Adaptive Control and Machine Learning for Particle Accelerator Beam Control and Diagnostics

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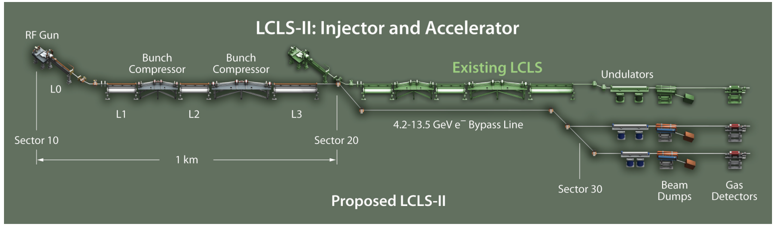
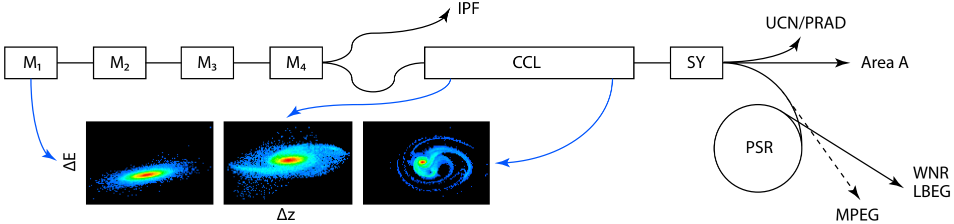
IBIC 2021

Los Alamos
NATIONAL LABORATORY
EST. 1943

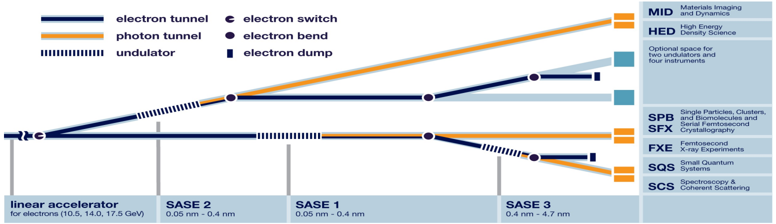
LCLS/LCLS-II



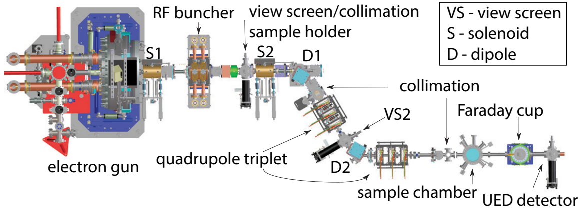
LANSCE



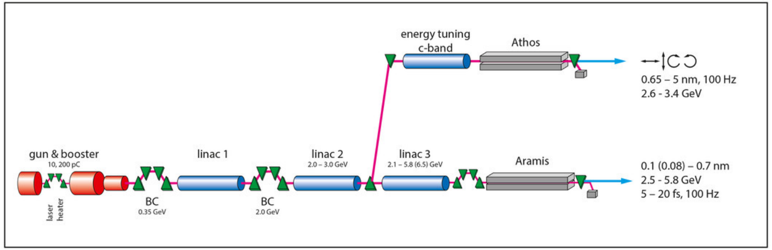
EuXFEL



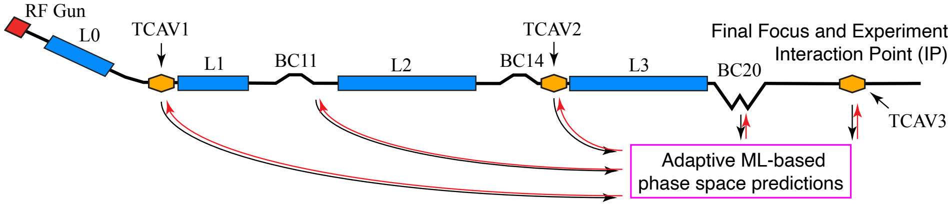
HiRES



Swiss XFEL, 0.6 fs pulses!



FACET-II

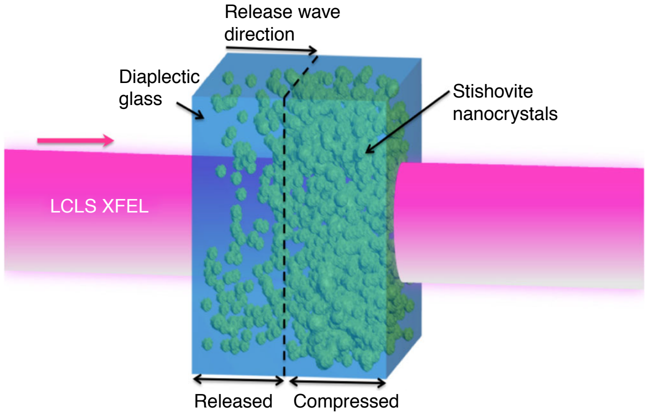


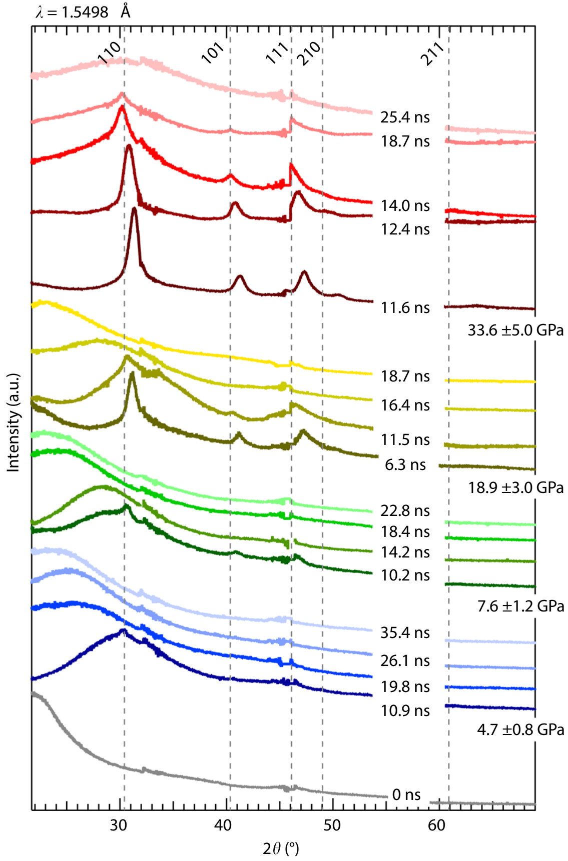
Time-resolved diffraction of shock-released SiO_2 and diaplectic glass formation

