6D Phase Space Diagnostics Based on Adaptive Tuning of the Latent Space of Encoder-Decoder Convolutional Neural Networks

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Funding

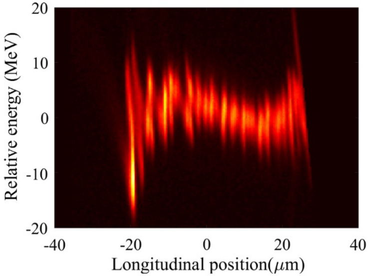
Los Alamos National Laboratory
Laboratory Directed Research and Development (LDRD)
Directed Research (DR) Project
20220074DR Charged Particle Beam Control and Diagnostics using Adaptive Machine Learning

Department of Energy, Office of Science, High Energy Physics
Accelerator Stewardship, LAB 20-2262
Advanced Adaptive Control Systems for Compact Particle Accelerators

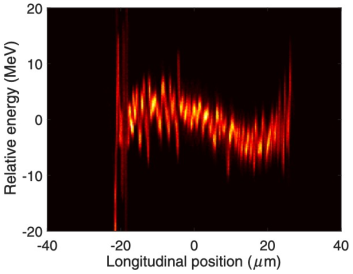
Motivation: Initial beam distributions are time-varying and beam dynamics are governed by complex collective effects such as wakefields, space charge, and coherent synchrotron radiation

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

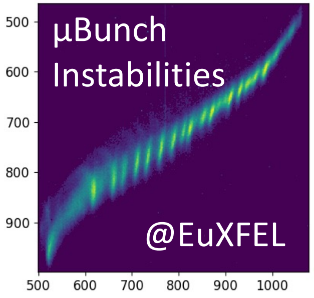
J. Qiang et al. PRAB, 20, 054402, 2017

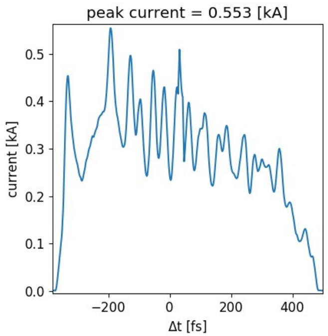


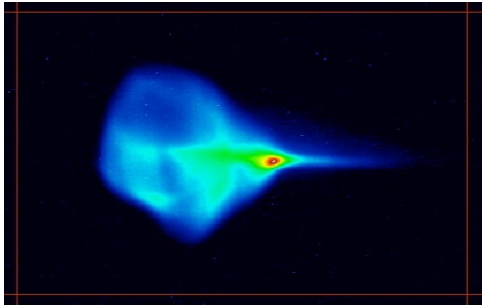
(a) measurement



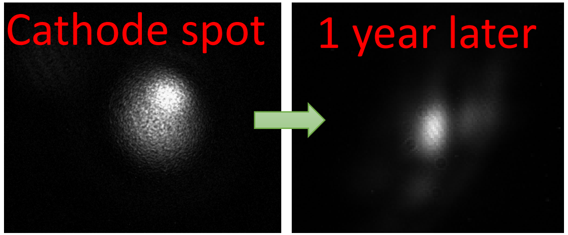
(b) simulation







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

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

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

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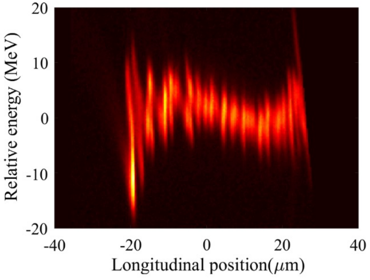

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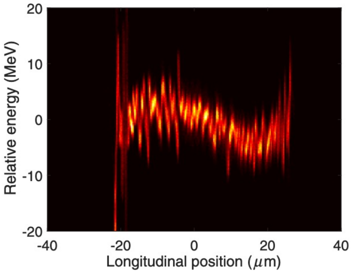
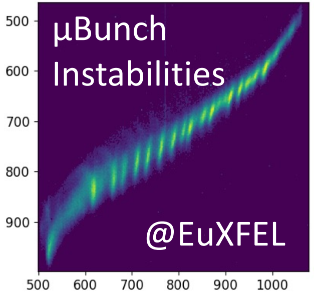
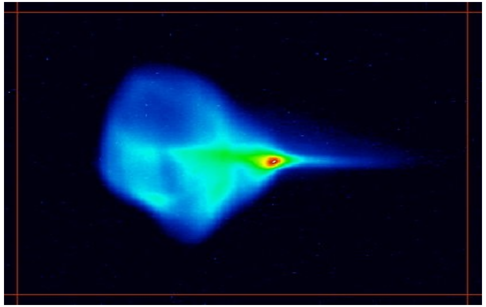


(b) simulation





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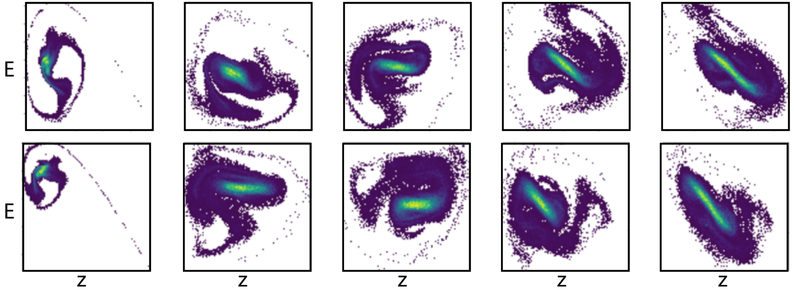
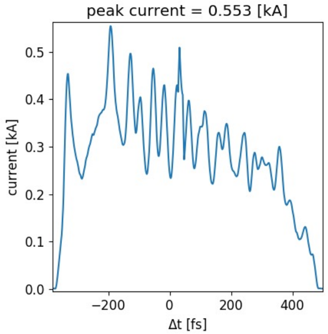
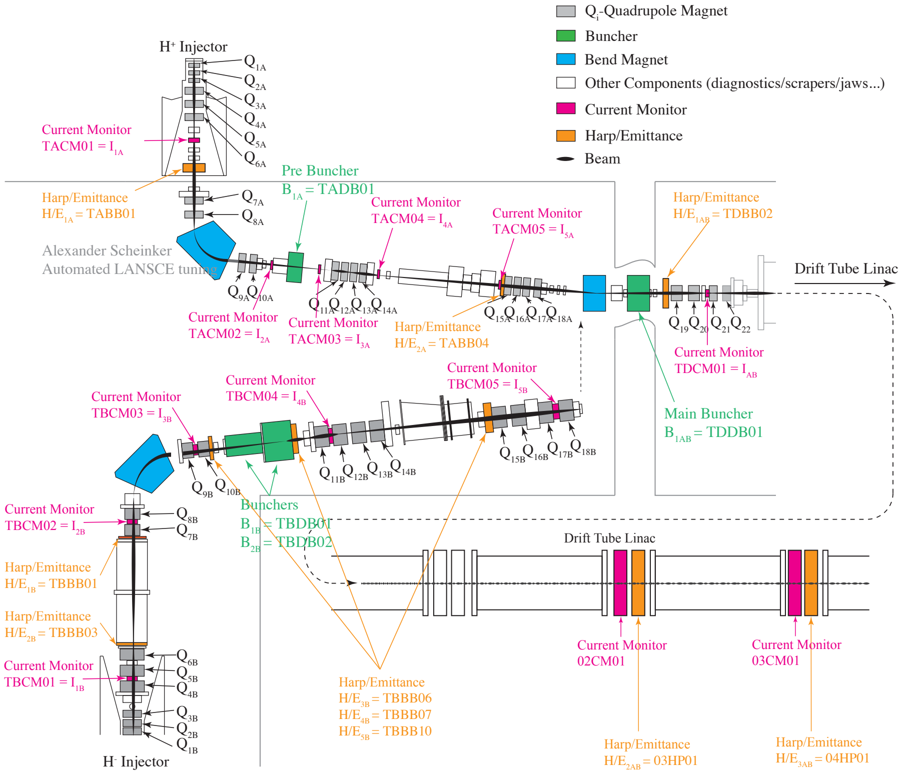


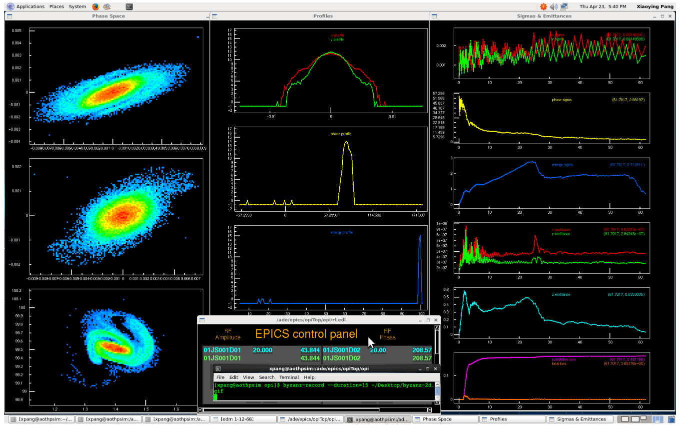
LANSCE: Space Charge

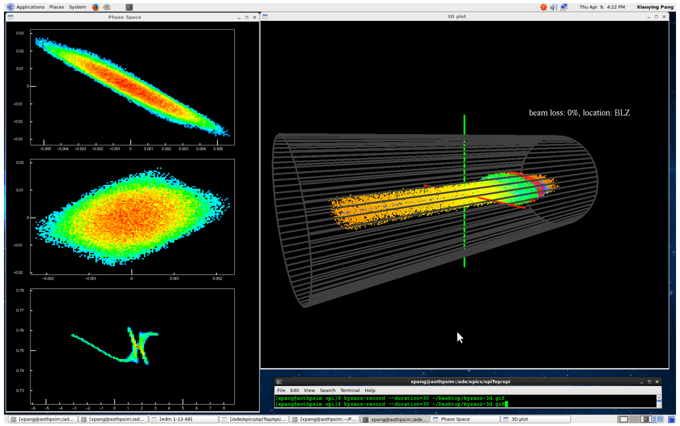


Bunch compression amplifies small time-varying perturbations in initial beam distributions.

Even for fast simulations, correct initial conditions are unknown

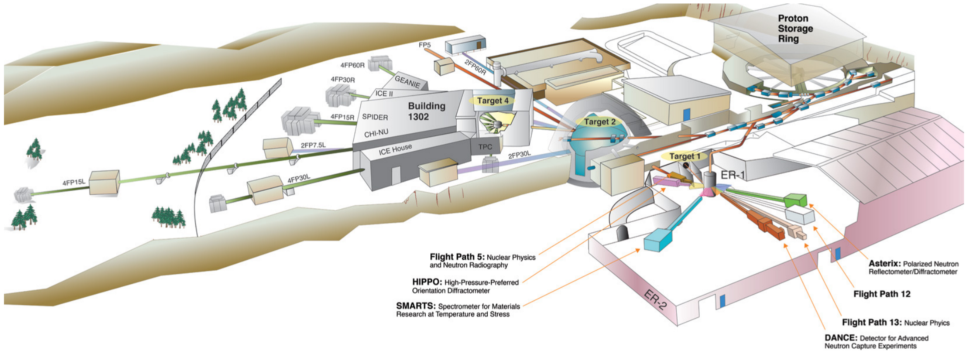


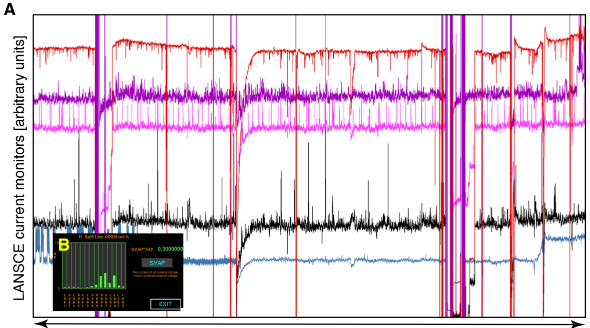




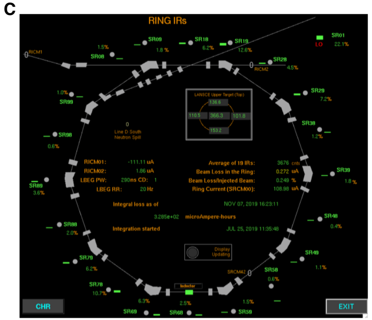
LANSCE

~5-6 weeks of tune up time, performance drifts

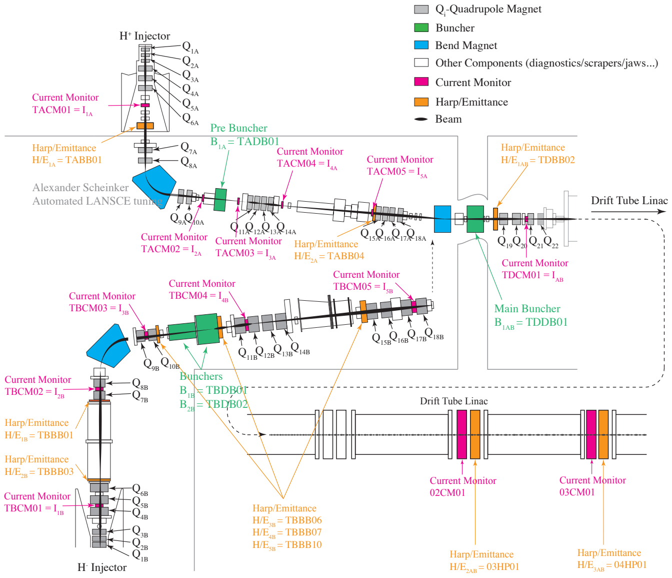




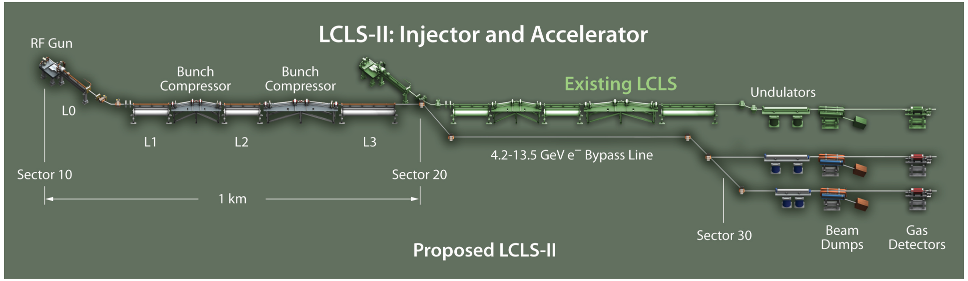
12 hours without changing accelerator parameters



