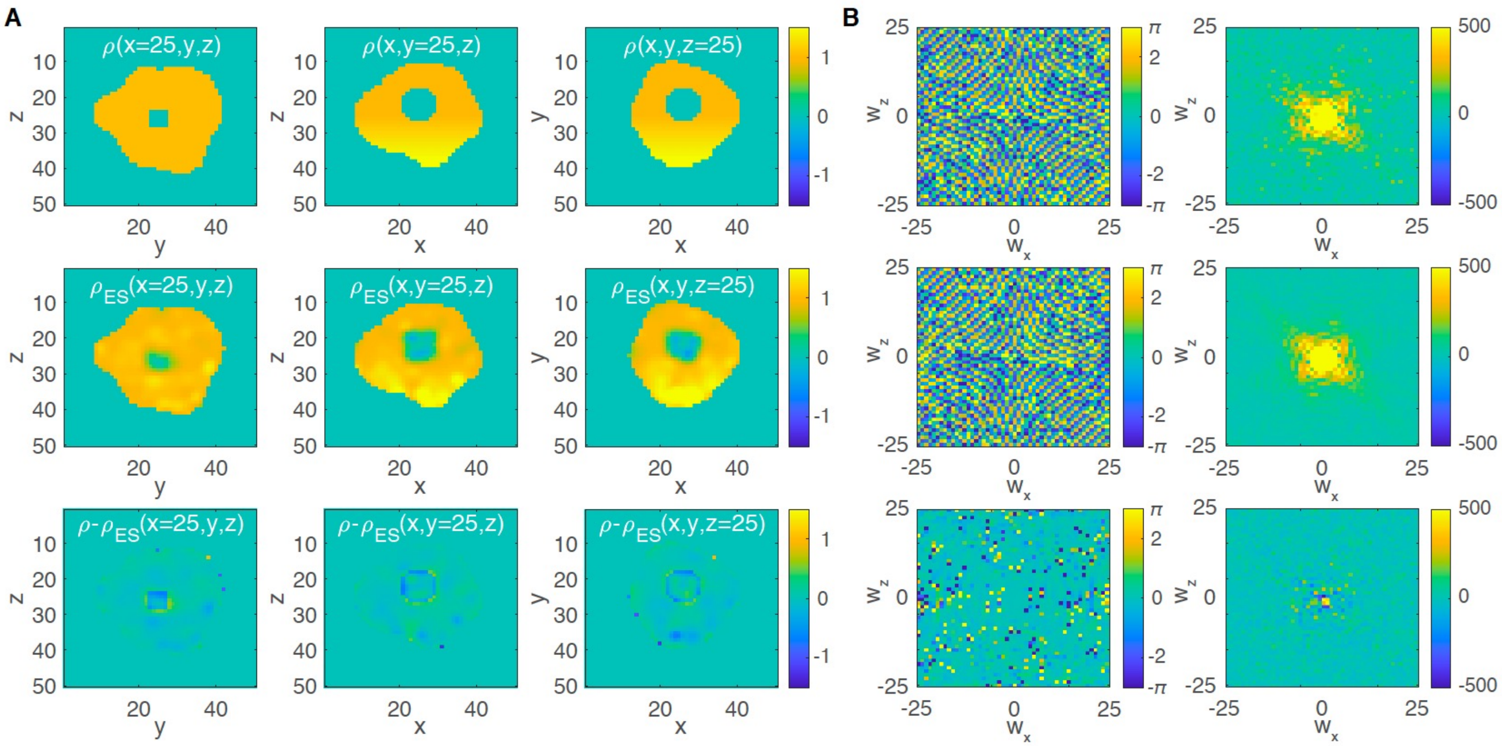
Non-uniform 3D Structures



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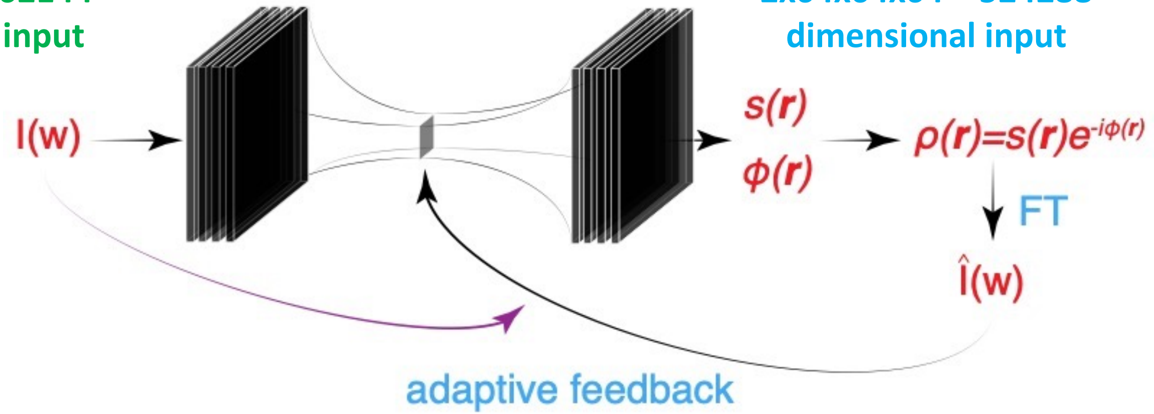
Encoder-Decoder 3D Convolutional Neural Networks