A. E. Gleason et al., **Nature Communications**, 8:1481, 2017

~ 8 keV 60 fs duration X-ray pulses,

~ 10^{12} photons per pulse, 75 μm diameter laser spot size

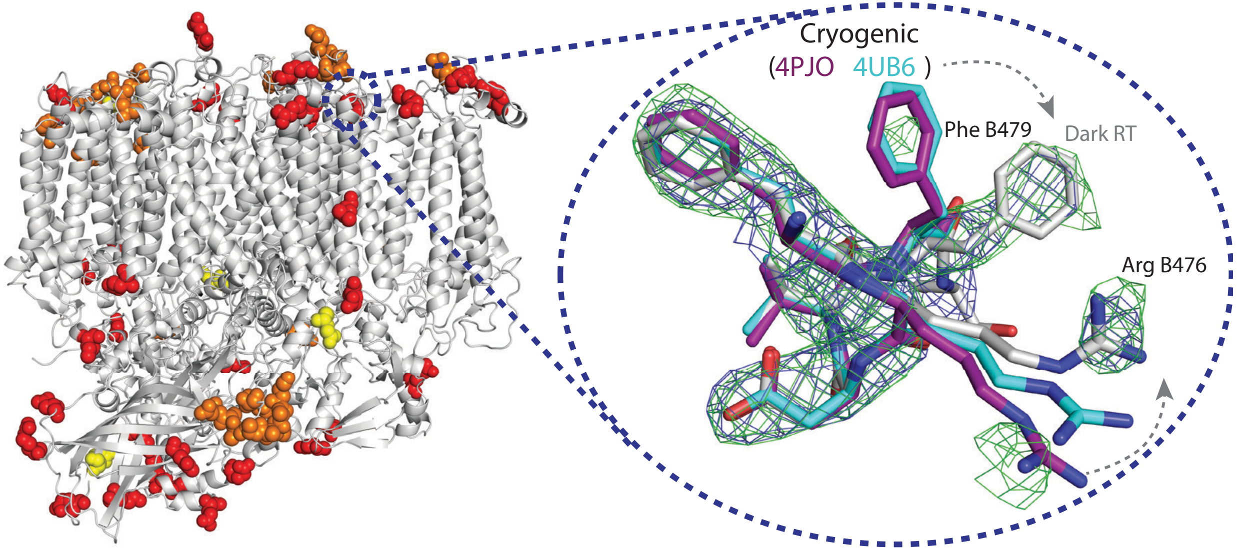




Structure of photosystem II and substrate binding at room temperature

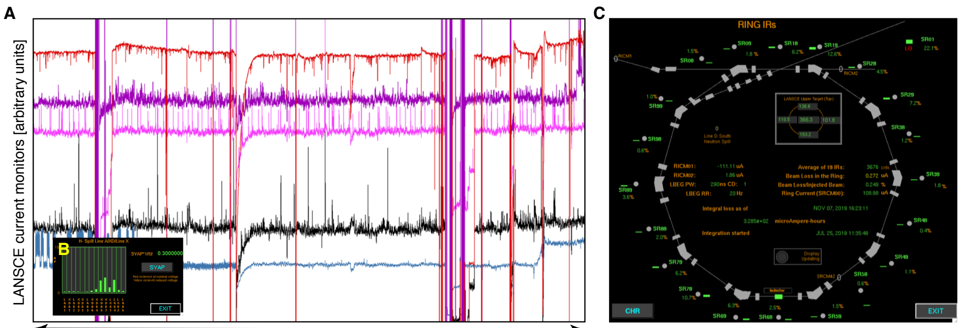
I. D. Young et al., **Nature**, 540, 2016

“Femtosecond pulses from an X-ray free electron laser (XFEL) to obtain damage-free, room temperature structures ... measurements at room temperature are required to study the structural landscape of proteins under functional conditions“



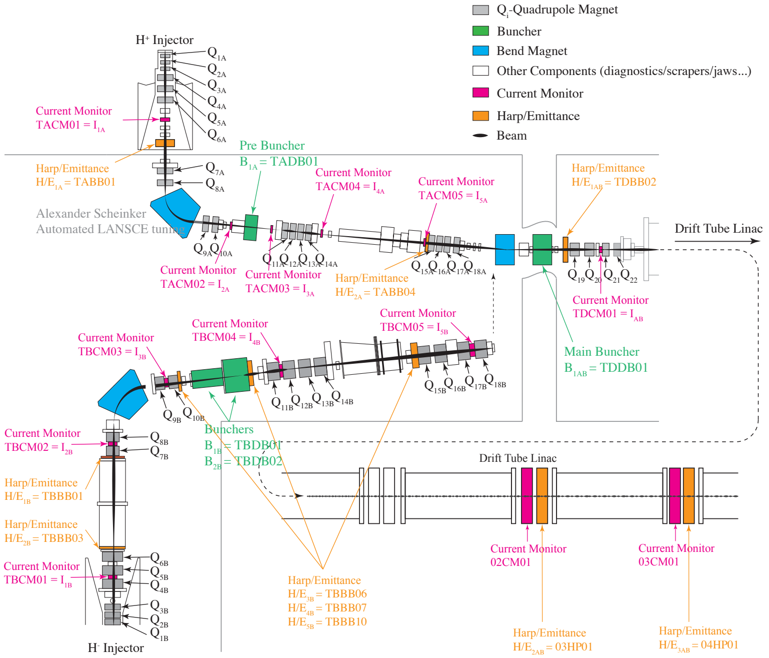
Accelerator Tuning Challenges

- Components drift unpredictably with time, misalignments
  - Uncertain and time varying beam distributions
- Complex collective effects:
  - Wakefields
  - Space charge
  - Coherent synchrotron radiation
- Limited non-invasive diagnostics



