6D Phase Space Diagnostics Based on Adaptively Tuned Physics-Informed Generative Convolutional Neural Networks

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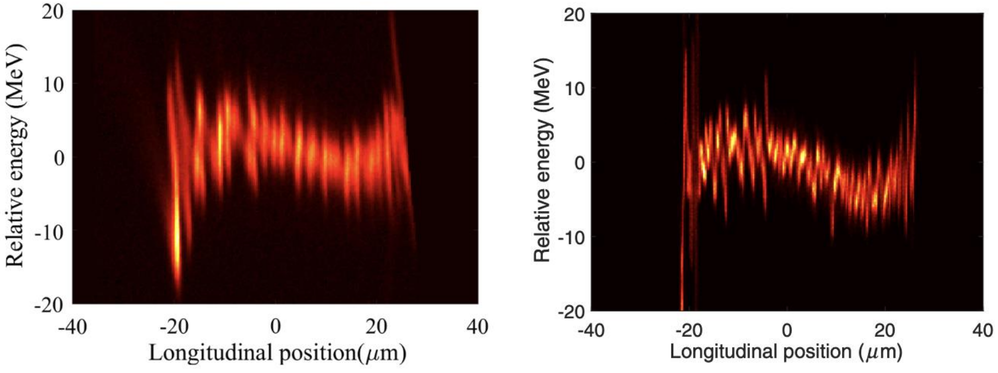
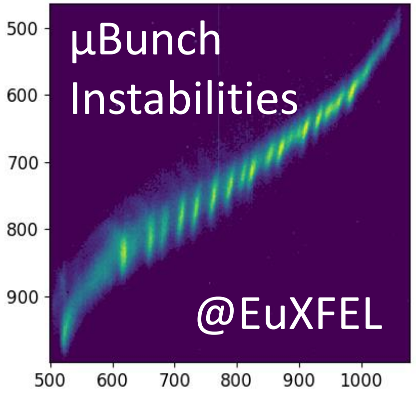
Motivation: Initial beam distributions are time-varying and beam dynamics are governed by complex collective effects such as wakefields, space charge, and coherent synchrotron radiation

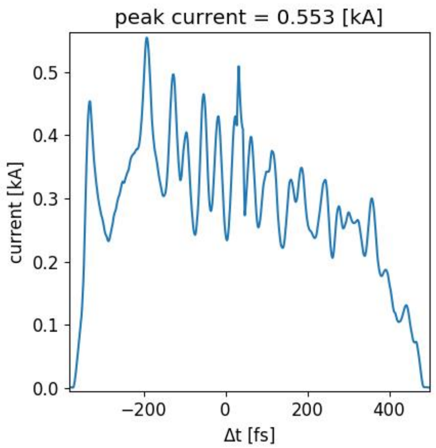
Physics based models can simulate exquisite detail including µBunch instabilities (10 hours on thousands of NERSC cores!).

J. Qiang et al. PRAB, 20, 054402, 2017

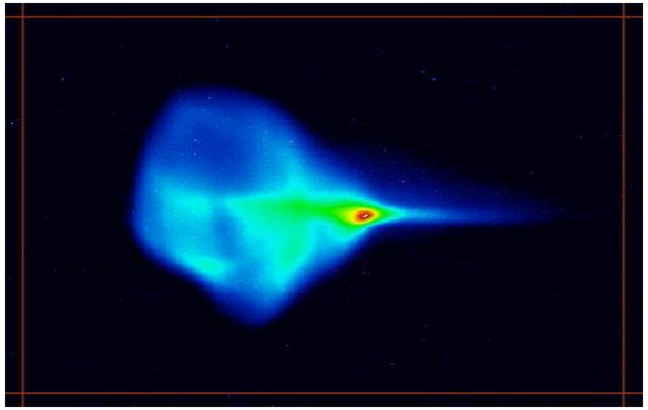


(a) measurement (b) simulation

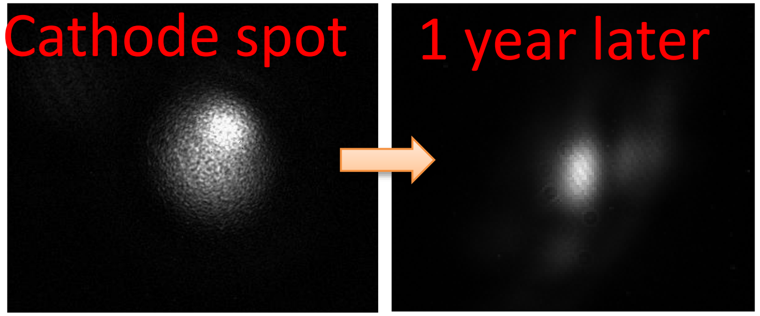




Bunch compression amplifies small time-varying perturbations in initial beam distributions.



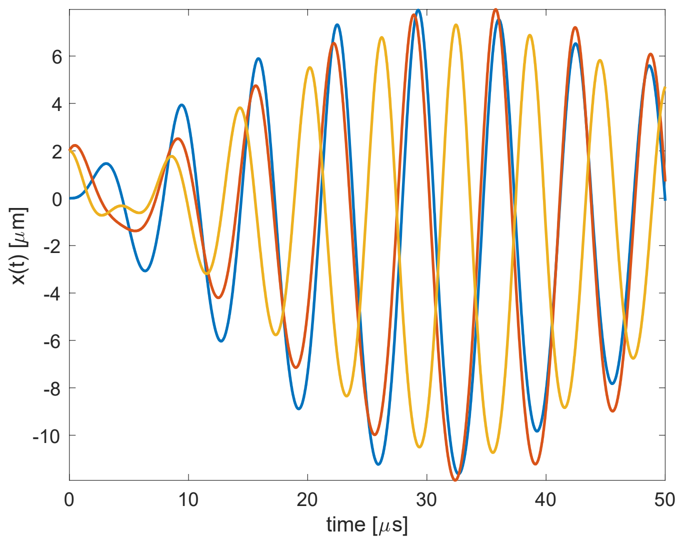
Typical 2D (x,y) beam profile, not a simple Gaussian.



Example images of laser spot (10 Aug. 2016, 11 Nov. 2017)

Time-Varying Input Beam Distributions

Motivation: Traditional ML methods fail for time-varying systems (distribution shift), requiring continuous re-training.

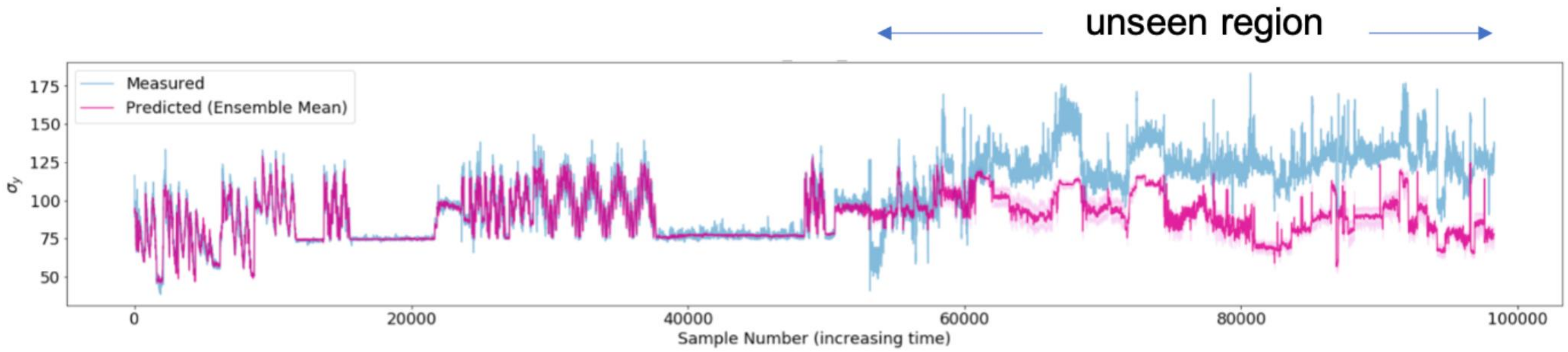


Simple numerical example: nonlinear simple harmonic oscillator with time-varying initial conditions, inputs, and parameters.