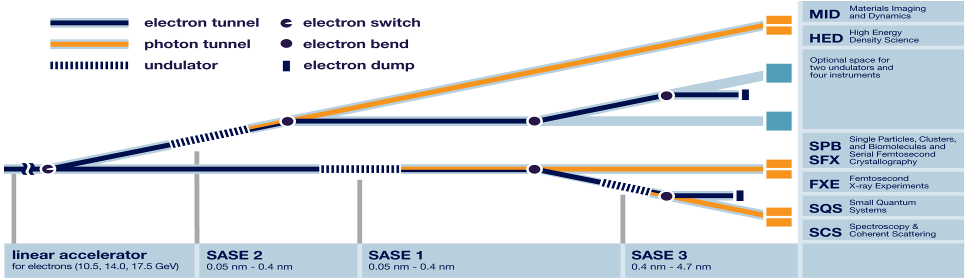
proton storage ring loss monitors



Advanced Light Sources: LCLS-I/II, EuXFEL, … DMMSC



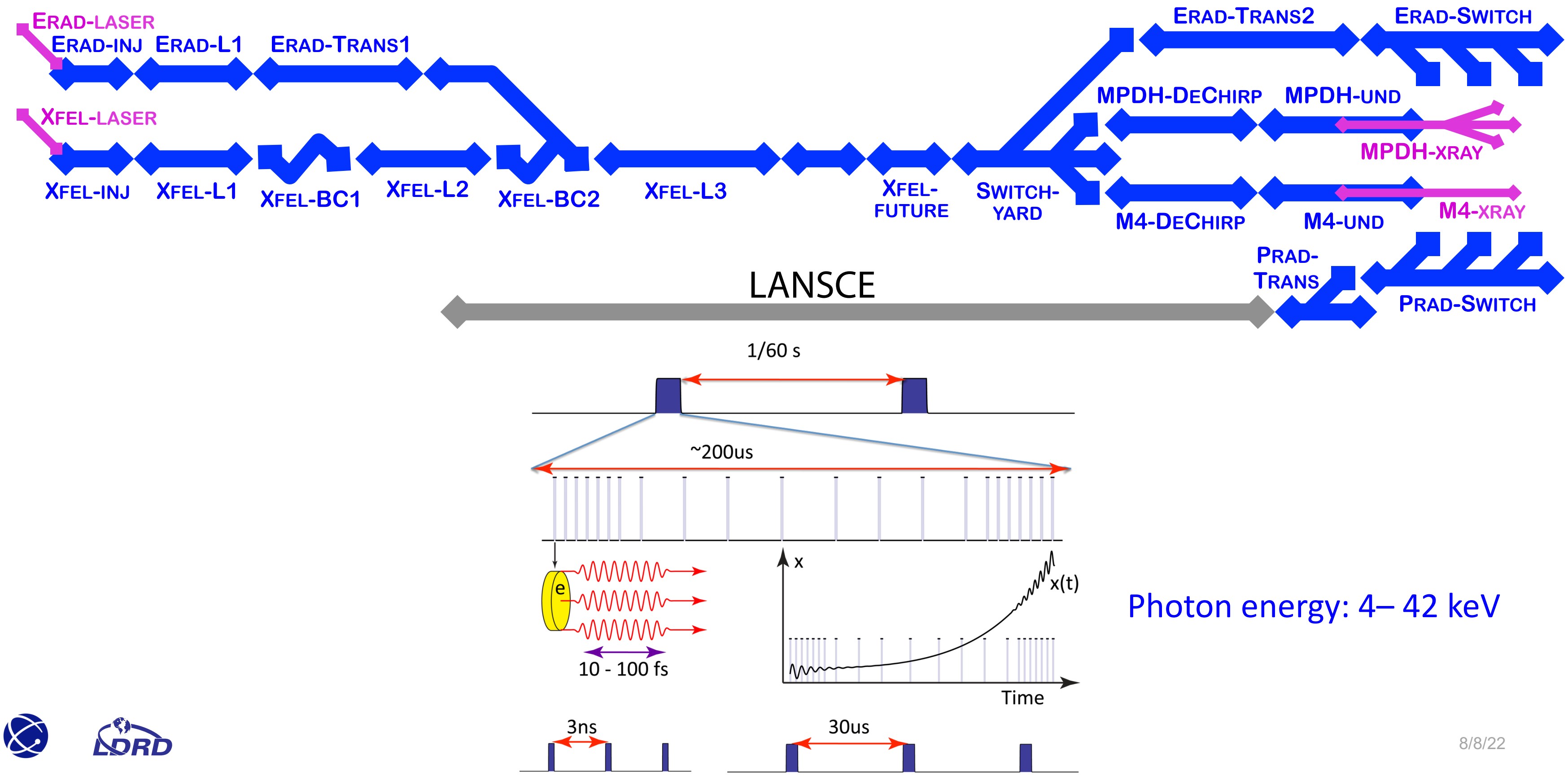
LCLS/LCLS-II



EuXFEL

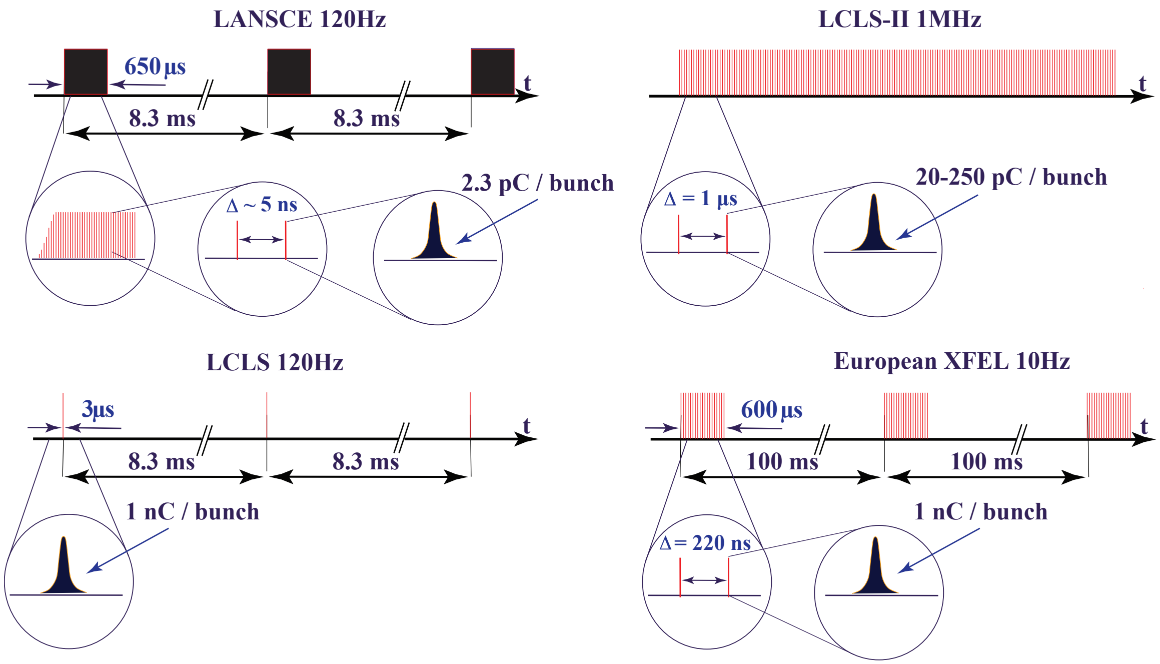
LCLS 2015: > 400 hours were spent in dedicated tuning ~10 user experiments and a $12M USD value in operation time.

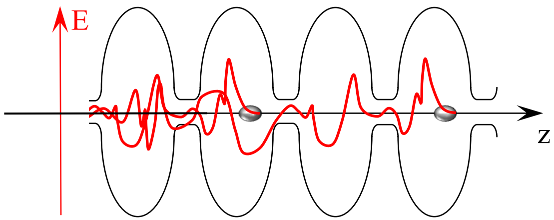
MaRIE for Dynamic Mesoscale Material Science Capability (DMMSC)



Photon energy: 4– 42 keV

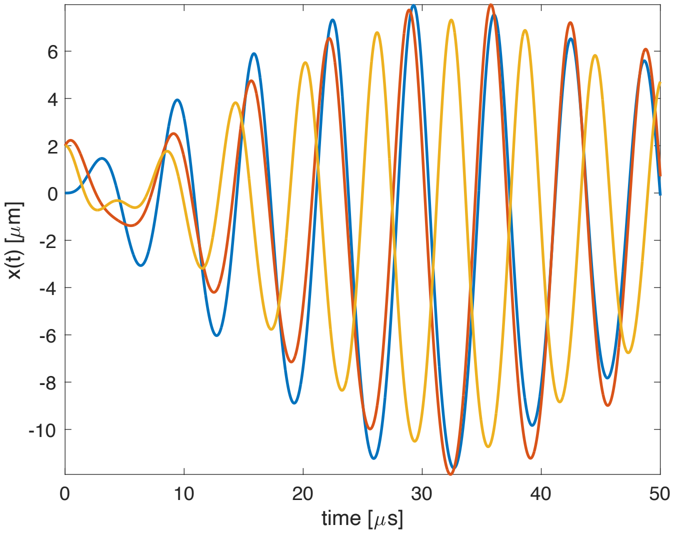
Advanced Accelerator Capabilities (DMMSC/MaRIE)



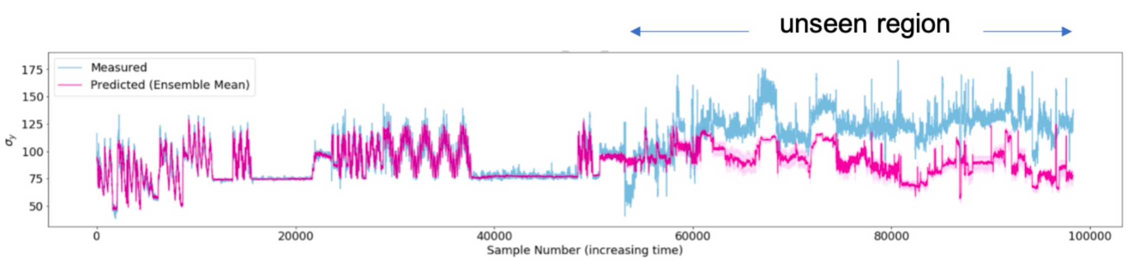


Need for new Robust Machine Learning Techniques for Time-Varying Systems (Distribution Shift).

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

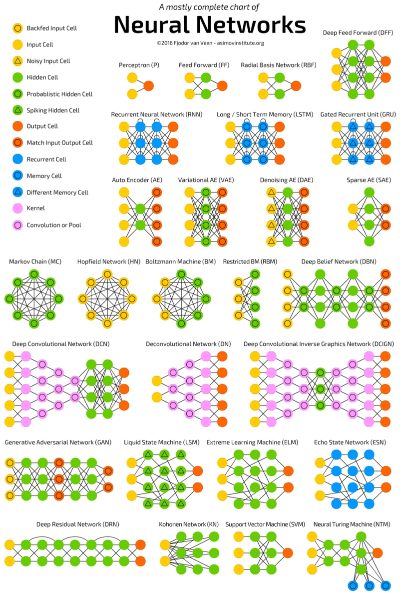


Neural network predicting σ_y beam size.