12 hours without changing accelerator parameters

proton storage ring loss monitors



Accelerator Tuning Challenges

- Components drift unpredictably with time, misalignments
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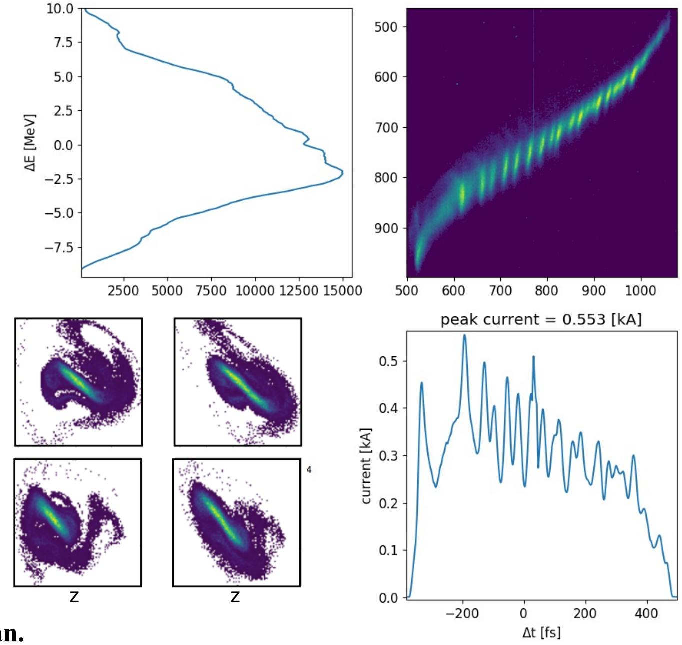
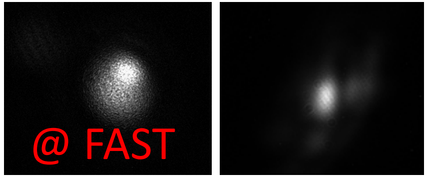
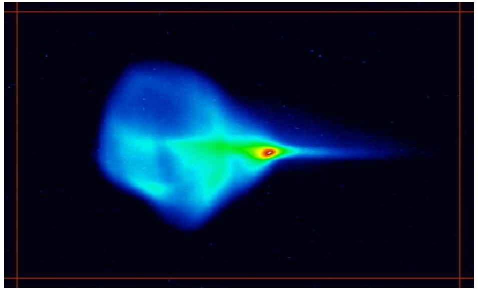
EuXFEL: µBunch Instabilities





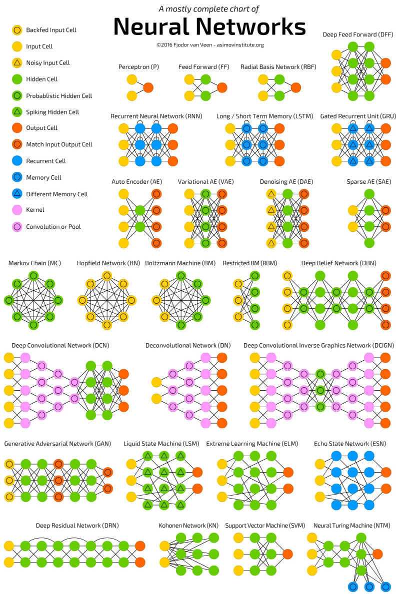
Example images of laser spot
(10 Aug. 2016, 11 Nov. 2017)



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

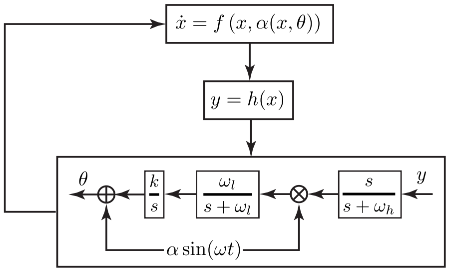
LCLS 2015: > 400 hours for tuning ~10 user experiments / $12M USD value.
LANSCE: > 3 weeks start up / tuning after each maintenance outage.