$$\ddot{x}(t) = -w^2 \left[x(t) + \epsilon x^2(t)\right] - b\dot{x}(t) + f(t)$$

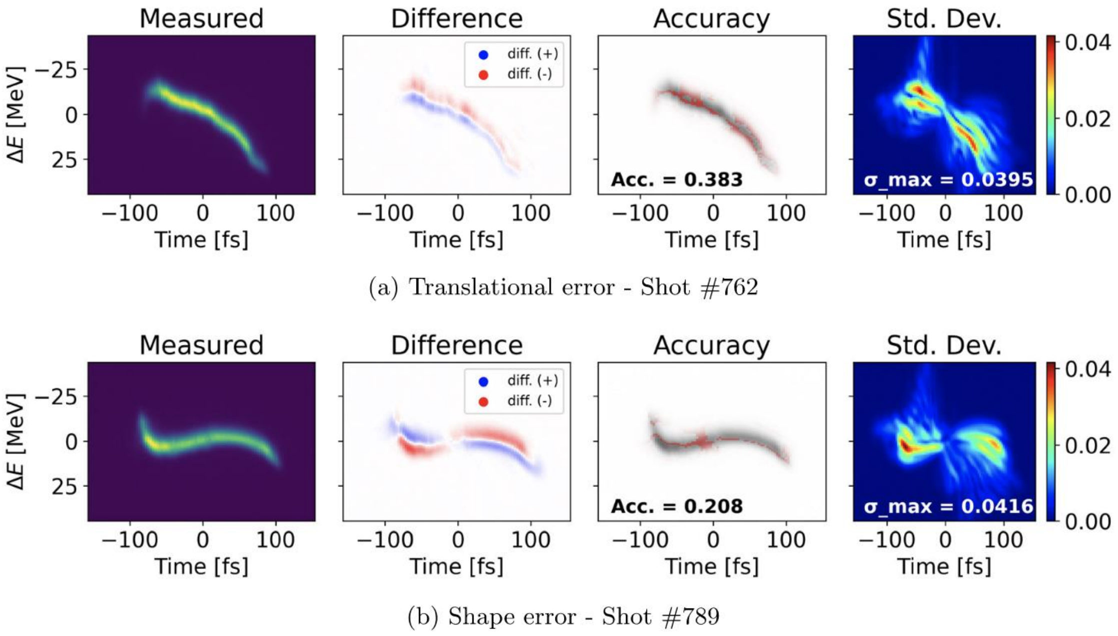
Small changes to the initial position, velocity, or non-linear coefficient ε, drastically change the trajectories.

Example shared by researchers from SLAC: time-varying system shows limitations of traditional ML approaches. - Neural network predicting σ_y beam size at some test stand.



Related work: Uncertainty quantification to understand how much an ML model can be trusted for a changing system (A. Hanuka).

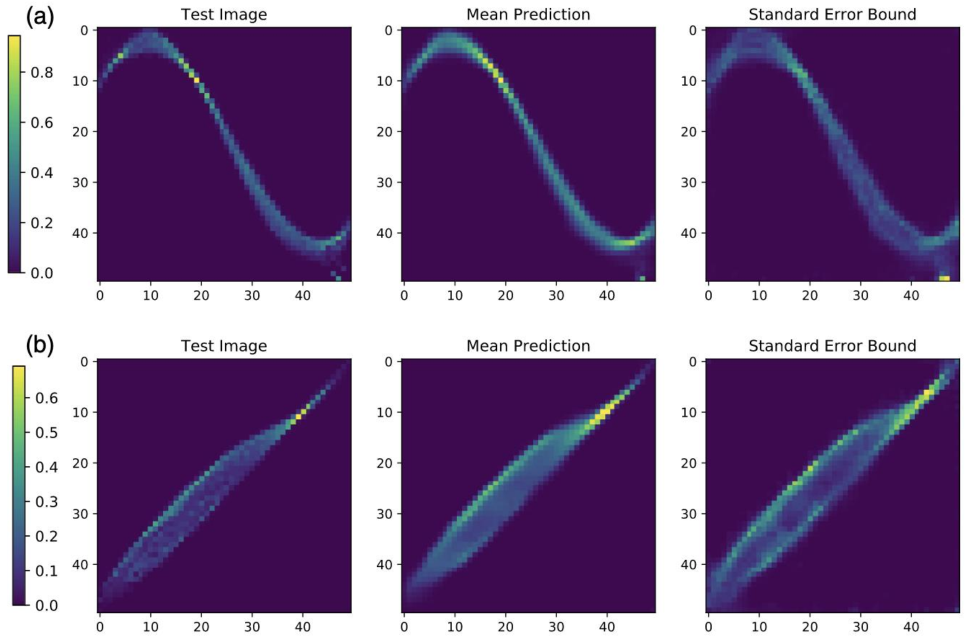
Ensembles of Deep Neural Networks



LCLS-II measured longitudinal phase space predictions.

Convery, O., Smith, L., Gal, Y., & Hanuka, A. (2021). Uncertainty quantification for virtual diagnostic of particle accelerators. *Physical Review Accelerators and Beams*, *24*(7), 074602.

Bayesian Neural Networks

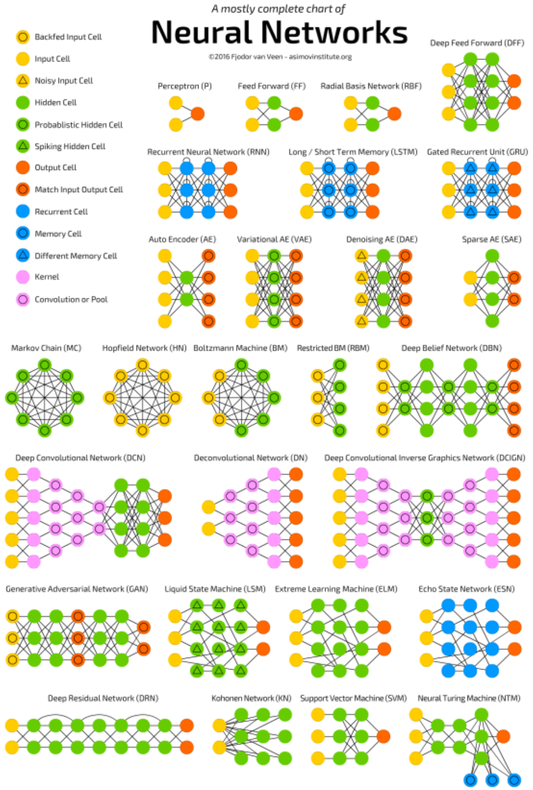


LCLS-II longitudinal phase space simulations predictions.

Mishra, Aashwin Ananda, et al. "Uncertainty quantification for deep learning in particle accelerator applications." *Physical Review Accelerators and Beams* 24.11 (2021): 114601.