64x64x64 = 262144
dimensional input

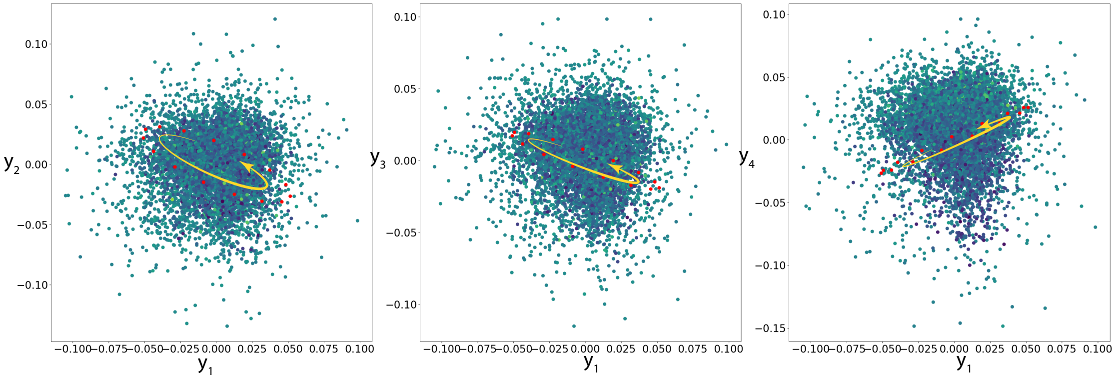
2x64x64x64 = 524288
dimensional input

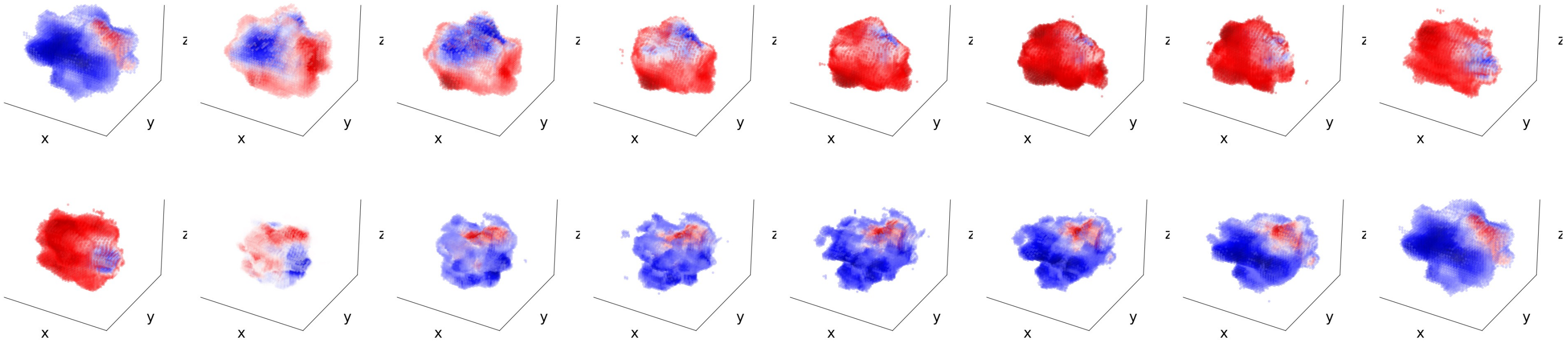


$y=(y_1,\ldots,y_{100})$
100 dimensional latent space

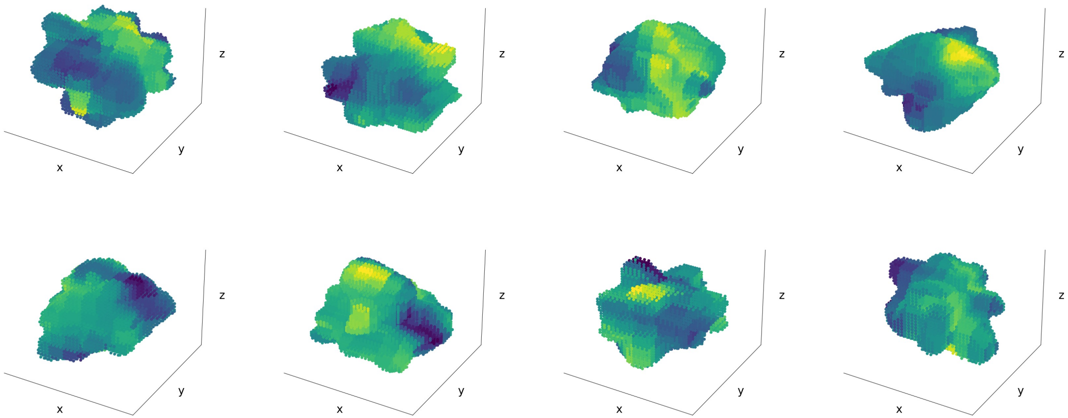
$$I^1_{i_1,j_1} = b^1 + \sum_{n=1}^{N_f} w_n \times f_n \left(b^0_n + \sum_{i=-1}^{1} \sum_{j=-1}^{1} F_{0,ij,n} \times I^0_{i_0+i,j_0+j} \right)$$