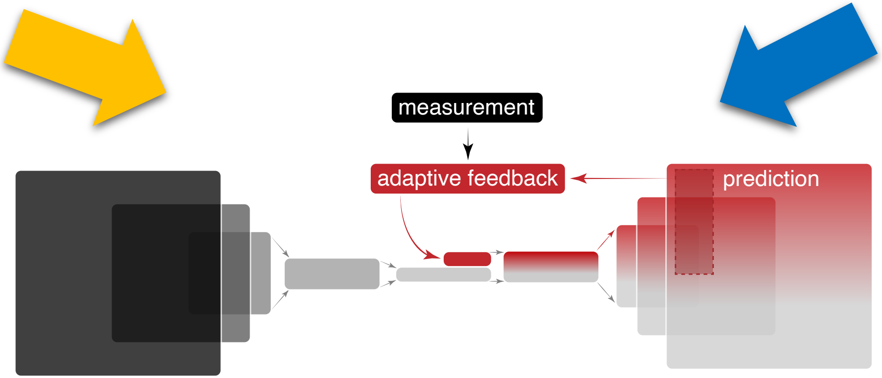
Approach: Adaptive ML combines robust model-independent adaptive feedback with deep physics-informed CNNs.

Machine Learning

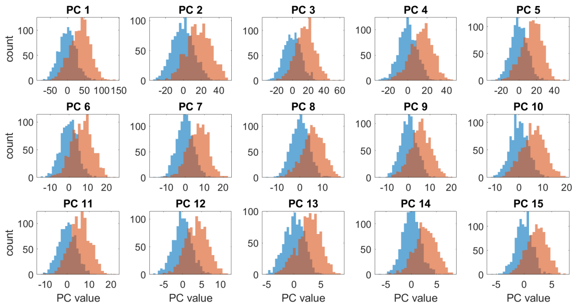


- Deep RL
- Global learning
- Cannot handle time-varying systems

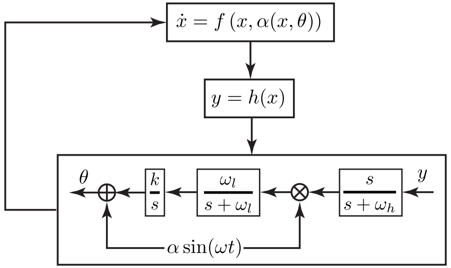
Robust Adaptive Machine Learning

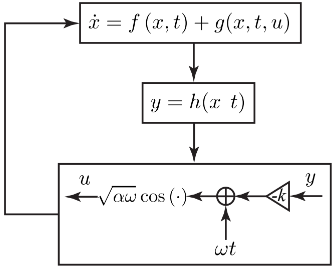


For Time-Varying systems with distribution shift



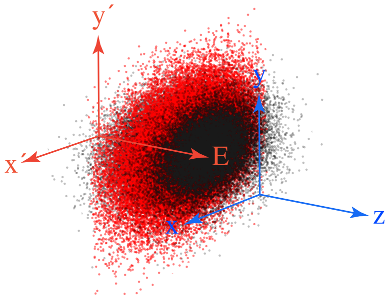
Model—Independent Feedback





- Adaptive Control
- 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

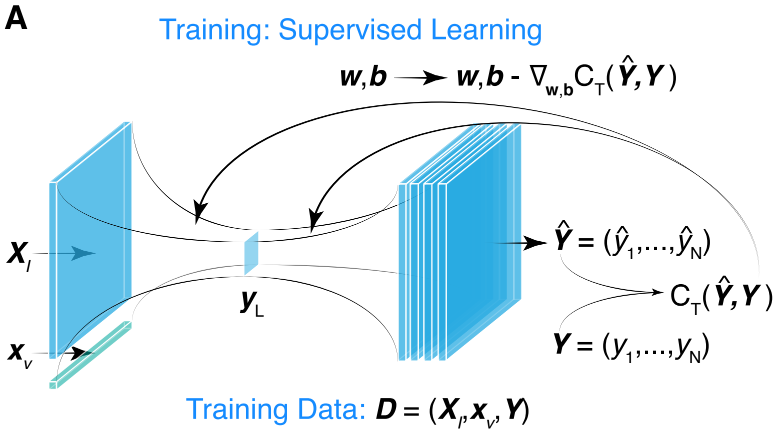
$(x, y), (x, z), (x, x'), (x, y'), (x, E)$

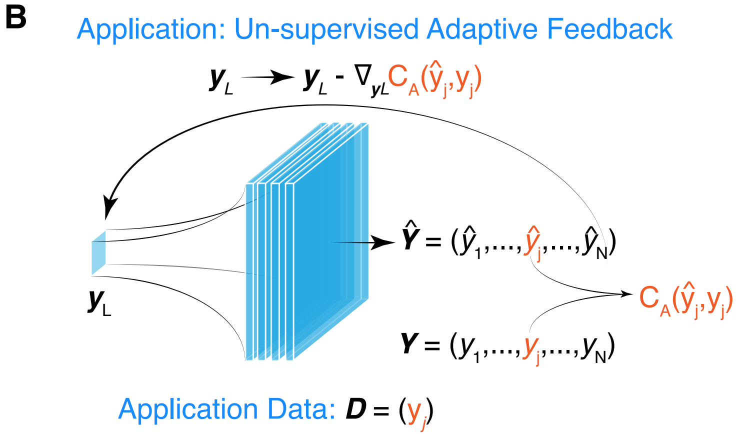
$(x', y), (x', z), (x', y'), (x', E)$

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

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

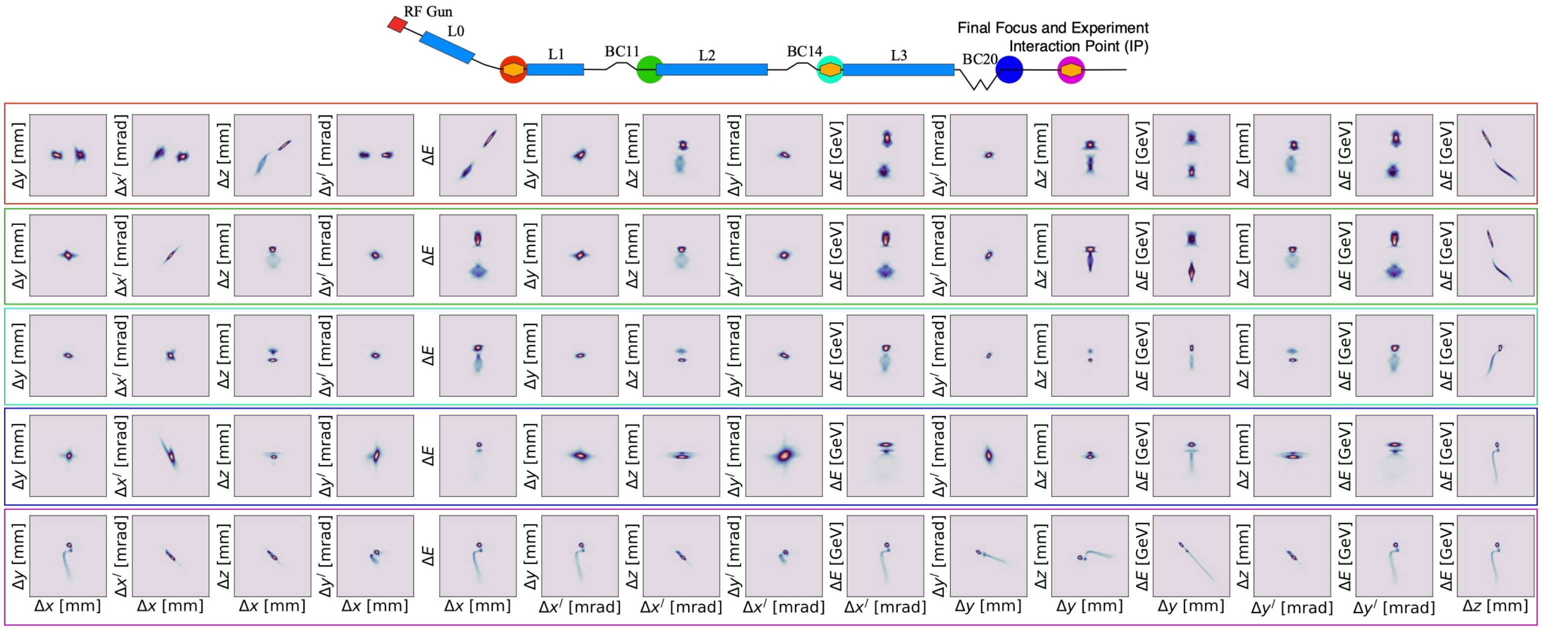
(z, E)



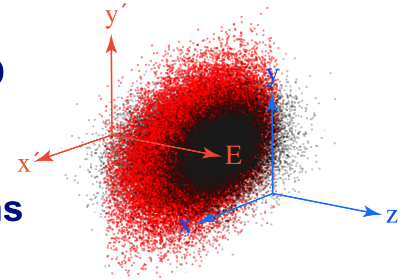


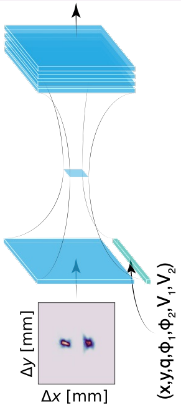
A. Scheinker. "Adaptive machine learning for time-varying systems: low dimensional latent space tuning." *Journal of Instrumentation* 16.10 (2021): P10008.

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



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





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

2D projections

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

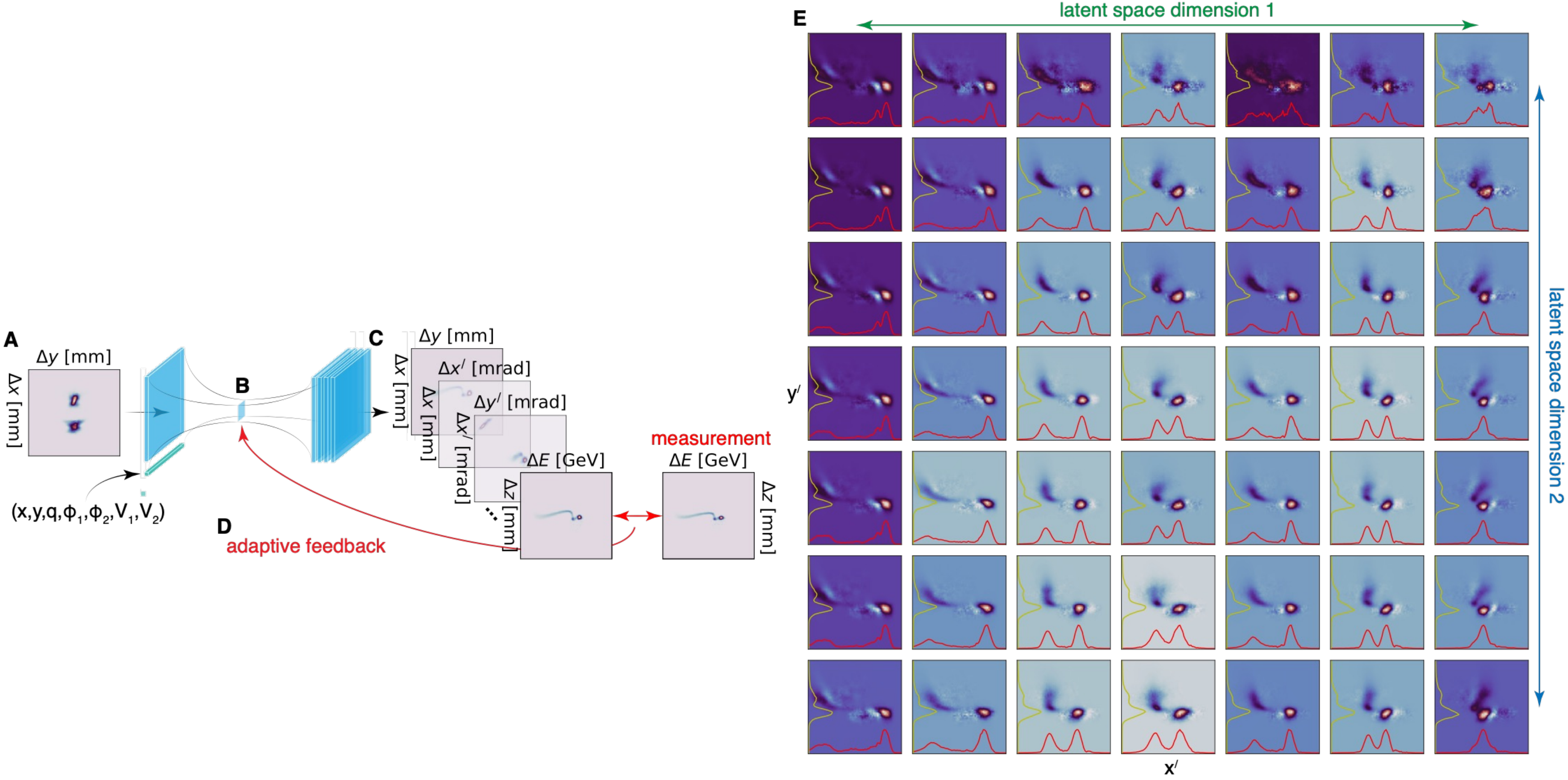
$(x', y), (x', z), (x', y'), (x', E)$

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

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

(z, E)