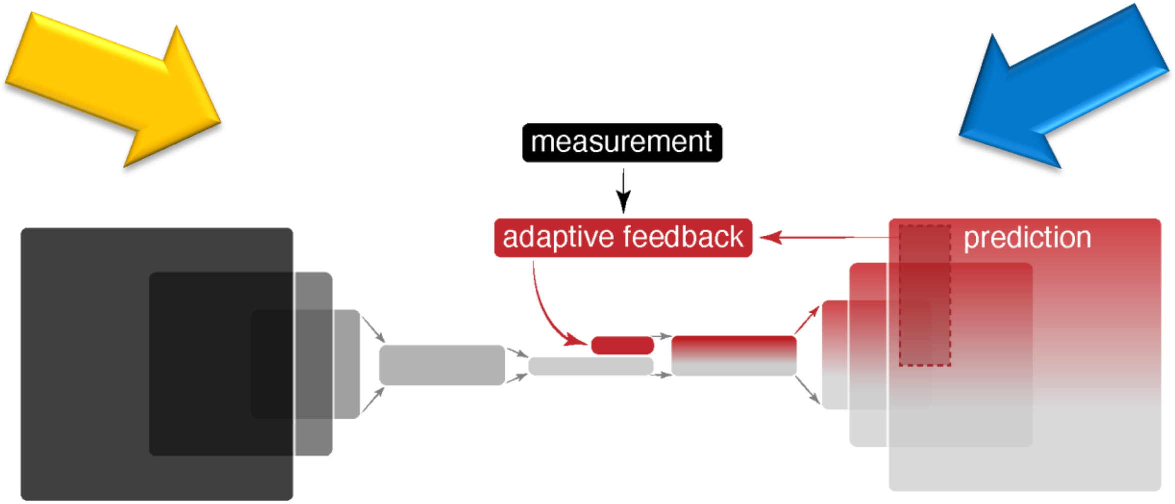
Approach: Adaptive ML combines robust model-independent adaptive feedback with deep physics-informed CNNs.

Machine Learning

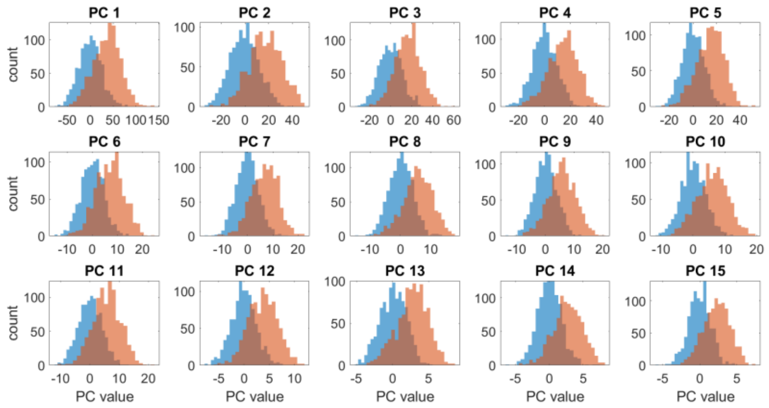


- Neural Networks
- Deep RL
- Global learning
- Cannot handle time-varying systems

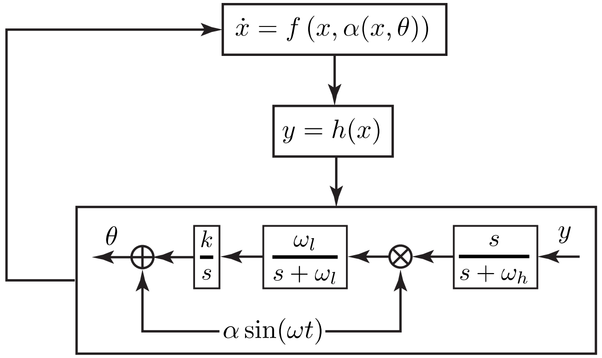
Robust Adaptive Machine Learning

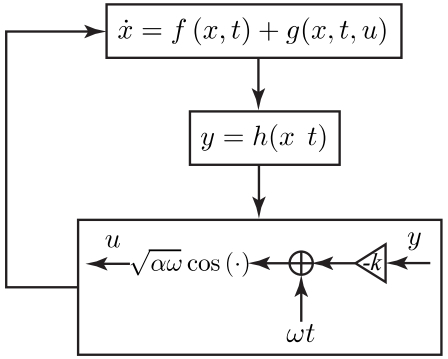


For Time-Varying systems with distribution shift



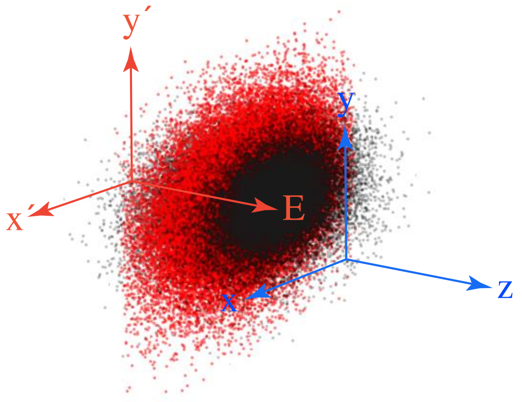
Model—Independent Feedback





- Adaptive Control
- Extremum Seeking
- Robust to time-variation
- Local feedback, local minima

Physics-Informed Adaptive ML for 6D phase space diagnostics. Observational biases introduced directly through data that embody the underlying physics to learn functions that reflect the physical structure of the data. Encoder-decoder CNN for nonlinear data compression: Low-dimensional latent space tuning.