Low-Dimension Latent Space Projections

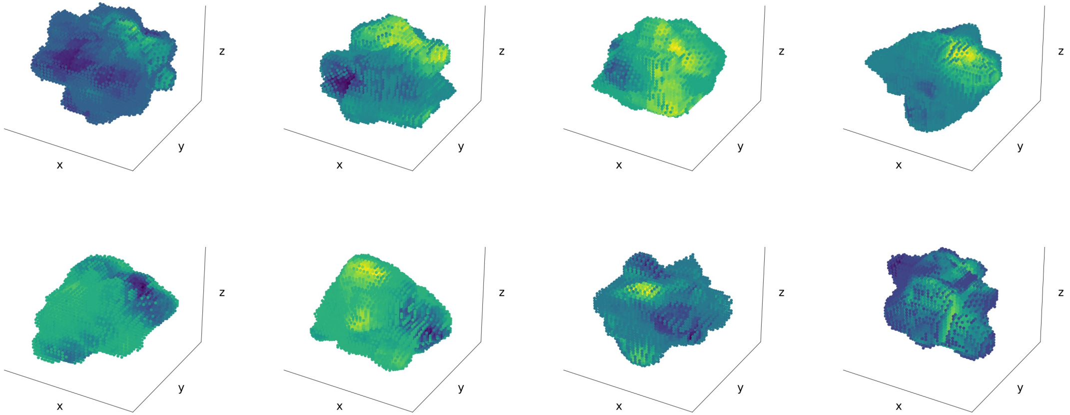




True

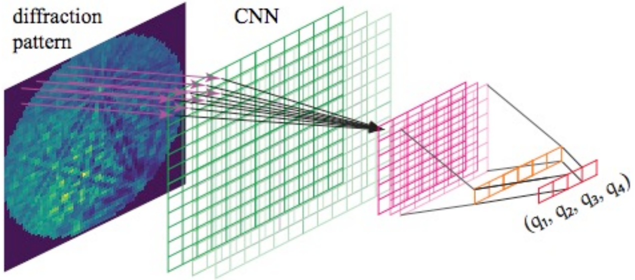


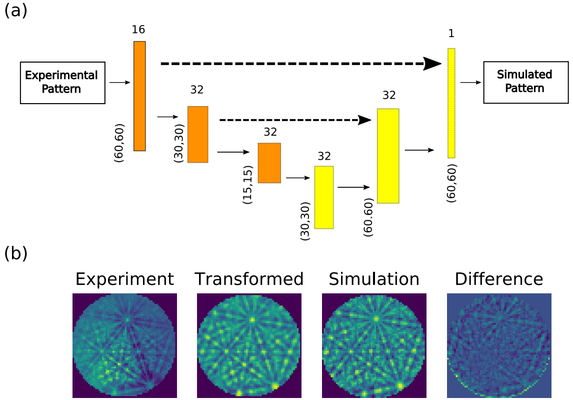
3D CNN Predictions

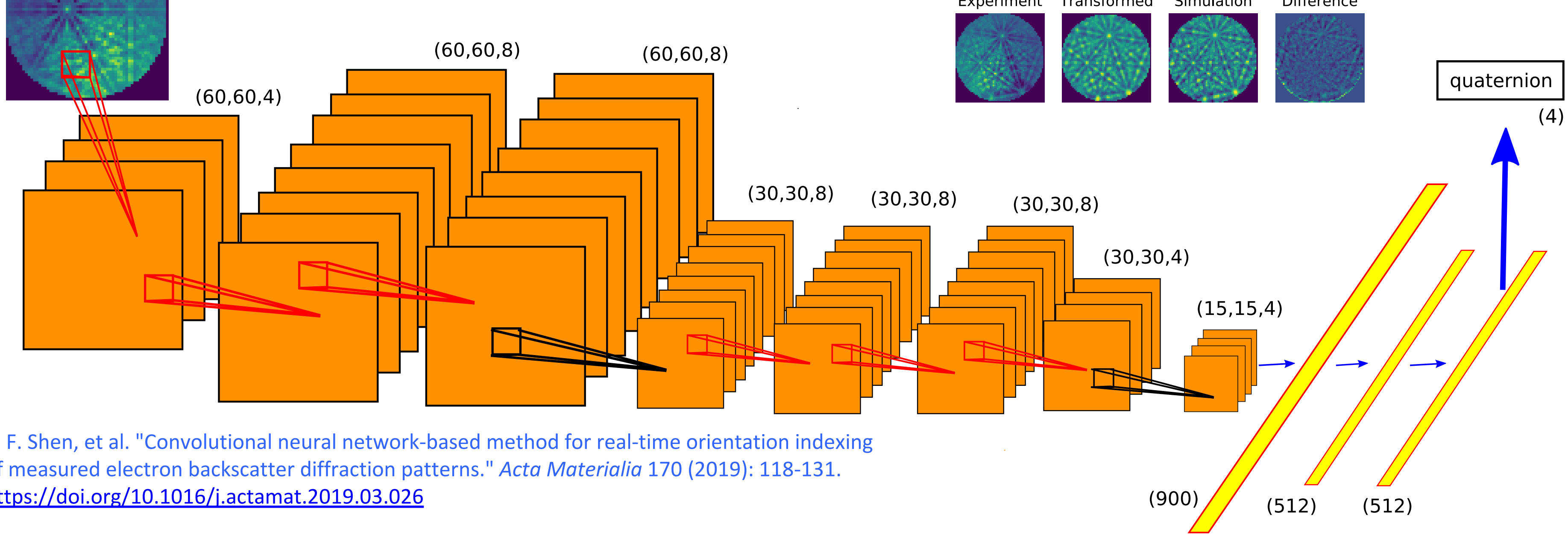


Electron Backscatter Diffraction (EBSD) Microscopy

Re-Training and Domain Transfer for Convolutional Neural Networks