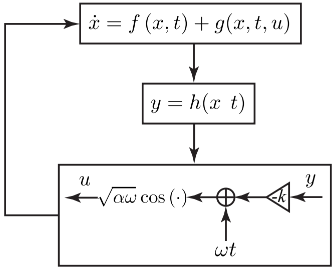
Machine Learning and Adaptive Feedback



Surrogate models
Big data
Global tuning
Anomaly detection

Adapative Feedback



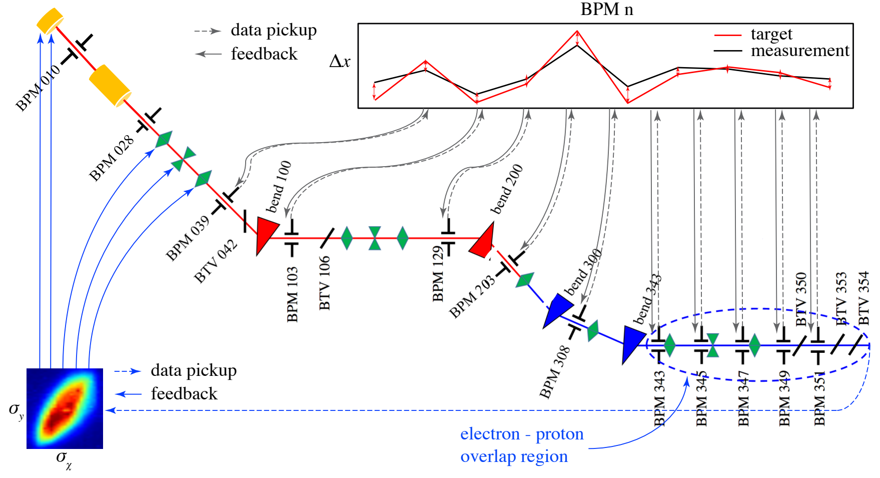


Virtual diagnostics
Real time feedback
Optimization
Phase space tuning

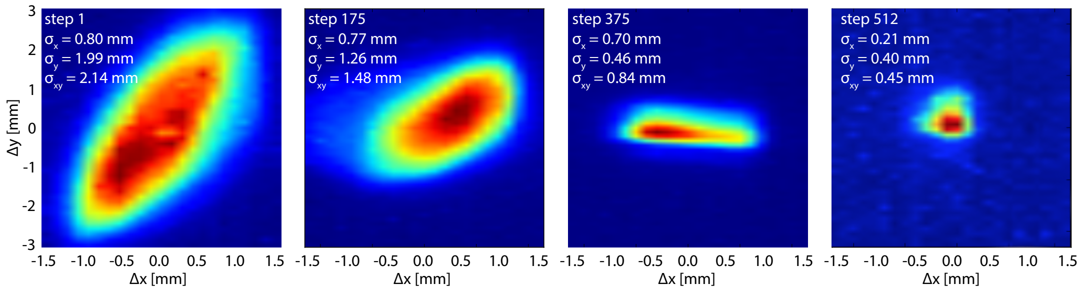
Adaptive Feedback for Particle Accelerators

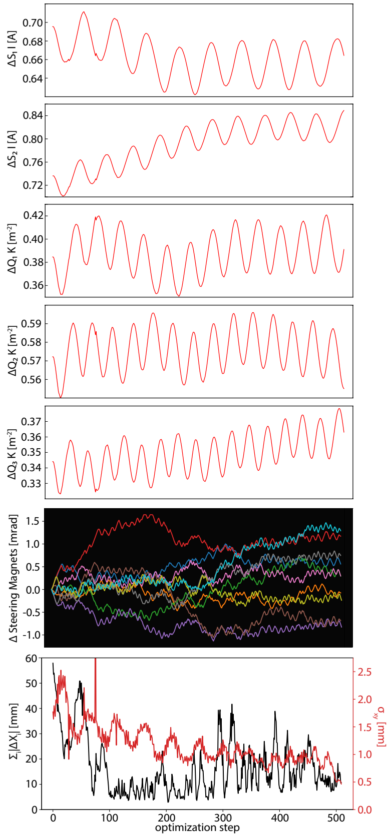
- Model-independent
- Tune many parameters simultaneously
- Robust to noise
- Time-varying systems
- Local minima

Real-Time Multi-objective Optimization at AWAKE



Tuning 15 components simultaneously: 2 solenoids, 3 quads, 10 steering magnets to simultaneously maintain the desired orbit and minimize emittance growth.

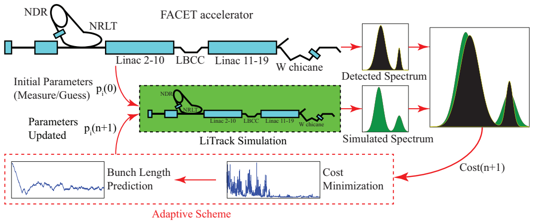


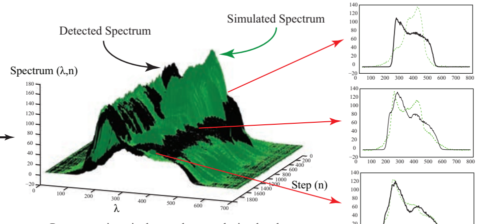


A. Scheinker, et al. “Online Mulit-Objective Particle Accelerator Optimization of the AWAKE Electron Beam Line for Simultaneous Emittance and Orbit Control.” *AIP Advances* 10.5 (2020): 055320 https://doi.org/10.1063/5.0003423

Adaptively tuned models for XTCAV longitudinal phase space predictions at **FACET**

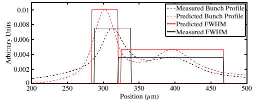
Spectrum-based online model tuning.



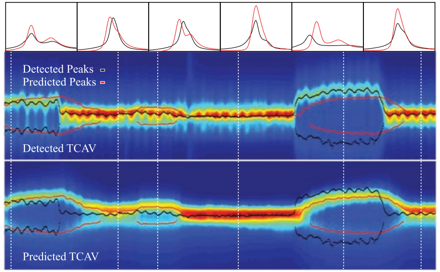


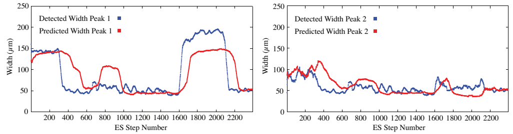
Parameters iteratively tuned to match simulated energy spread spectrum to actual detected sepctrum.

Energy spread spectrum matching leads to longitudinal bunch density prediction, as confirmed by comparison to detected TCAV measurements.



Time-varying bunch length predictions

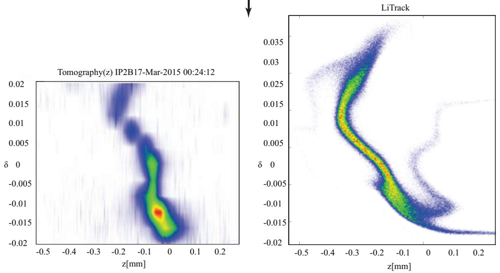




Bunch length and bunch-to-bunch separation tracking.

Time-varying phase space predictions

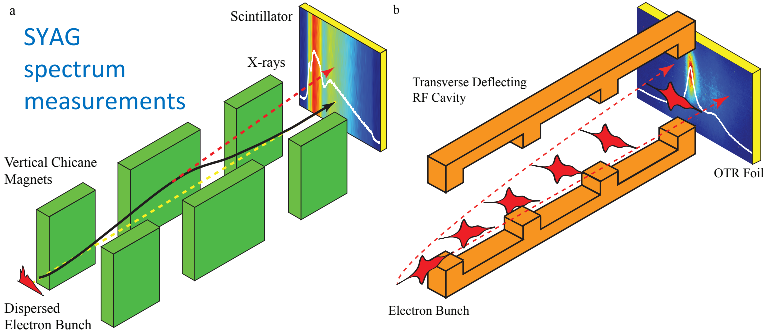
Longitudinal phase space prediction of XTCAV measurement.