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

2D projections

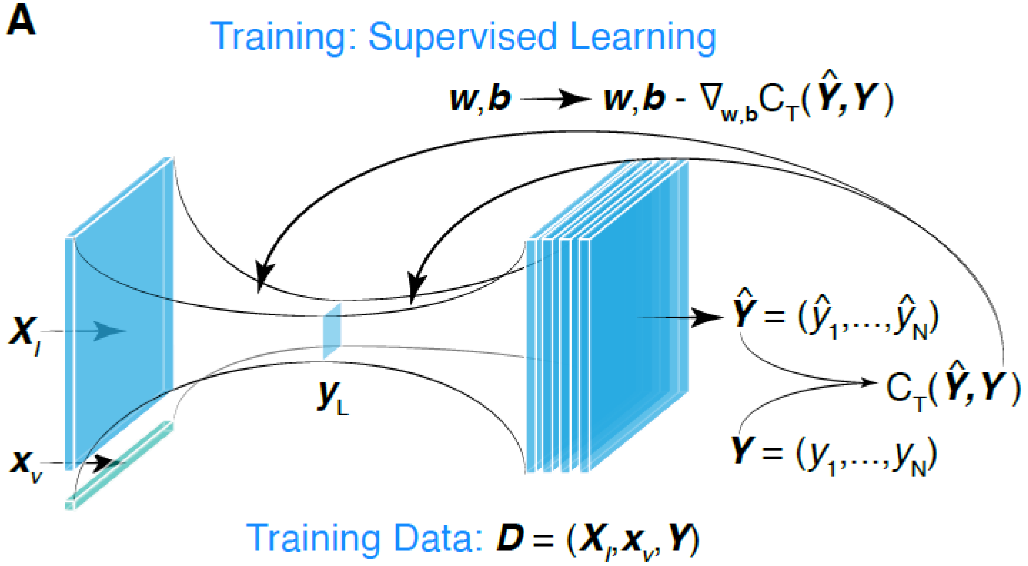
$(x,y), (x,z), (x,x'), (x,y'), (x,E)$

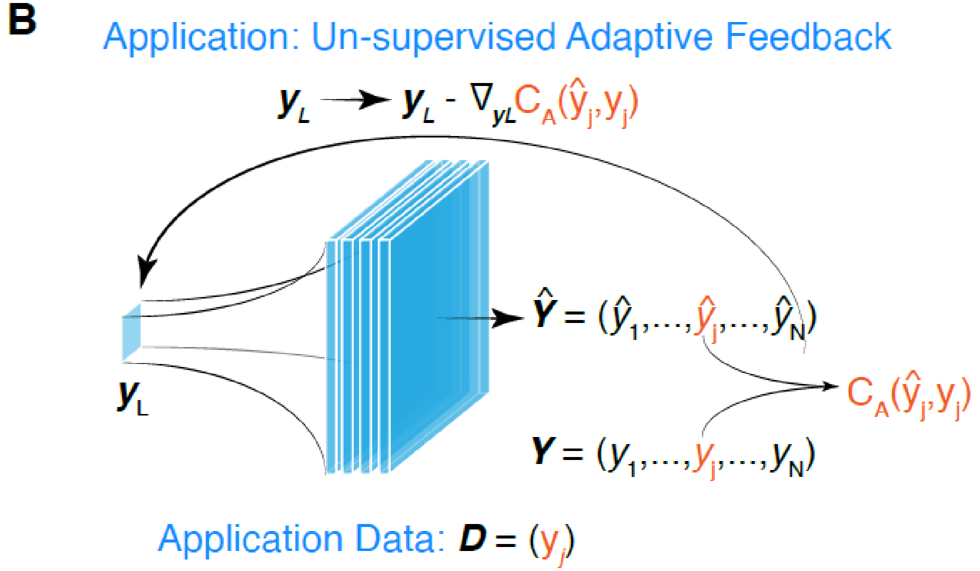
$(x',y), (x',z), (x',y'), (x',E)$

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

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

(z,E)



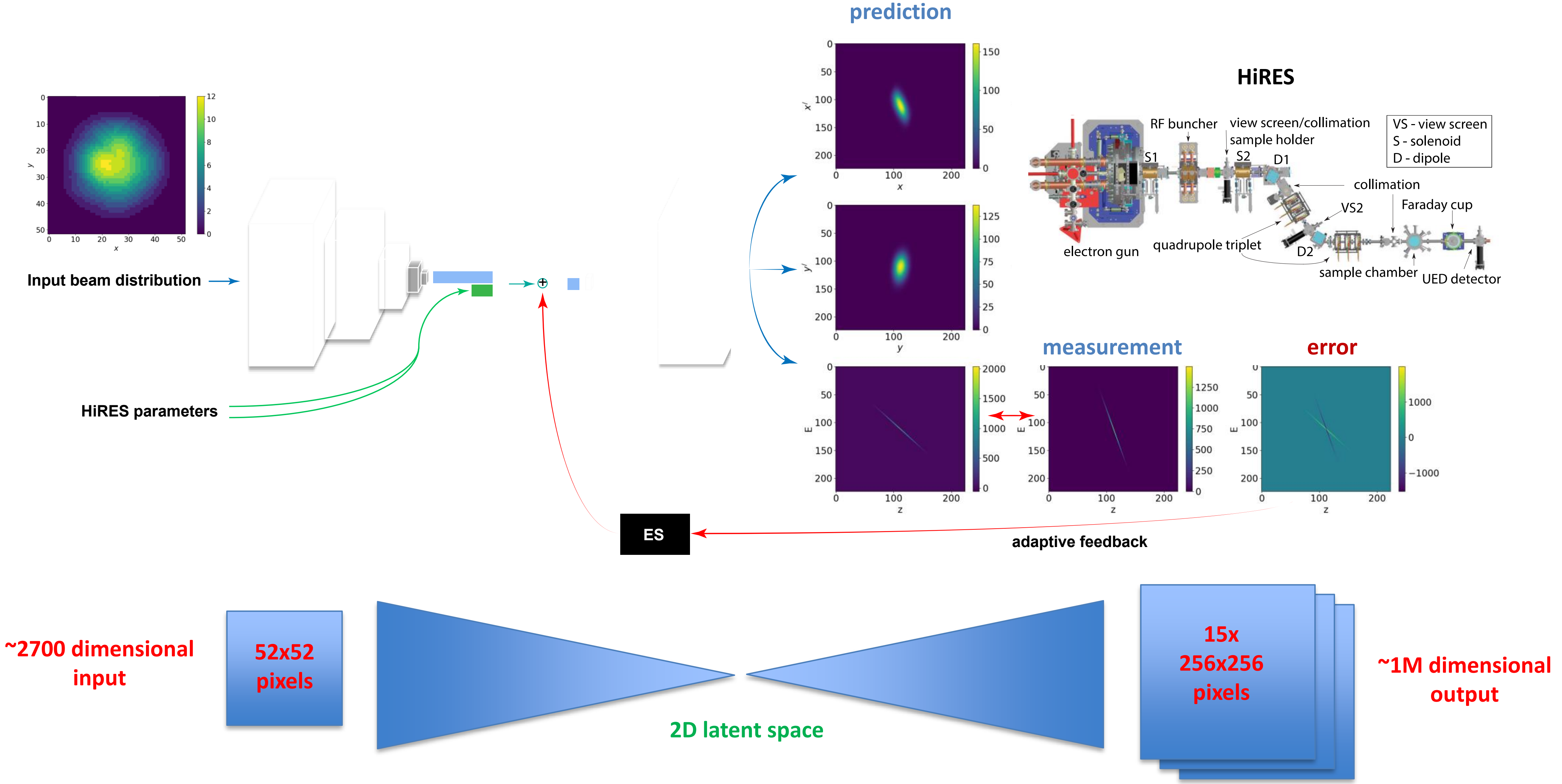


A. Scheinker. "Adaptive machine learning for time-varying systems: low dimensional latent space tuning." *Journal of Instrumentation* 16.10 (2021): P10008.

A. Scheinker, F. Cropp, S. Paiagua, & D. Filippetto. "An adaptive approach to machine learning for compact particle accelerators." *Scientific Reports* **11,** 19187, 2021.

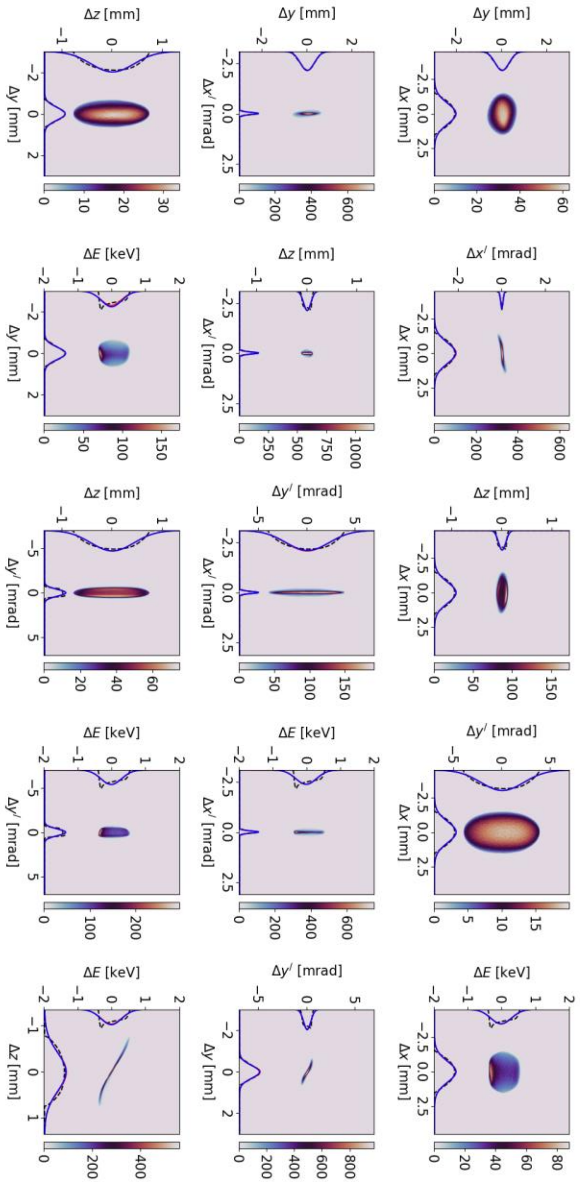
AML Development at HiRES – Compact Ultra-fast Electron Diffraction (UED)