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



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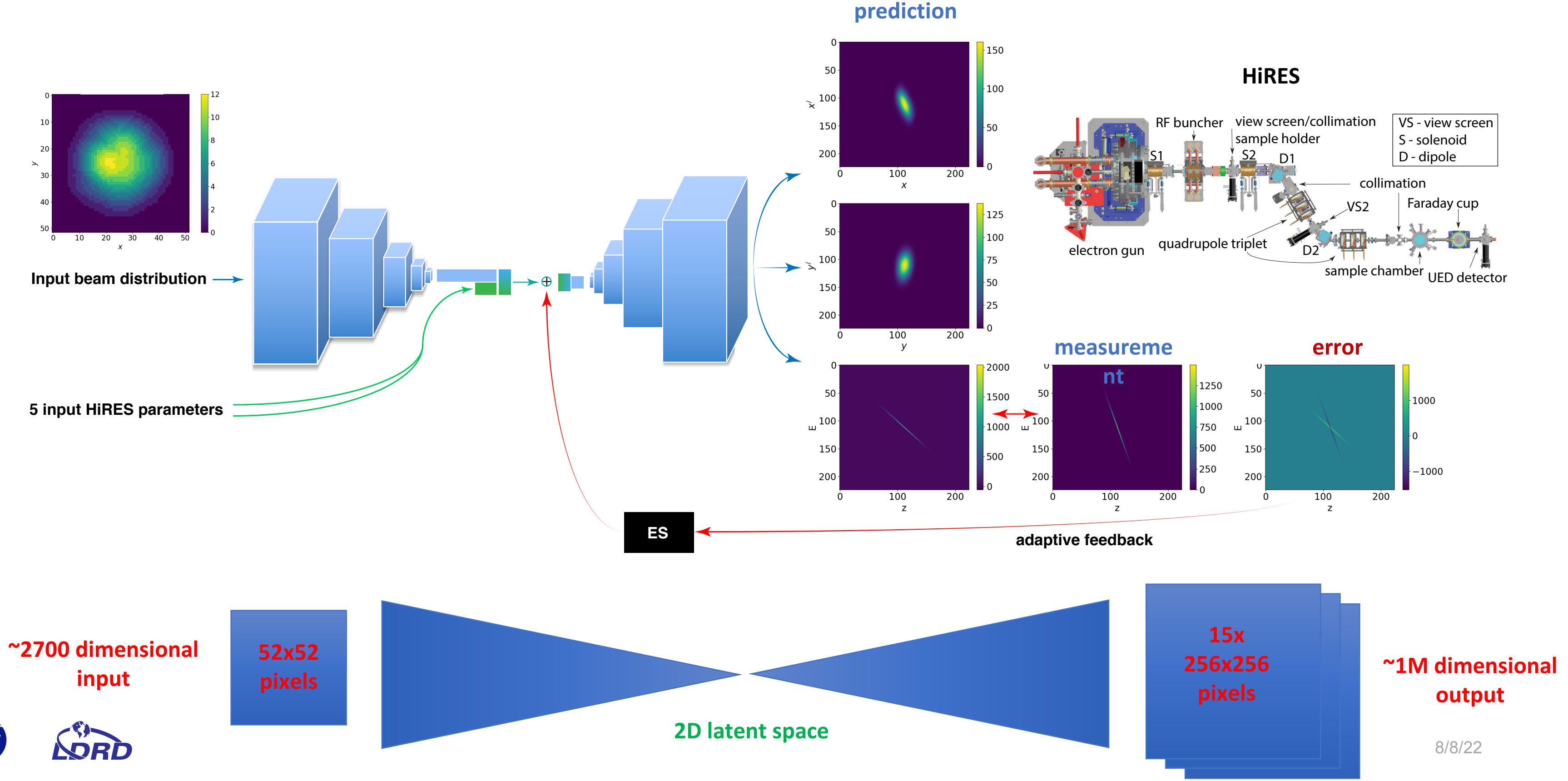
https://doi.org/10.1088/1748-0221/16/10/P10008

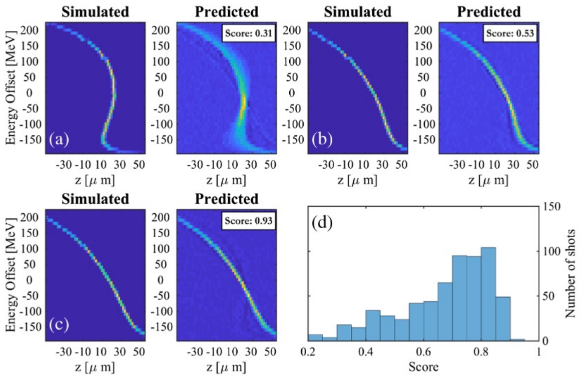
AML Development at HiRES – Compact Ultra-fast Electron Diffraction (UED)

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.

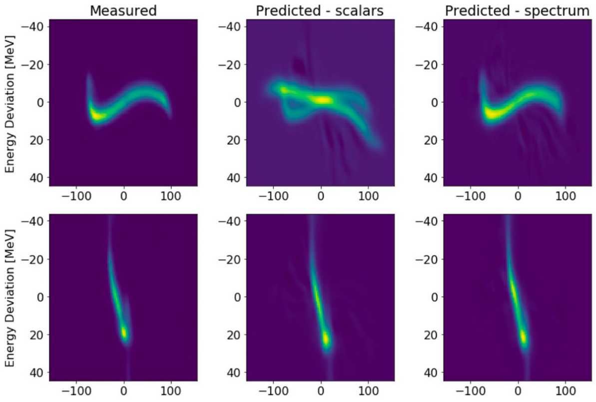


Adaptive, ML, and direct LPS measurements are widely available

LCLS, LCLS-II, FACET-II

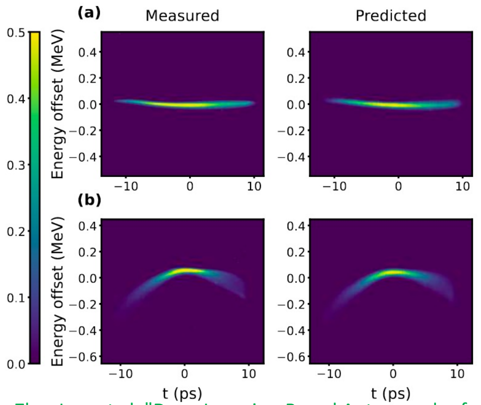


Emma, C., et al. "Machine learning-based longitudinal phase space prediction of particle accelerators." *Physical Review Accelerators and Beams* 21.11 (2018): 112802.

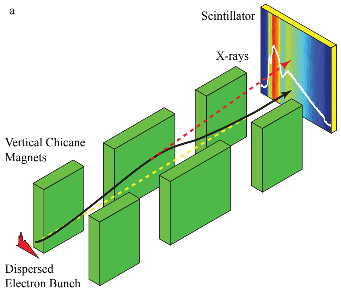


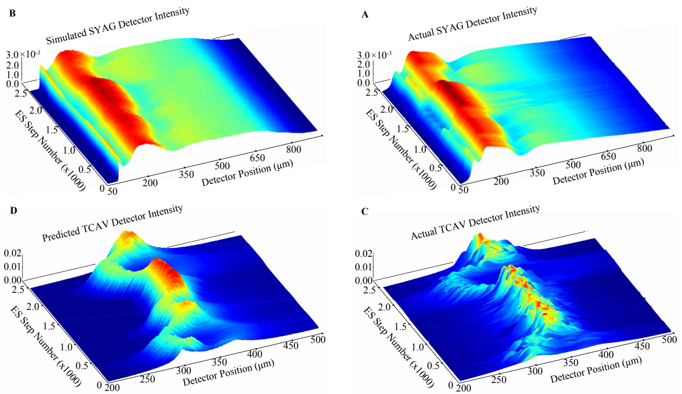
Hanuka, Adi, et al. "Accurate and confident prediction of electron beam longitudinal properties using spectral virtual diagnostics." *Scientific Reports* 11.1 (2021): 1-10.

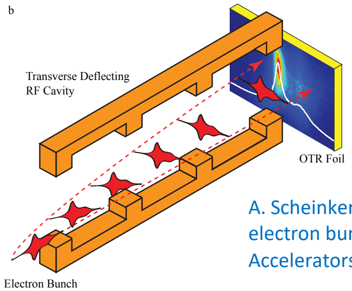
EuXFEL



Zhu, Jun, et al. "Deep Learning-Based Autoencoder for Data-Driven Modeling of an RF Photoinjector." *arXiv preprint arXiv:2101.10437* (2021).





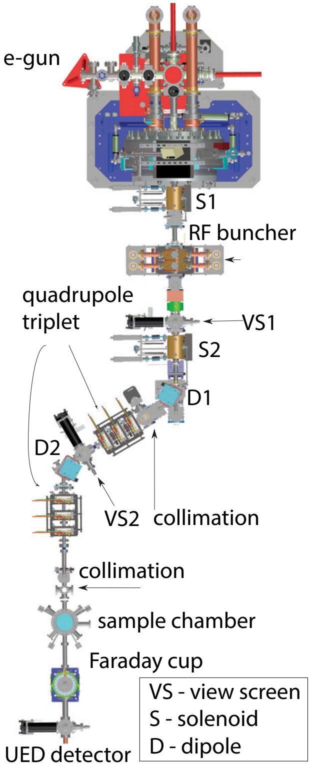


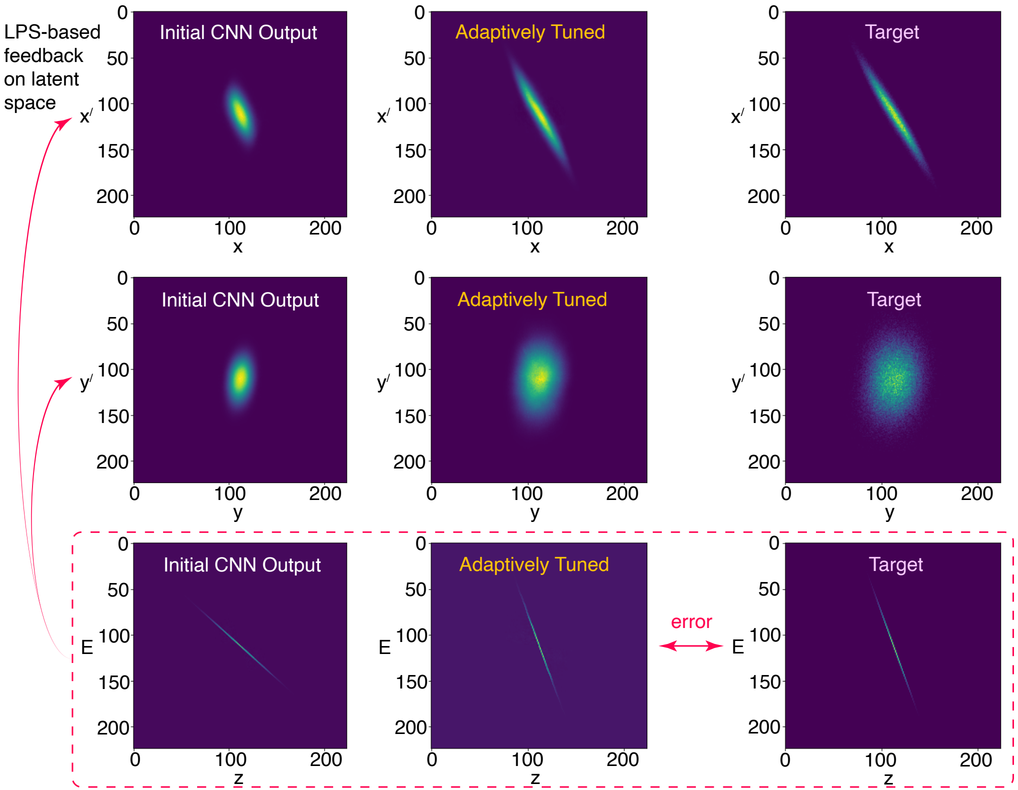
FACET

A. Scheinker and S. Gessner, "Adaptive method for electron bunch profile prediction." Physical Review Accelerators and Beams, 18(10), 102801, 2015.