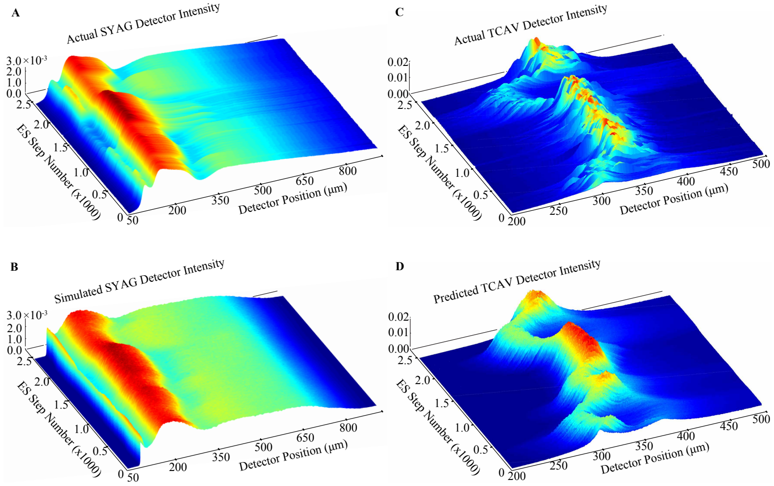


TCAV measurement

TCAV Prediction

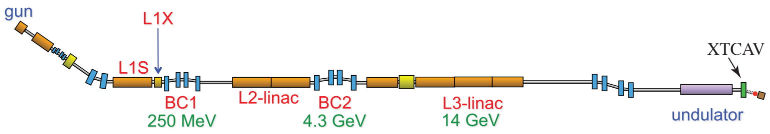
SYAG spectrum measurements

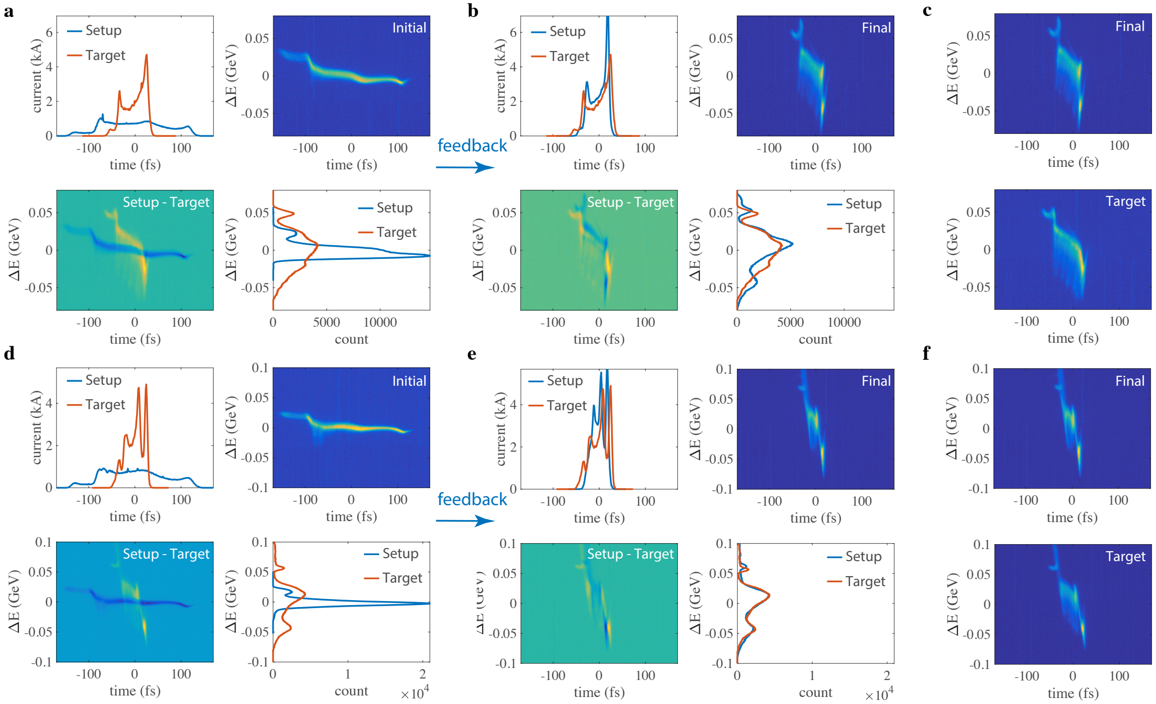




A. Scheinker and S. Gessner, “Adaptive method for electron bunch profile prediction.” Physical Review Accelerators and Beams, 18(10), 102801, 2015. https://doi.org/10.1103/PhysRevSTAB.18.102801

Adaptive feedback for automatic longitudinal phase space control at the **LCLS**





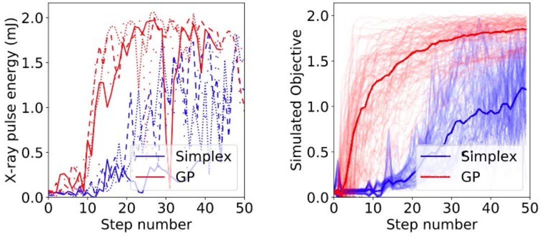
A. Scheinker, et al. "Demonstration of model-independent control of the longitudinal phase space of electron beams in the Linac-coherent light source with Femtosecond resolution." Physical Review Letters, 121.4, 044801, 2018. https://doi.org/10.1103/PhysRevLett.121.044801