Longitudinal phase space measurements used to guide adaptive feedback within 2D latent space to predict all 2D projections of a beam's 6D phase space.

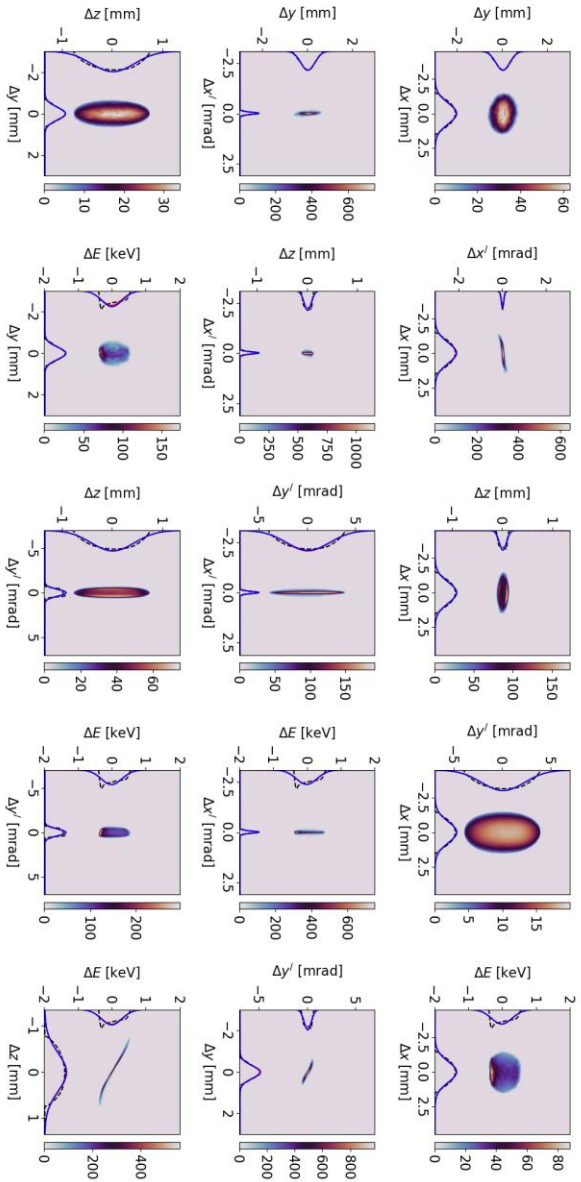


15 projections of 6D phase space @ Q=0.25 pC, S=4.65 Amps

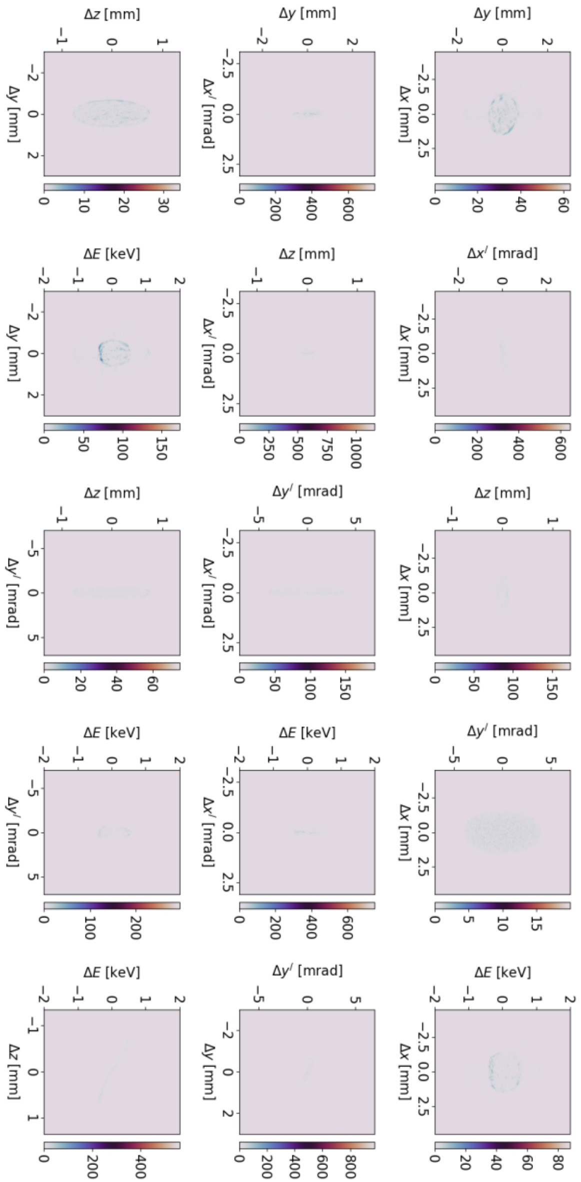
True



CNN

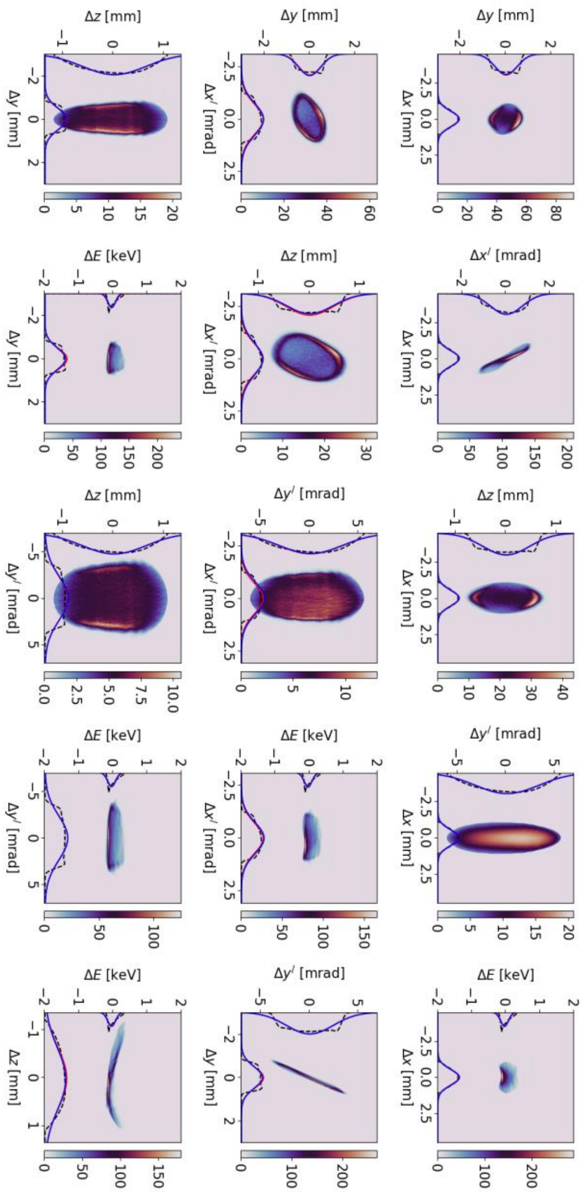