Adaptive ML-Based Diagnostics @ HiRES

Work with: Eric Cropp and Daniele Filippetto





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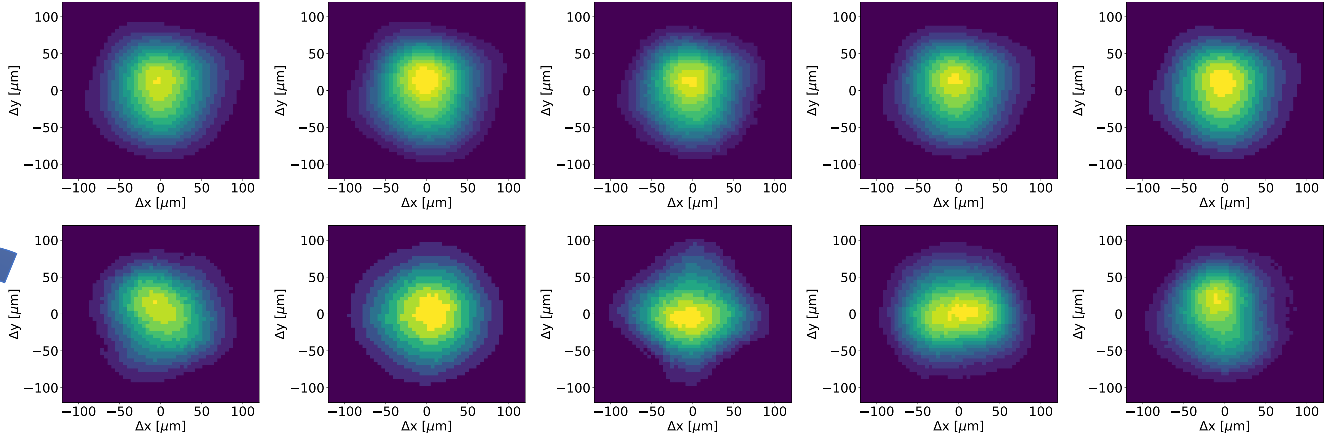
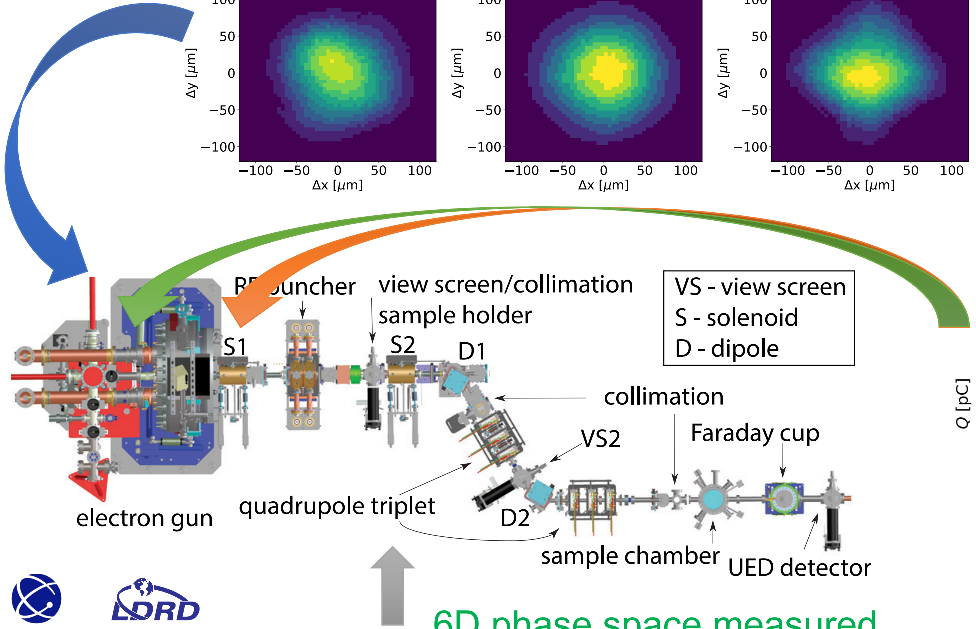
https://doi.org/10.1088/1748-0221/16/10/P10008

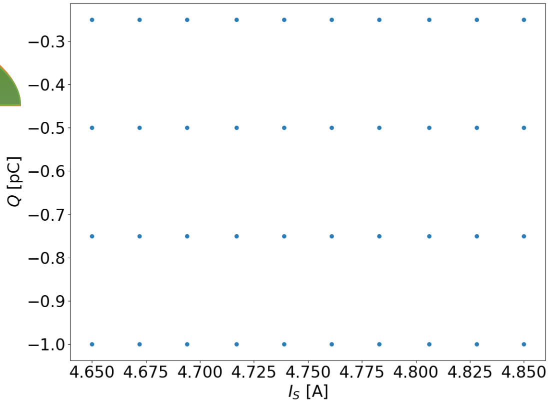
HiRES Numerical Study – AML for 6D Phase Space