Machine Learning for Particle Accelerators

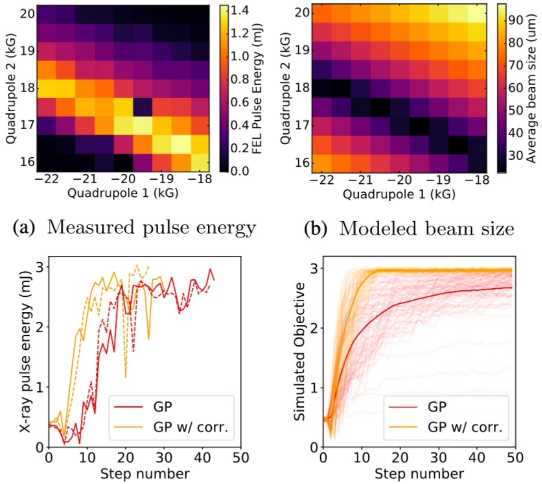
- Learn directly from data
- Extract complex physics
- Global understanding of large systems
- Time-varying systems

Gaussian Processes for Optimization

LCLS



(a) Live 12 quadrupole optimization
(b) Simulated 12 quadrupole optimization

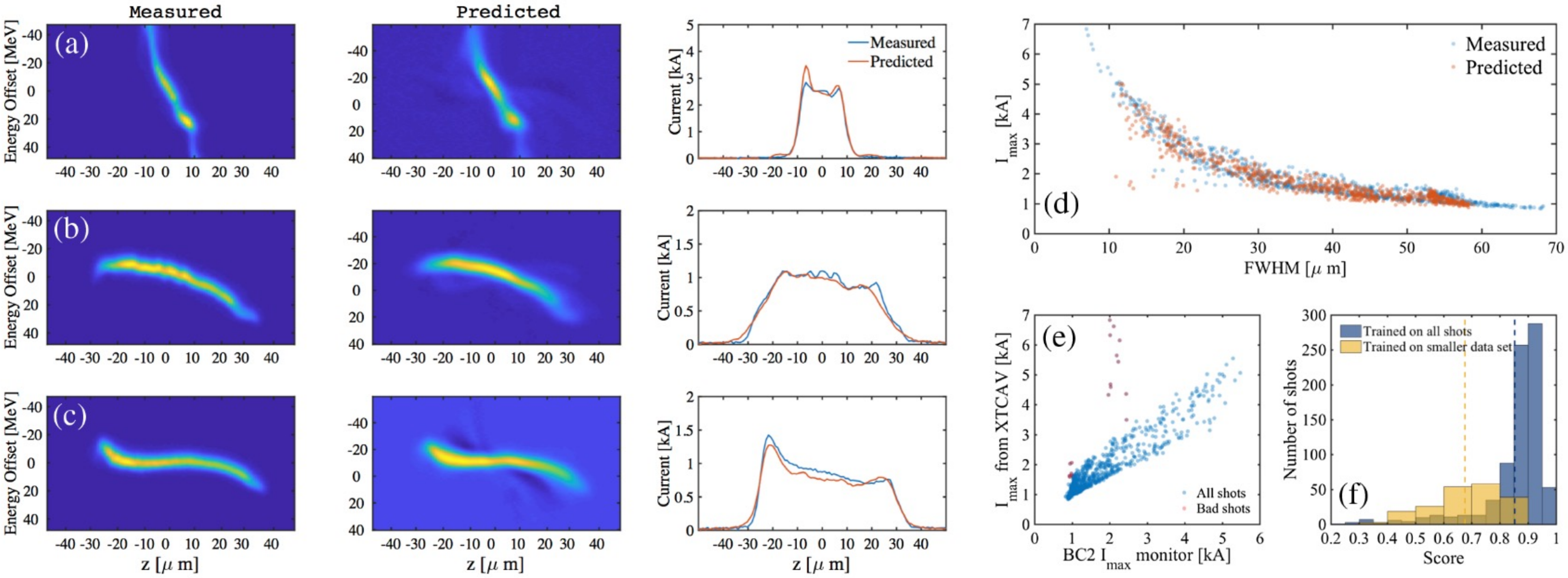


(a) Measured pulse energy
(b) Modeled beam size
(c) Live 4 quadrupole optimization
(d) Simulated 4 quadrupole optimization

Duris, Joseph, et al. "Bayesian optimization of a free-electron laser." *Physical review letters* 124.12 (2020): 124801.