Difference

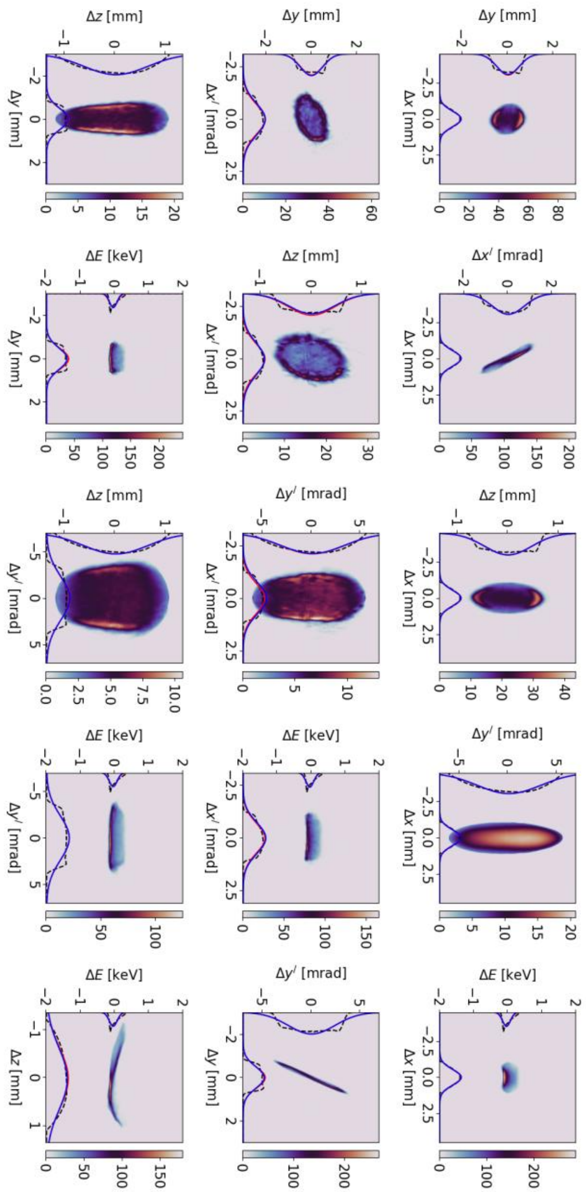


15 projections of 6D phase space @ Q=1.0 pC, S=4.85 Amps

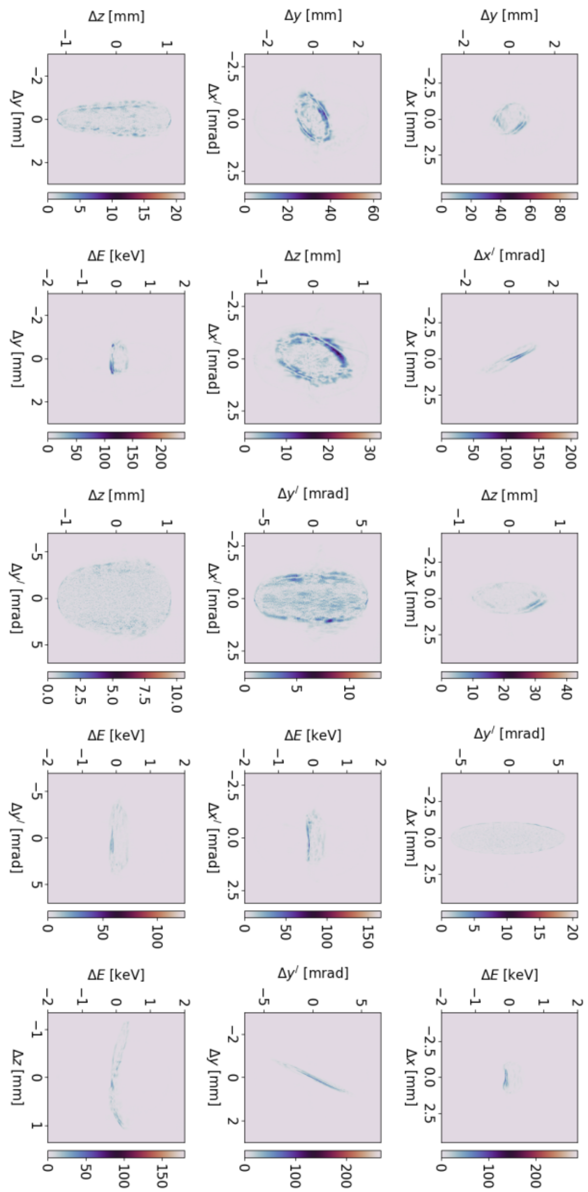
True



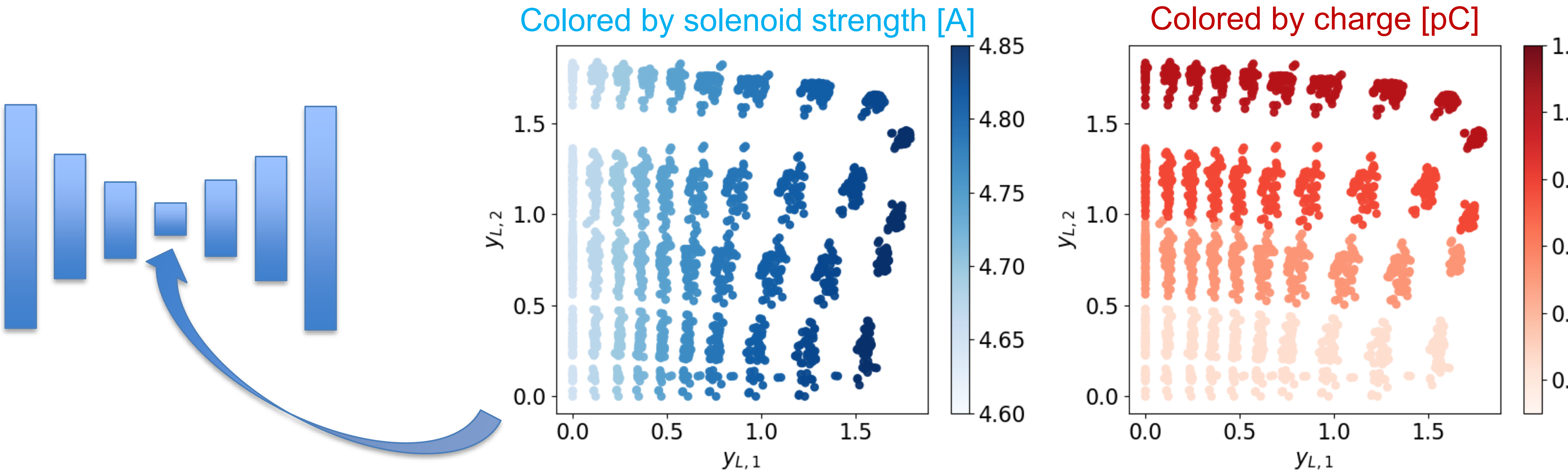
CNN

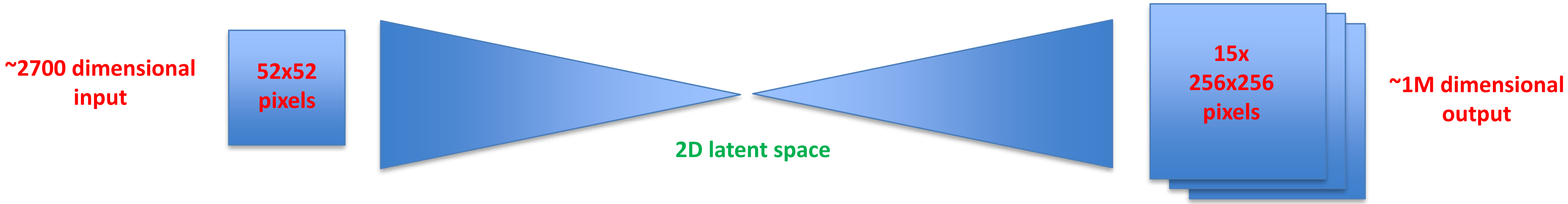


Difference

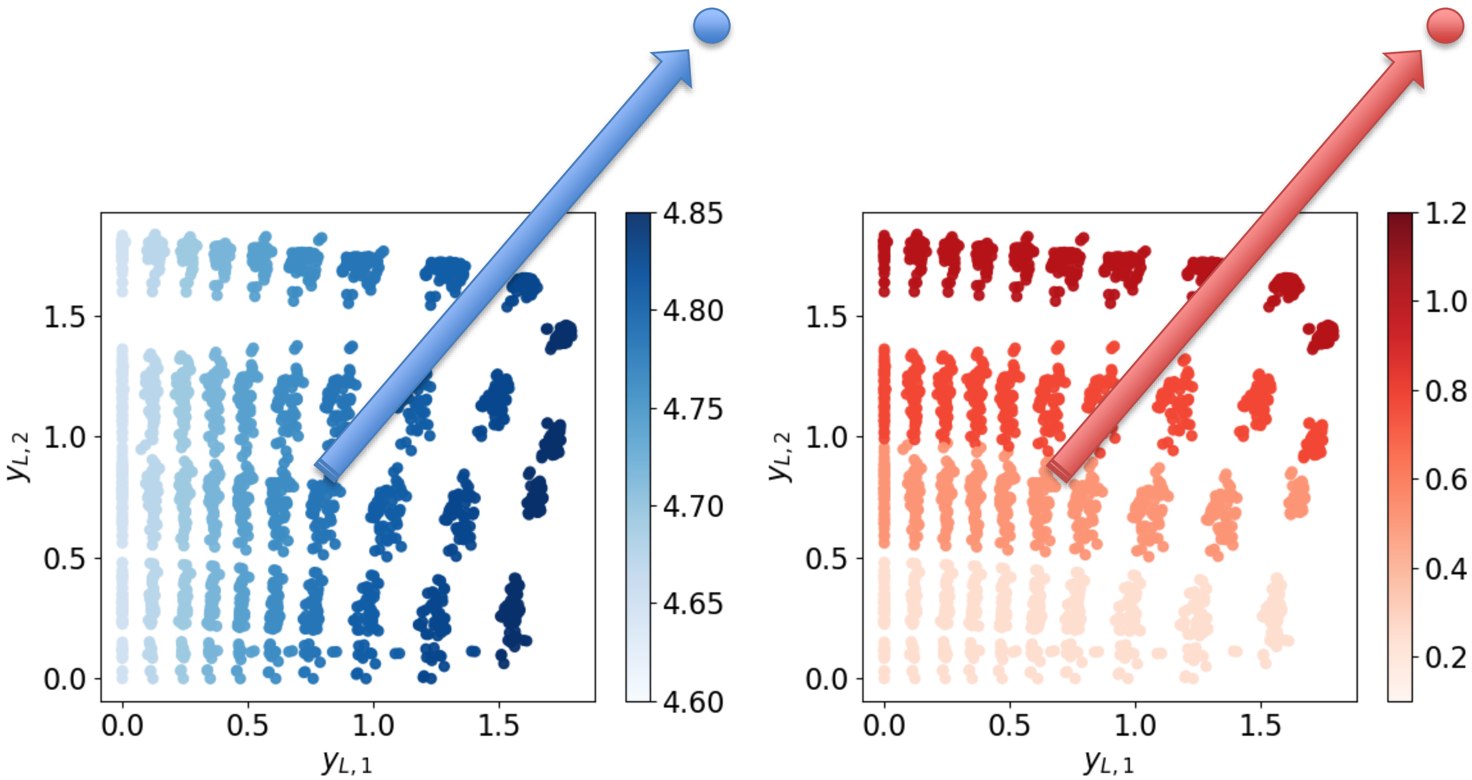