Trained with Measured and Synthetic Input Images



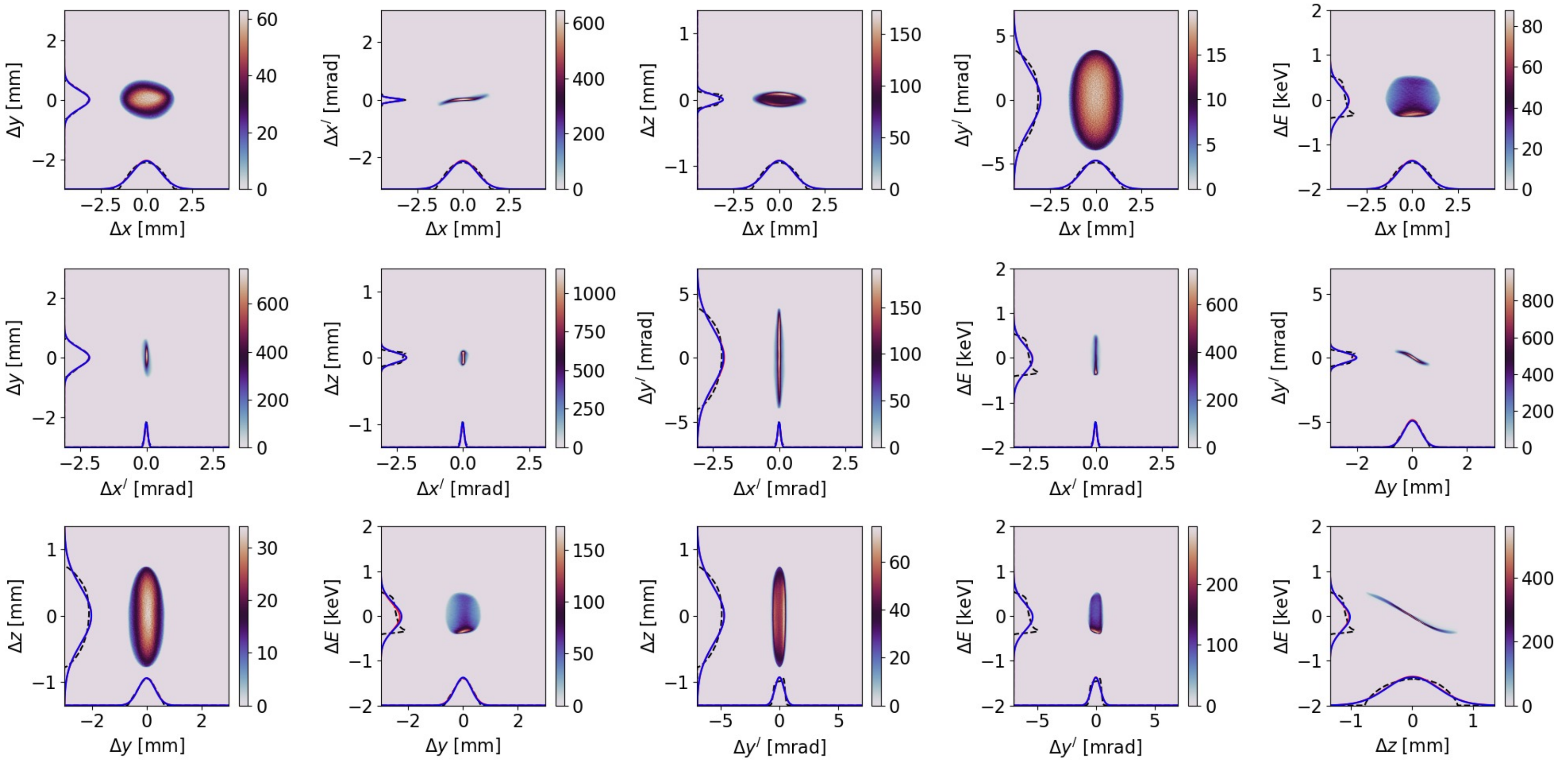


6D phase space measured

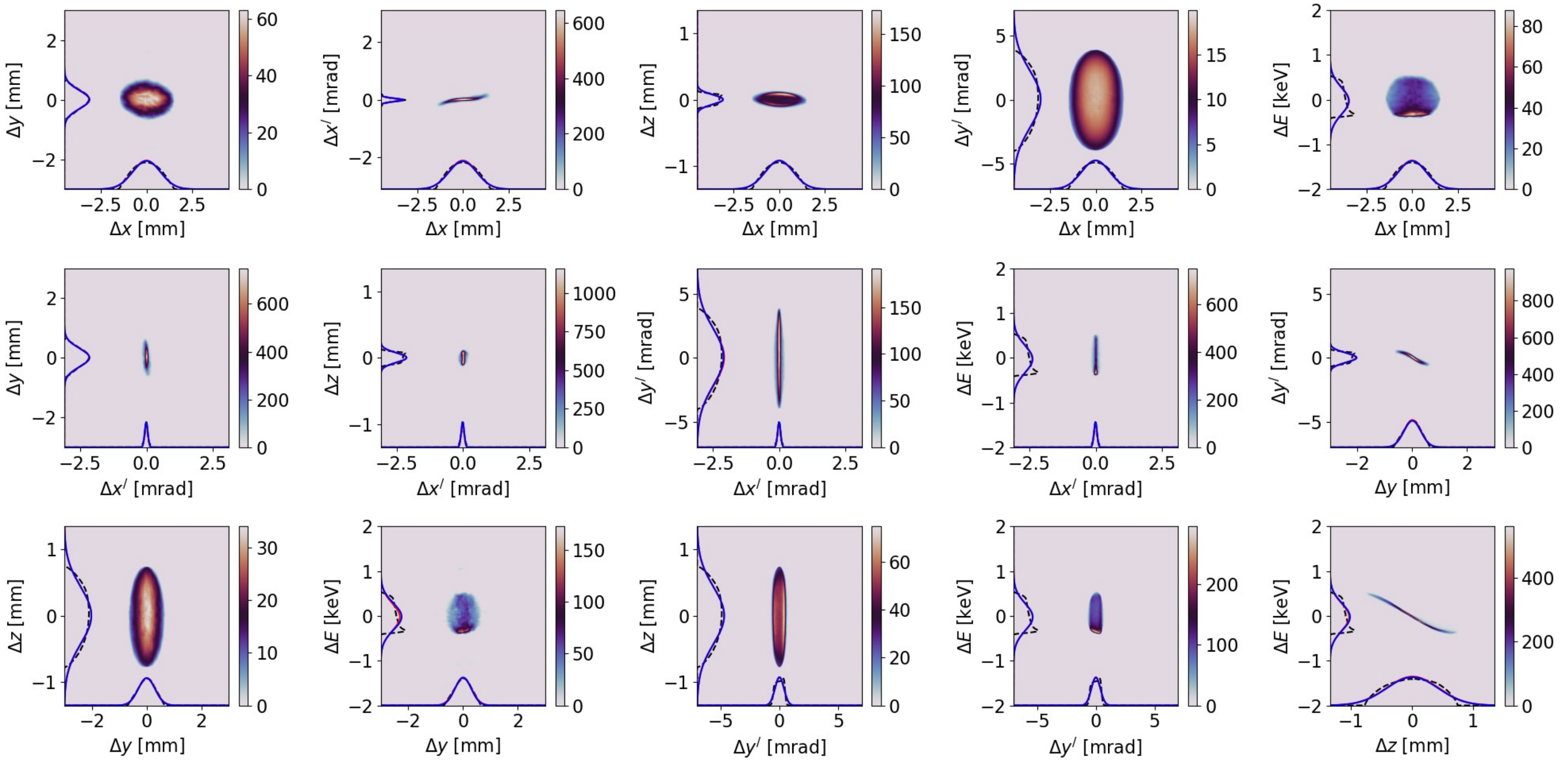


Each image simulated over a grid of 4 bunch charges and 10 solenoid currents

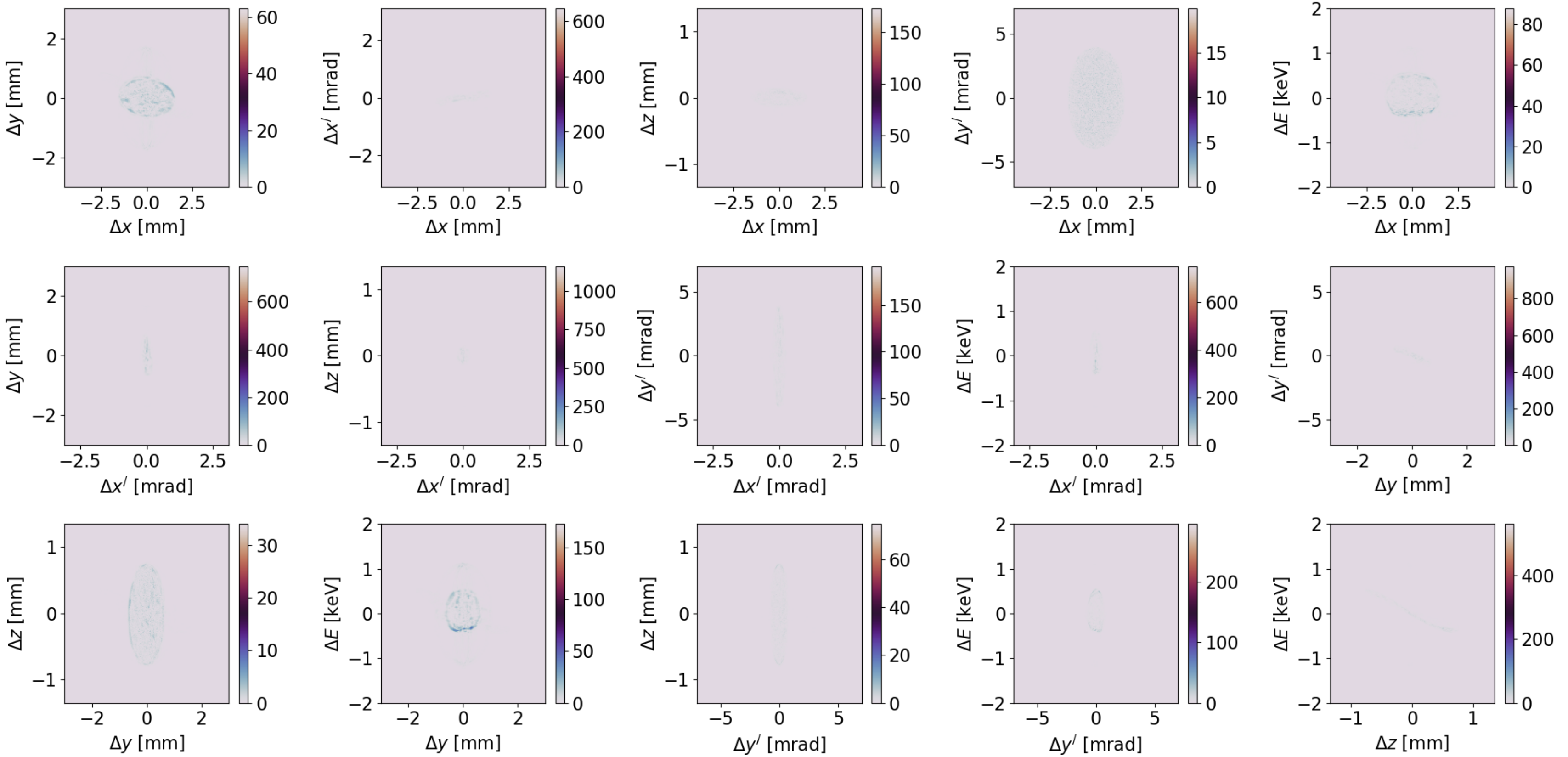
15 projections of 6D phase space @ Q=0.25 pC, S=4.650 Amps



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



Difference



Δy [mm]
2
0
−2
−2.5 0.0 2.5
Δx [mm]
60
40
20
0
Δx′ [mrad]
2
0
−2
−2.5 0.0 2.5
Δx [mm]
600
400
200
0
Δz [mm]
1
0
−1
−2.5 0.0 2.5
Δx [mm]
150
100
50
0
Δy′ [mrad]
5
0
−5
−2.5 0.0 2.5
Δx [mm]
15
10
5
0
ΔE [keV]
2
1
0
−1
−2
−2.5 0.0 2.5
Δx [mm]
80
60
40
20
0
Δy [mm]
2
0
−2
−2.5 0.0 2.5
Δx′ [mrad]
600
400
200
0
Δz [mm]
1
0
−1
−2.5 0.0 2.5
Δx′ [mrad]
1000
750
500
250
0
Δy′ [mrad]
5
0
−5
−2.5 0.0 2.5
Δx′ [mrad]
150
100
50
0
ΔE [keV]
2
1
0
−1
−2
−2.5 0.0 2.5
Δx′ [mrad]
600
400
200
0
Δy′ [mrad]
5
0
−5
−2 0 2
Δy [mm]
800
600
400
200
0
Δz [mm]
1
0
−1
−2 0 2
Δy [mm]
30
20
10
0
ΔE [keV]
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Δy [mm]
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Δz [mm]
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−1
−5 0 5
Δy′ [mrad]
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20
0
ΔE [keV]
2
1
0
−1
−2
−5 0 5
Δy′ [mrad]
200
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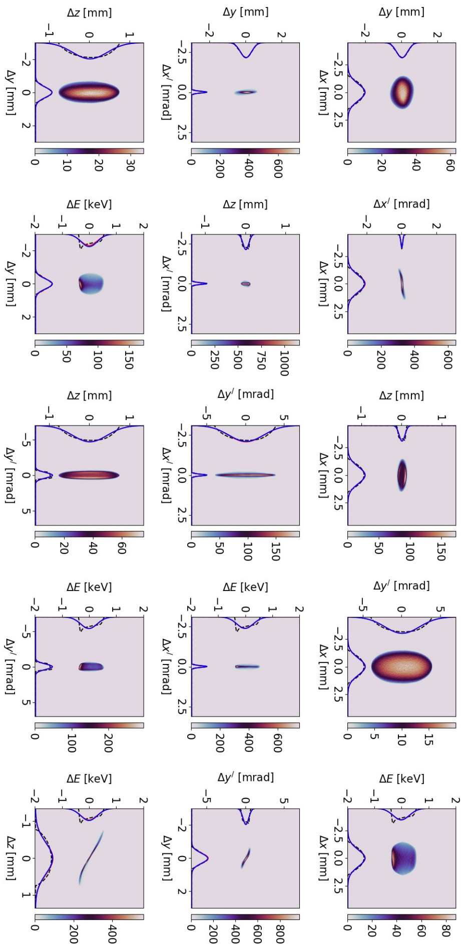
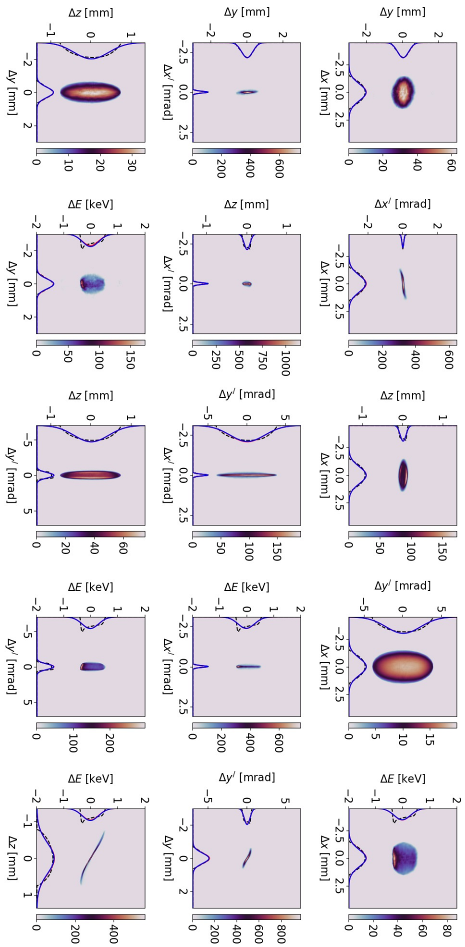
0
ΔE [keV]
2
1
0
−1
−2
−1 0 1
Δz [mm]
400
200
0