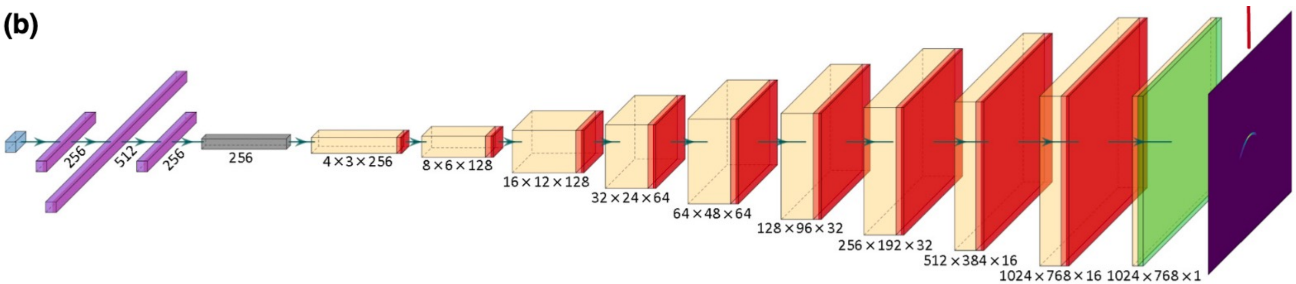
Neural Network-based Diagnostics

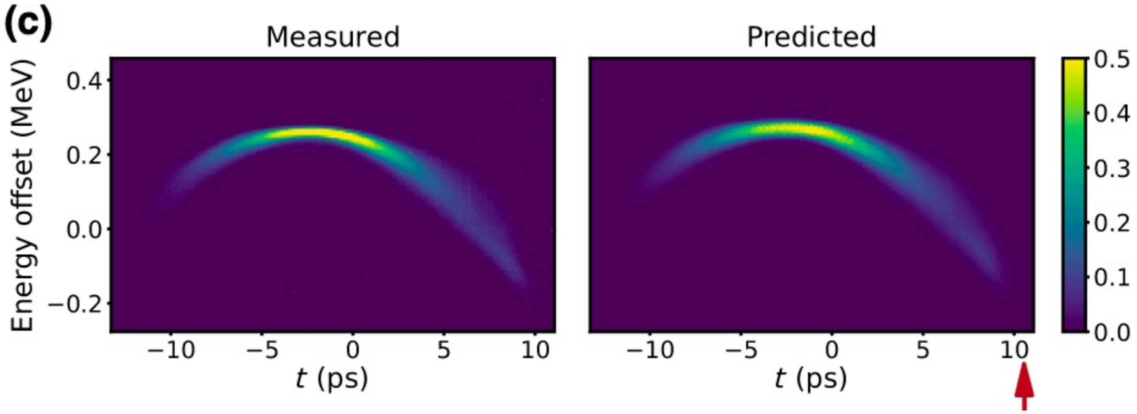
LCLS



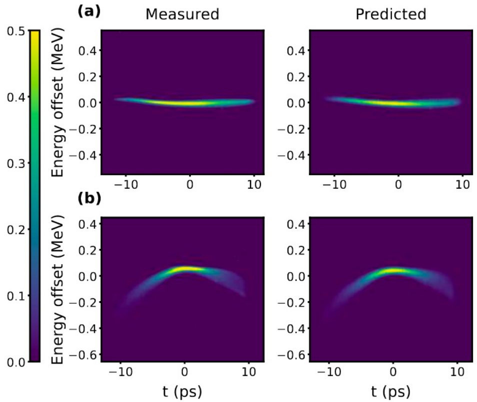
Emma, C., et al. "Machine learning-based longitudinal phase space prediction of particle accelerators." *Physical Review Accelerators and Beams* 21.11 (2018): 112802.