Looking into the CNN's 2D Latent space representation of 100 input beams, we see that it has naturally clustered bunches by solenoid strength and charge.





Robustness test: Moving far beyond the span of the training data to an unseen input beam distribution, higher solenoid strength, and larger charge.

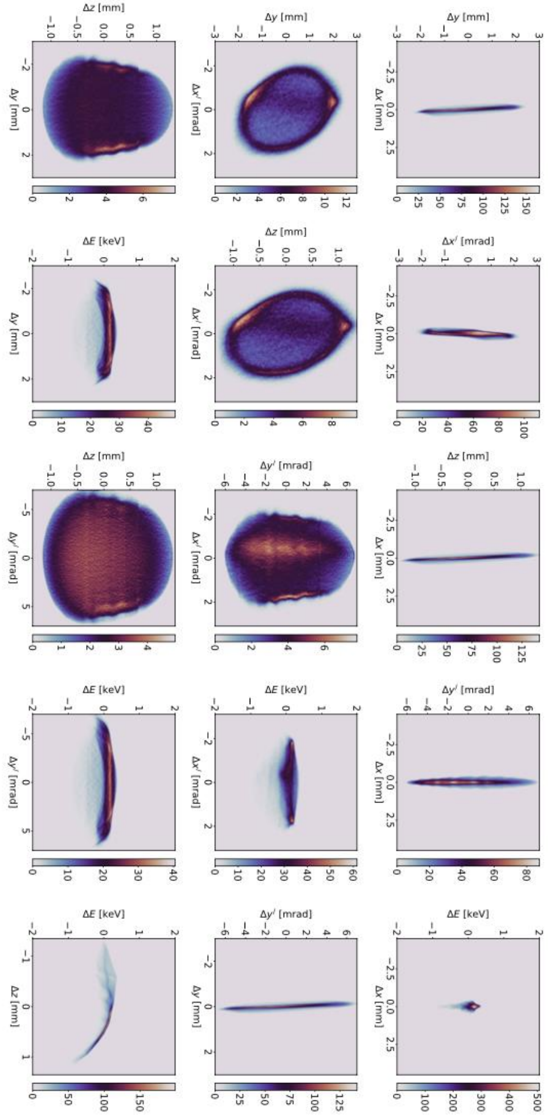


Colored by solenoid strength [A]