Y. F. Shen, et al. "Convolutional neural network-based method for real-time orientation indexing of measured electron backscatter diffraction patterns." *Acta Materialia* 170 (2019): 118-131. https://doi.org/10.1016/j.actamat.2019.03.026

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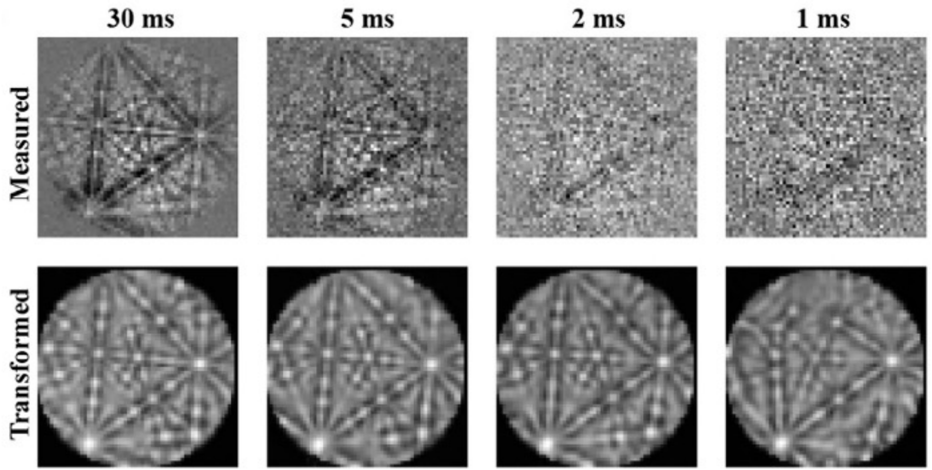

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