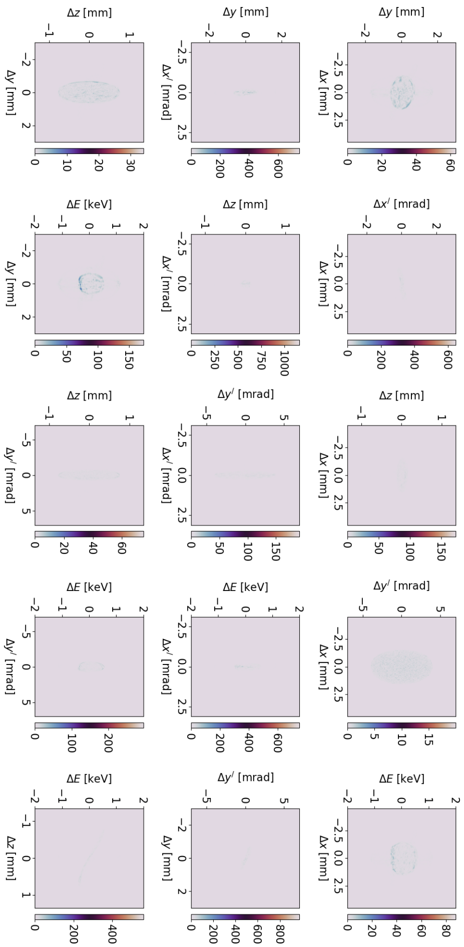
True



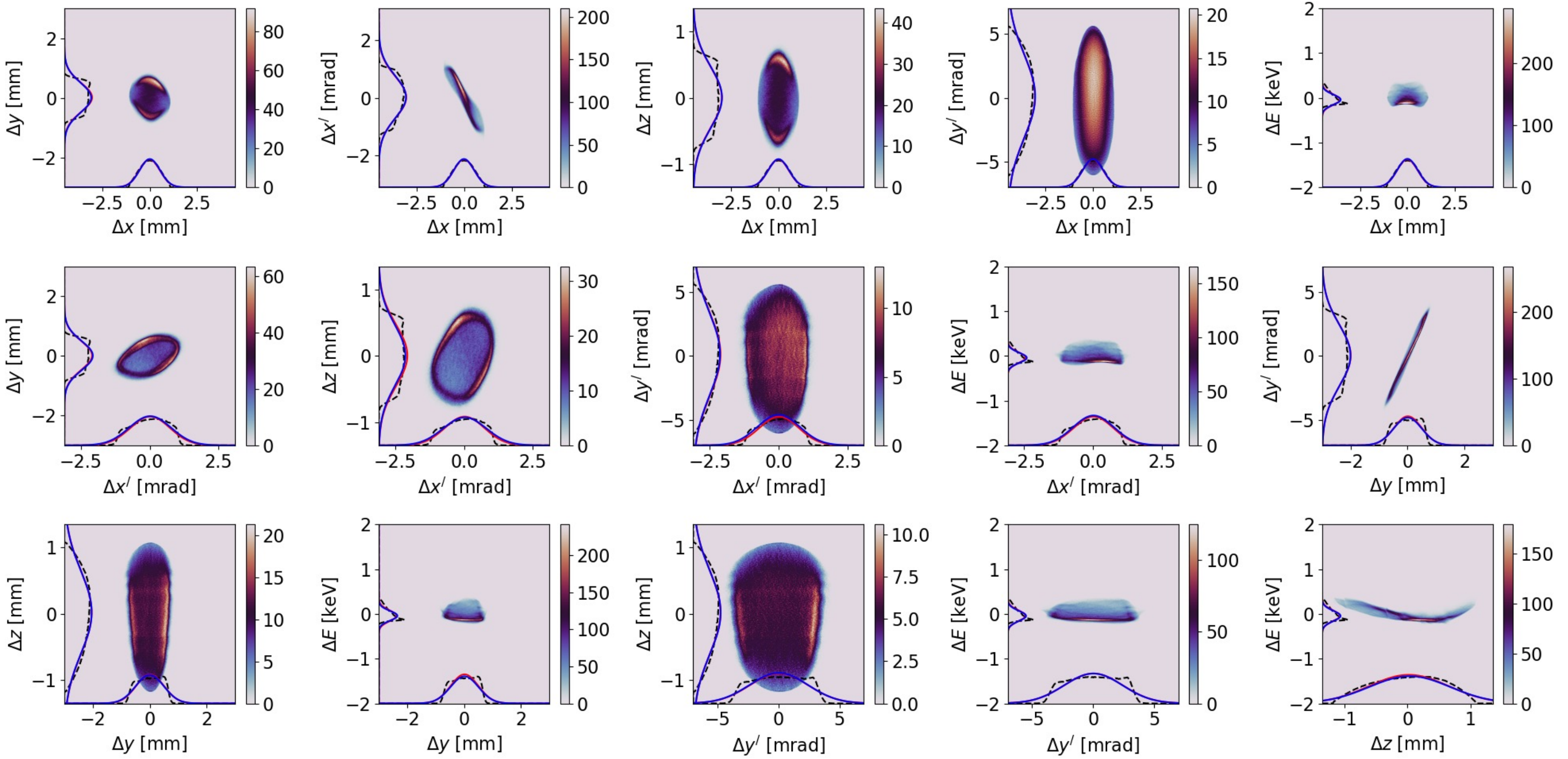
CNN



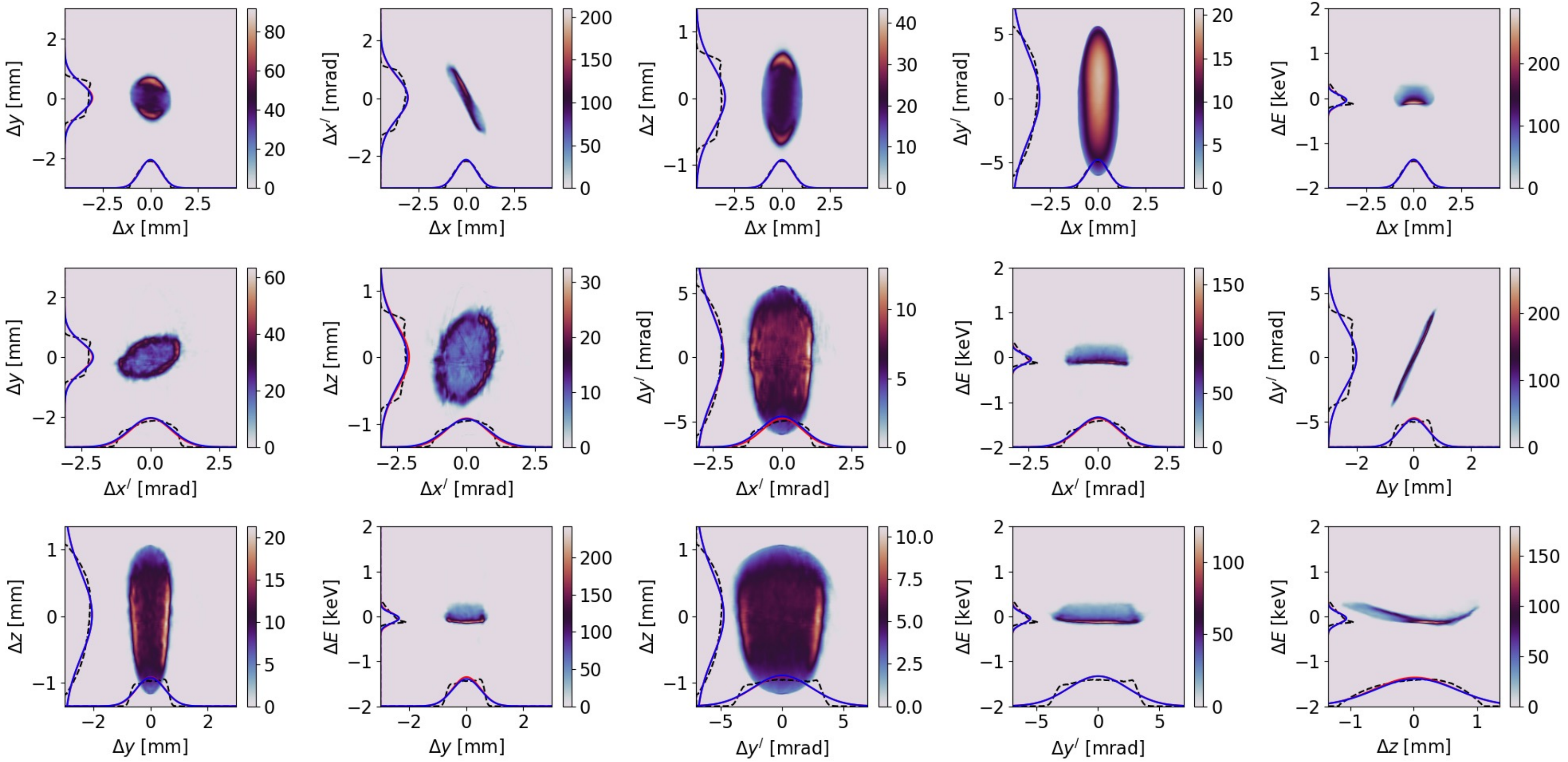
Difference



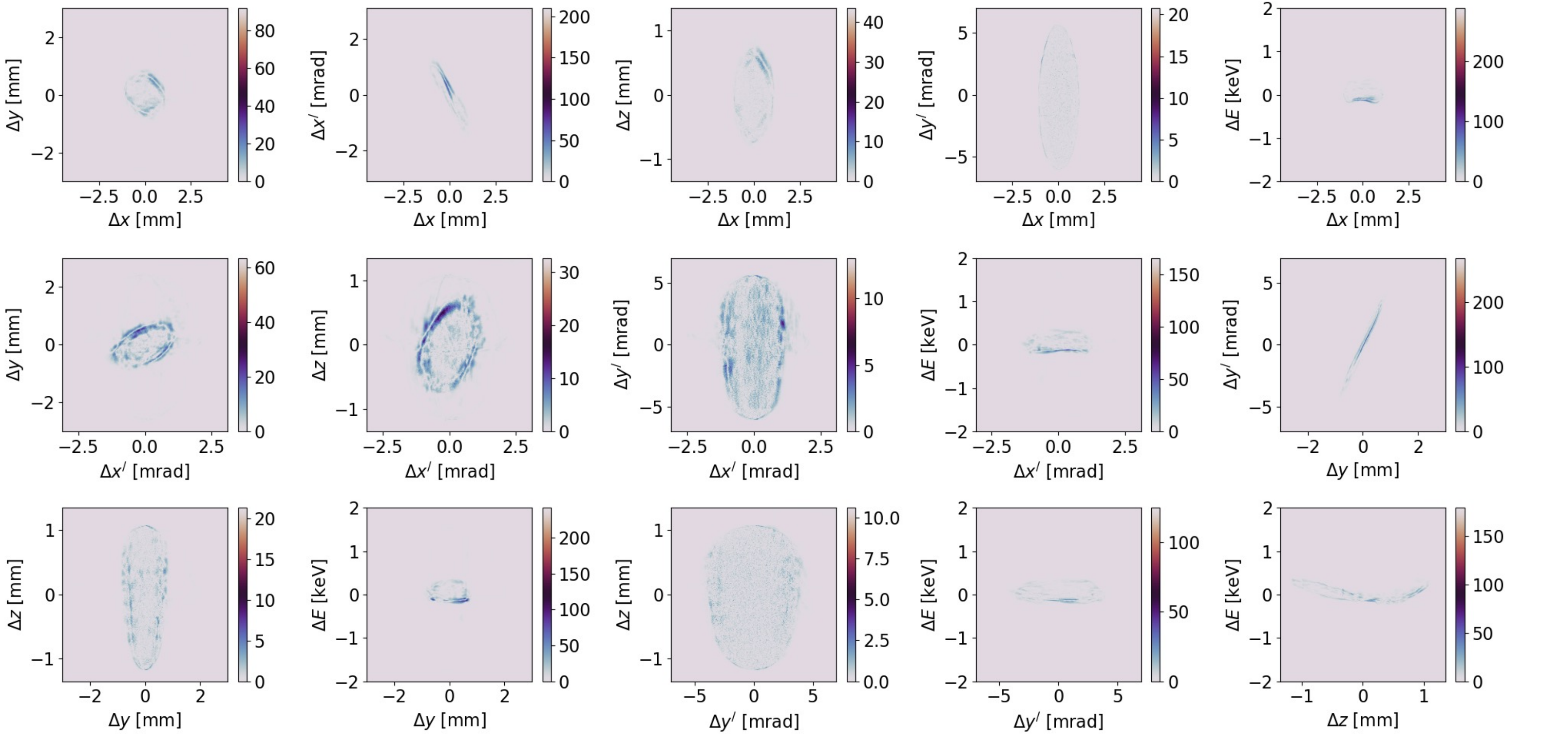
15 projections of 6D phase space @ Q=1.0 pC, S=4.85 Amps



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

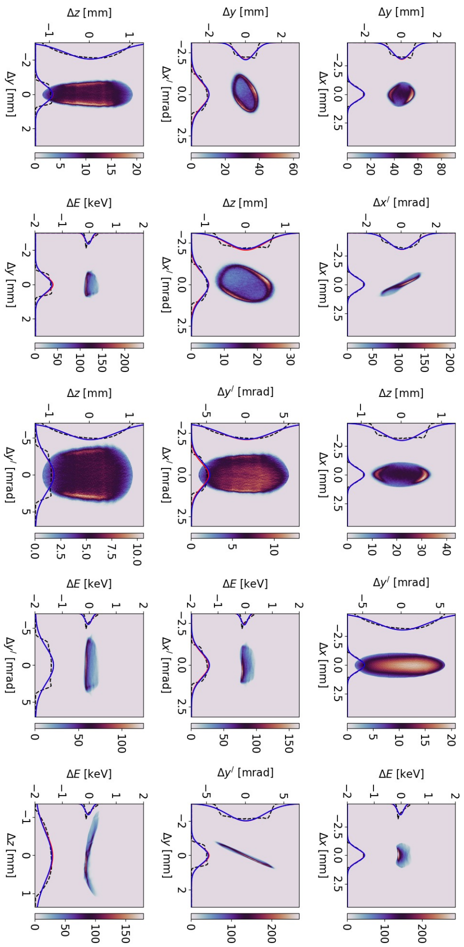


Difference

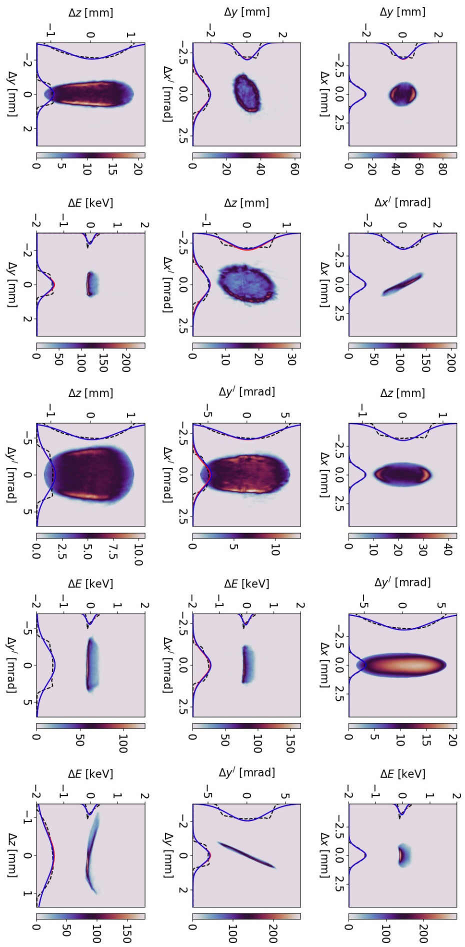


Δy [mm]
Δx [mm]
Δx' [mrad]
Δx [mm]
Δz [mm]
Δx [mm]
Δy' [mrad]
Δx [mm]
ΔE [keV]
Δx [mm]
Δy [mm]
Δx' [mrad]
Δz [mm]
Δx' [mrad]
Δy' [mrad]
Δx' [mrad]
ΔE [keV]
Δx' [mrad]
Δy' [mrad]
Δy [mm]
Δz [mm]
Δy [mm]
ΔE [keV]
Δy [mm]
Δz [mm]
Δy' [mrad]
ΔE [keV]
Δy' [mrad]
ΔE [keV]
Δz [mm]