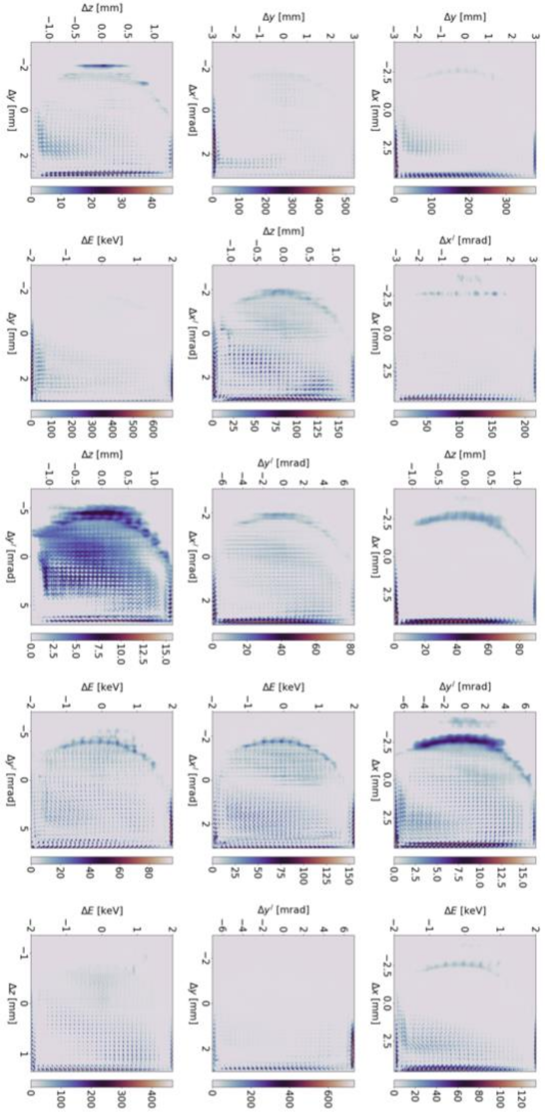
Colored by charge [pC]

6D phase space projections for beam and parameters far outside of training set.

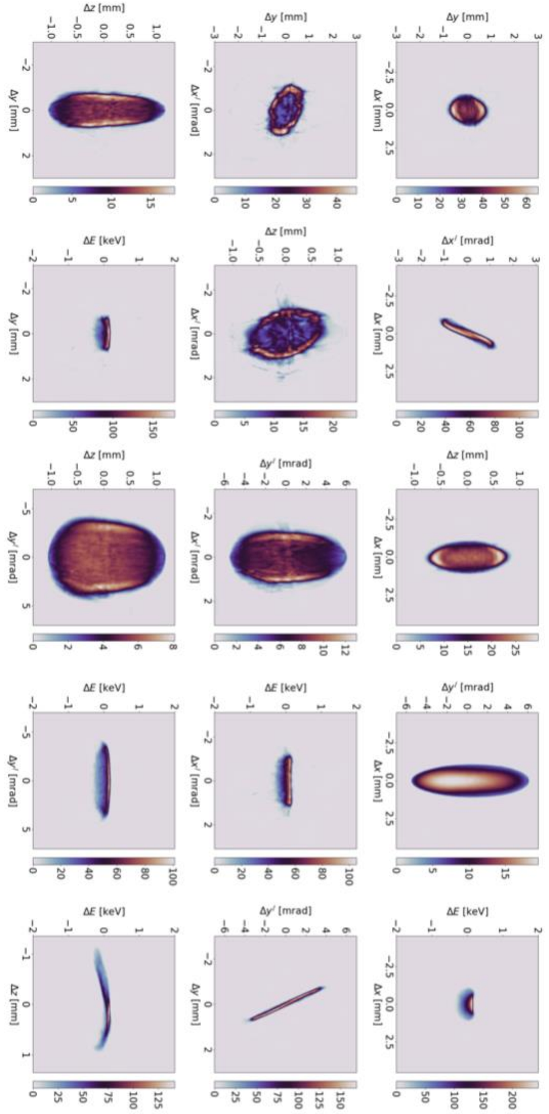
True



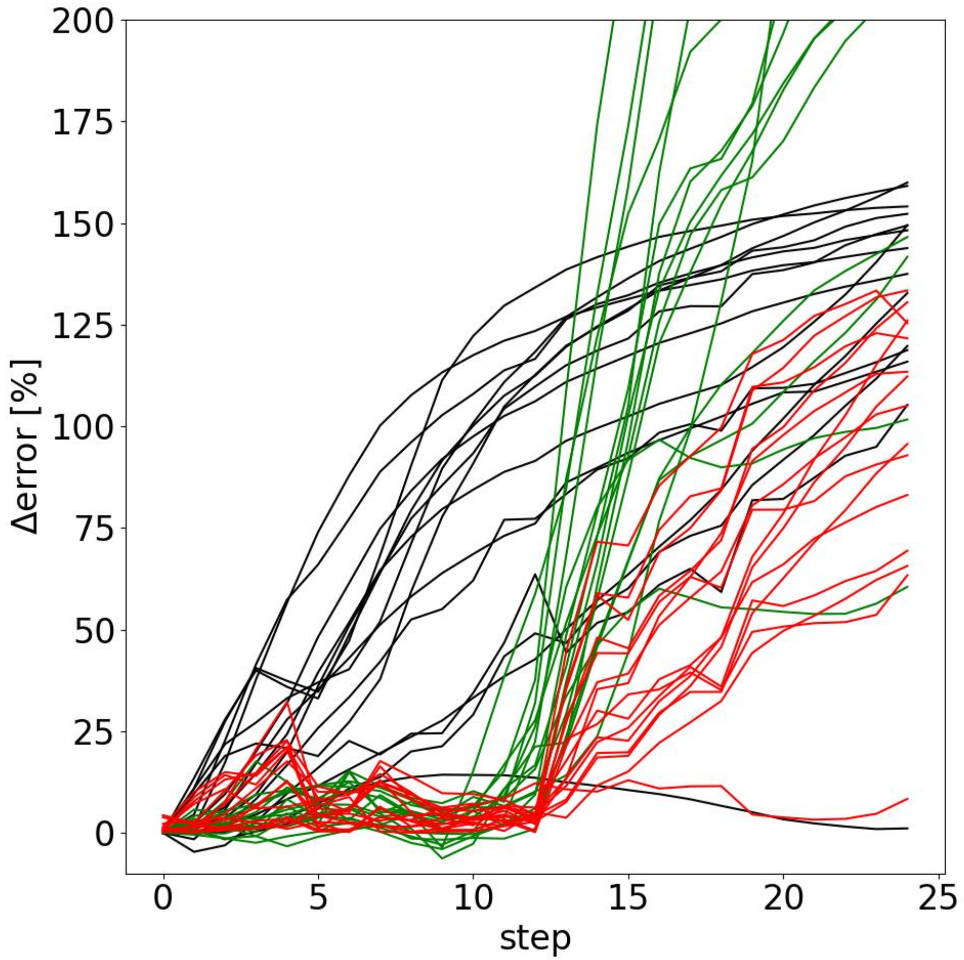
CNN using known beam distribution, solenoid, and charge as inputs



AML with adaptive feedback and unknown beam distribution, solenoid, and charge.



Showing the errors [%] of 15 projections of the 6D phase space as the input beam distribution, solenoid current and bunch charge leave the span of the training set .



Change: % difference of the 15 projections relative to initial input and parameter settings as the beam changes.

CNN: % difference of the 15 projections if the input beam and parameter settings are known. The error remains small within the span of the training set and then the CNN catastrophically fails as the training set is left behind (it is actually worse than doing nothing), as expected.

AML: % error of the 15 projections if the input beam and parameter settings are unknown, but adaptive ML is used for active feedback based on (z,E) measurements, resulting in higher accuracy tracking and <u>no catastrophic failure</u> with this robust approach.