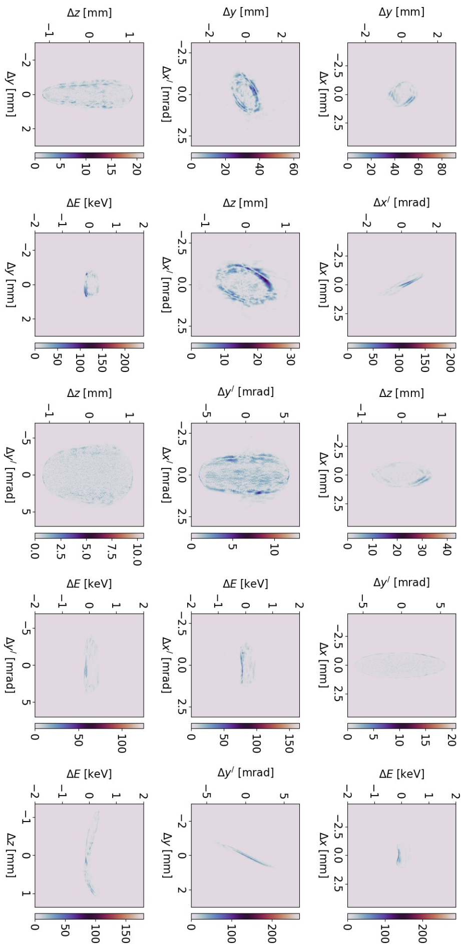
True



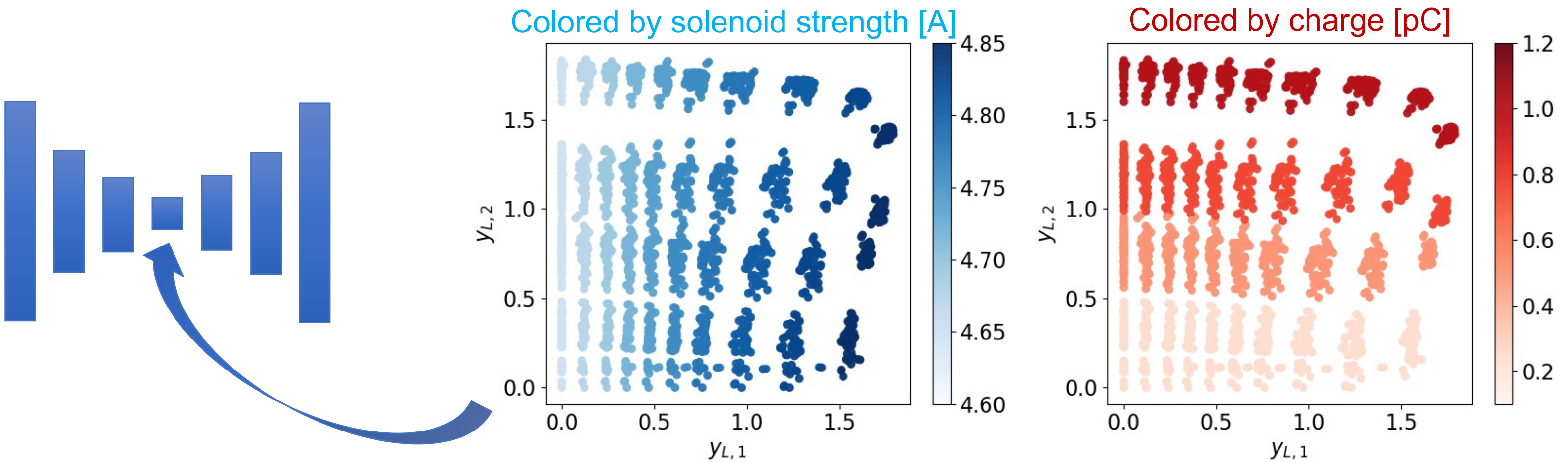
CNN



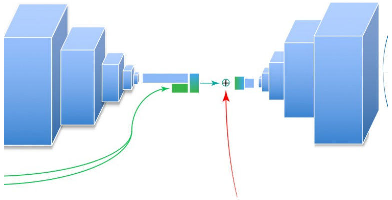
Difference

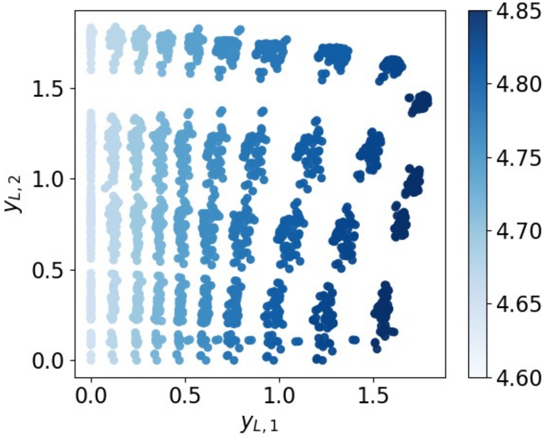


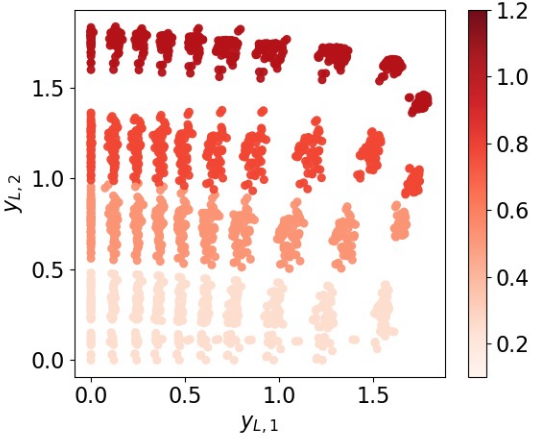
Looking into the CNN's 2D Latent space representation of 100 input beams, we see that it has naturally clustered bunches by solenoid strength and charge.

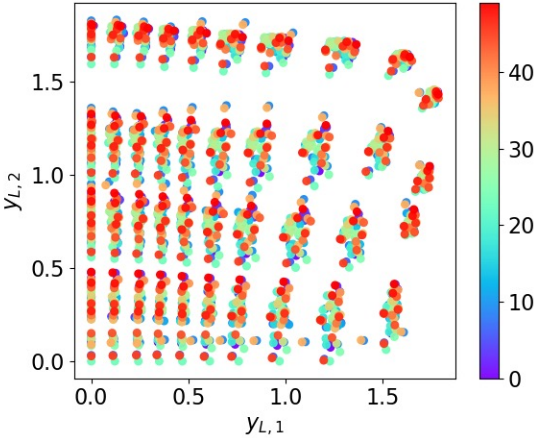


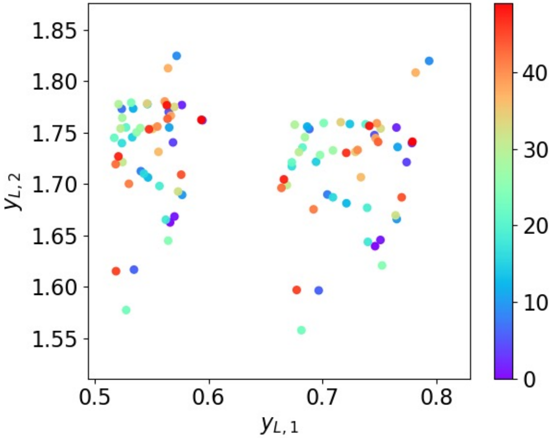
HiRES – Latent space representation

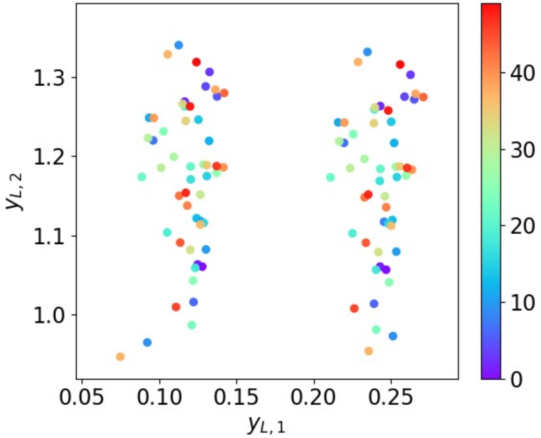




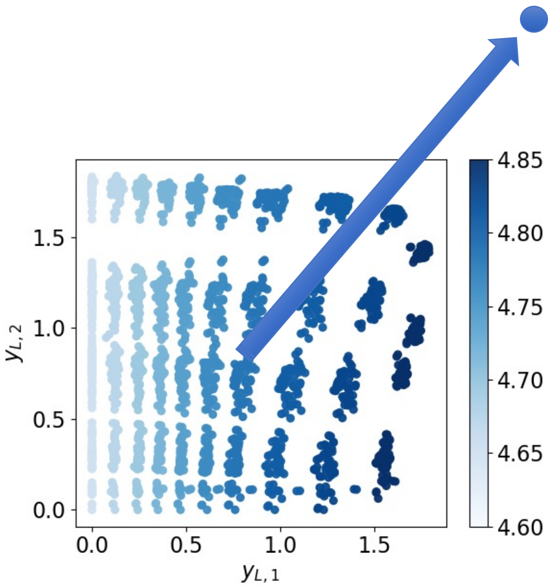




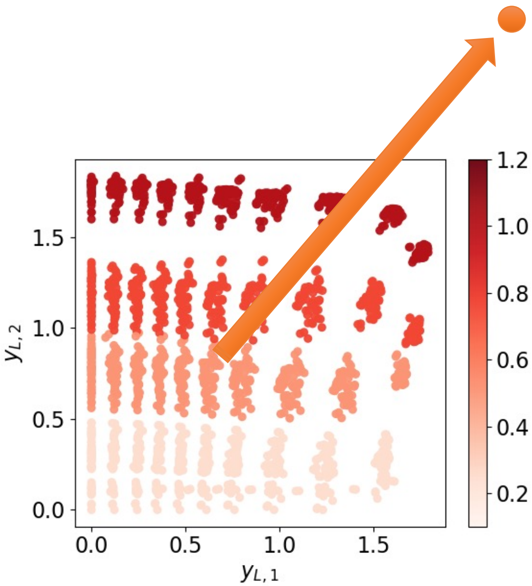




Robustness test: Moving far beyond the span of the training data to a unseen input beam distribution, higher solenoid strength, and larger charge.



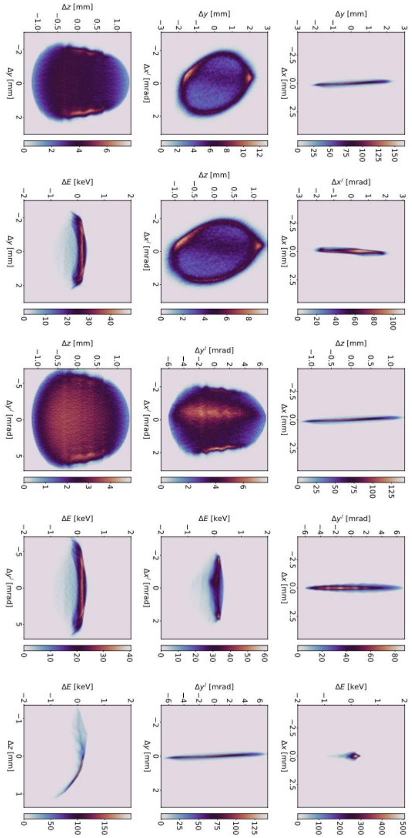
Colored by solenoid strength [A]



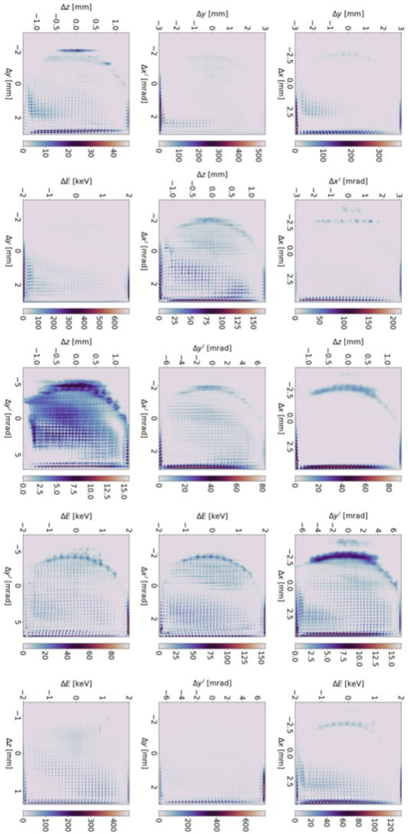
Colored by charge [pC]

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

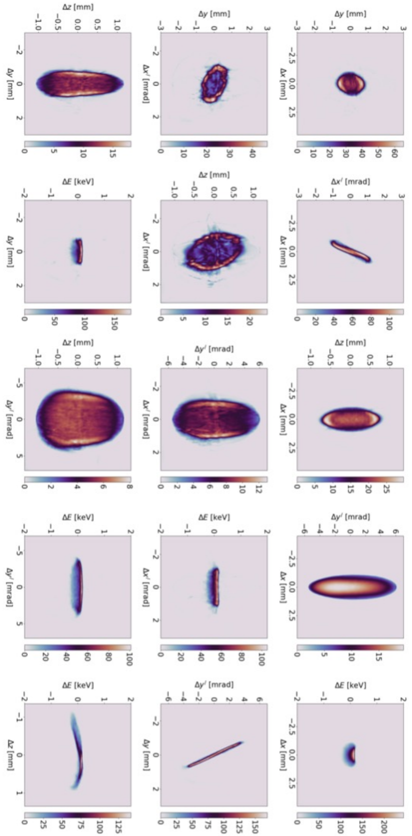
True



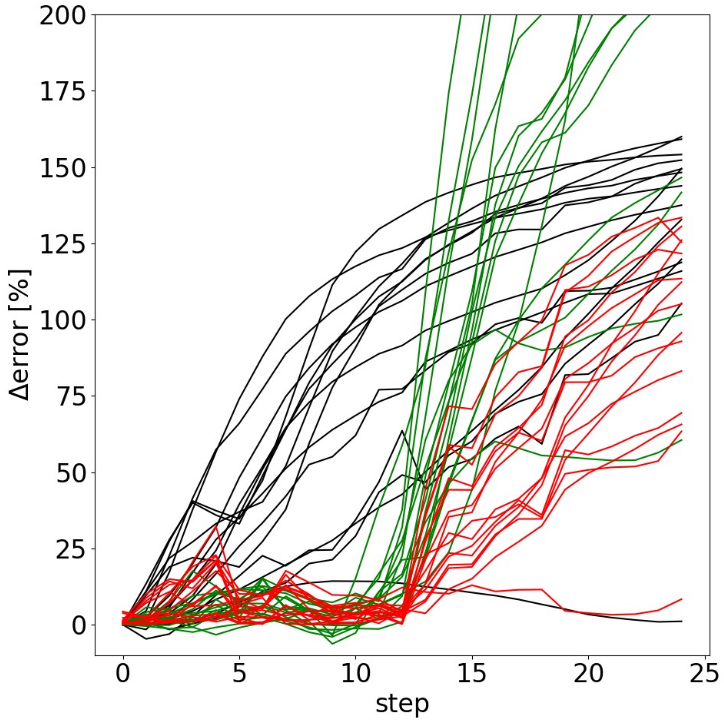
CNN using known beam distribution, solenoid, and charge as inputs



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.