Neural Network-based Diagnostics



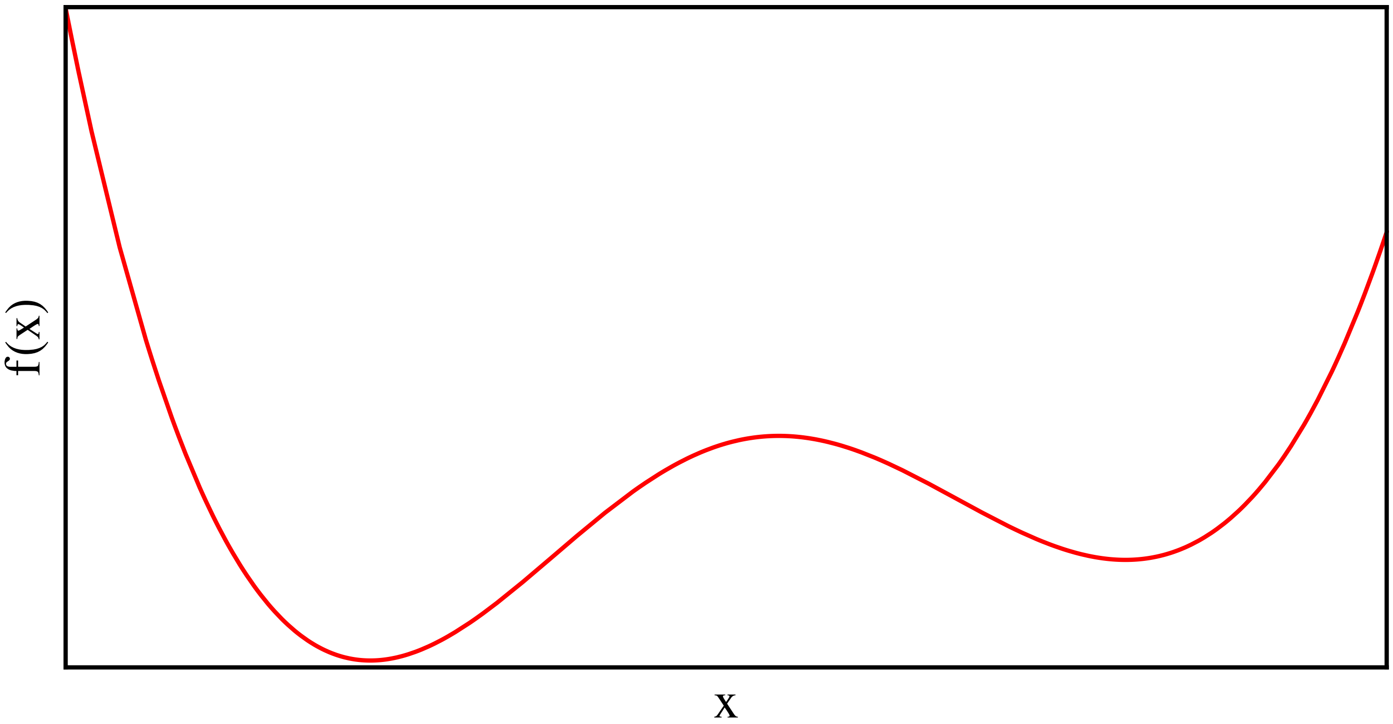


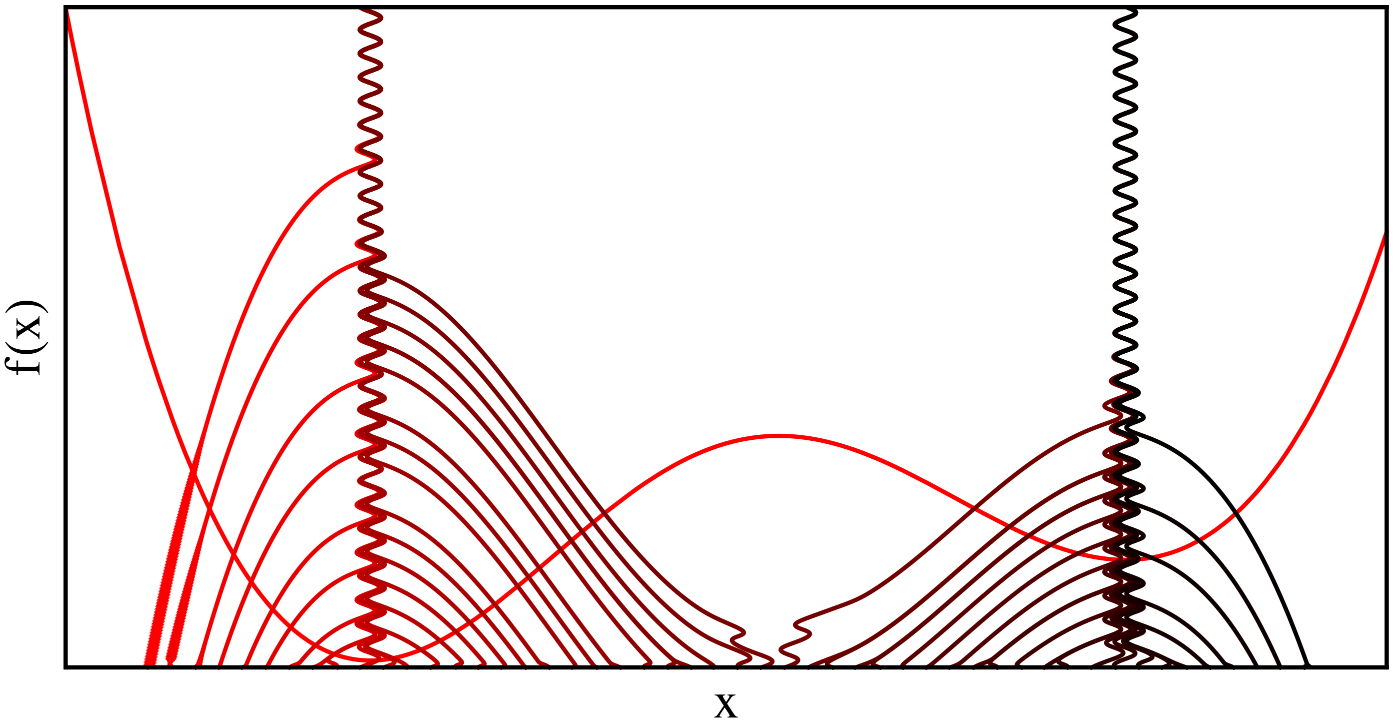
EuXFEL



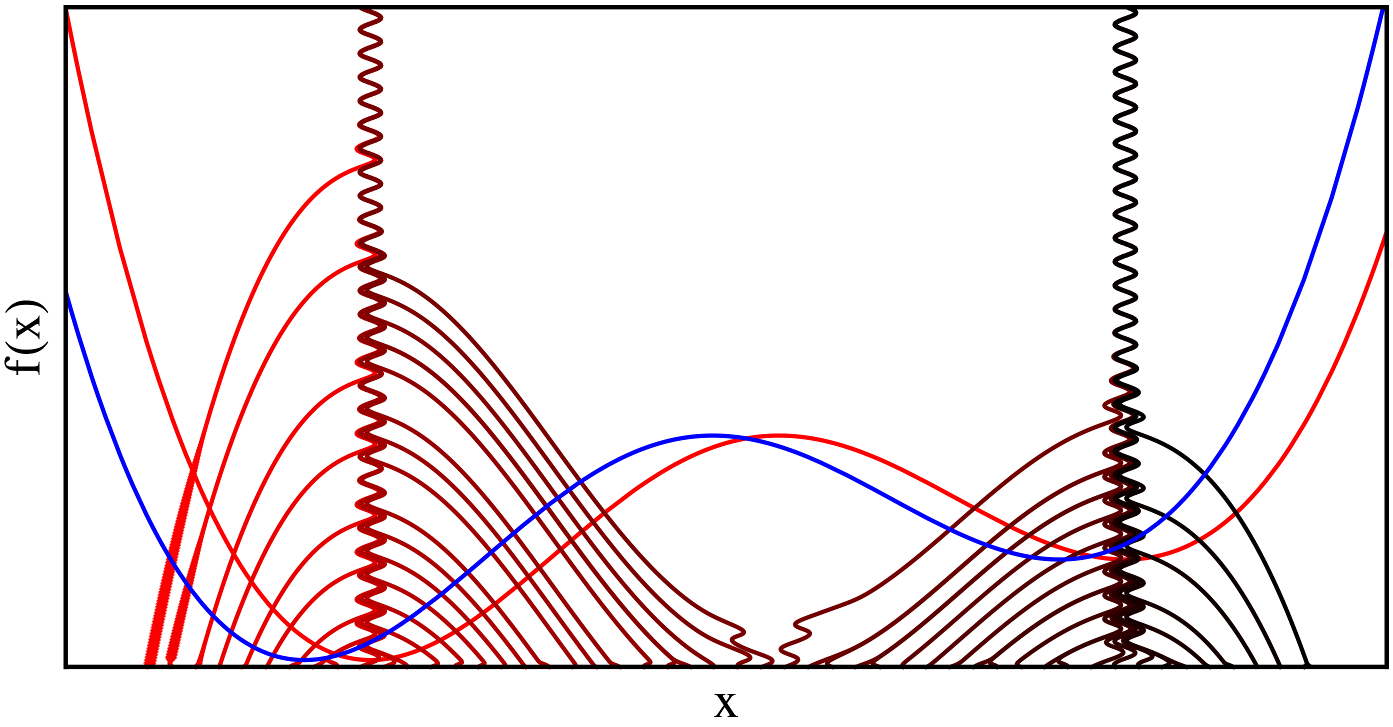
Zhu, J., et al. "High-Fidelity Prediction of Megapixel Longitudinal Phase-Space Images of Electron Beams Using Encoder-Decoder Neural Networks." *Physical Review Applied* 16.2 (2021): 024005.

Limitations of ML for Time-Varying Systems

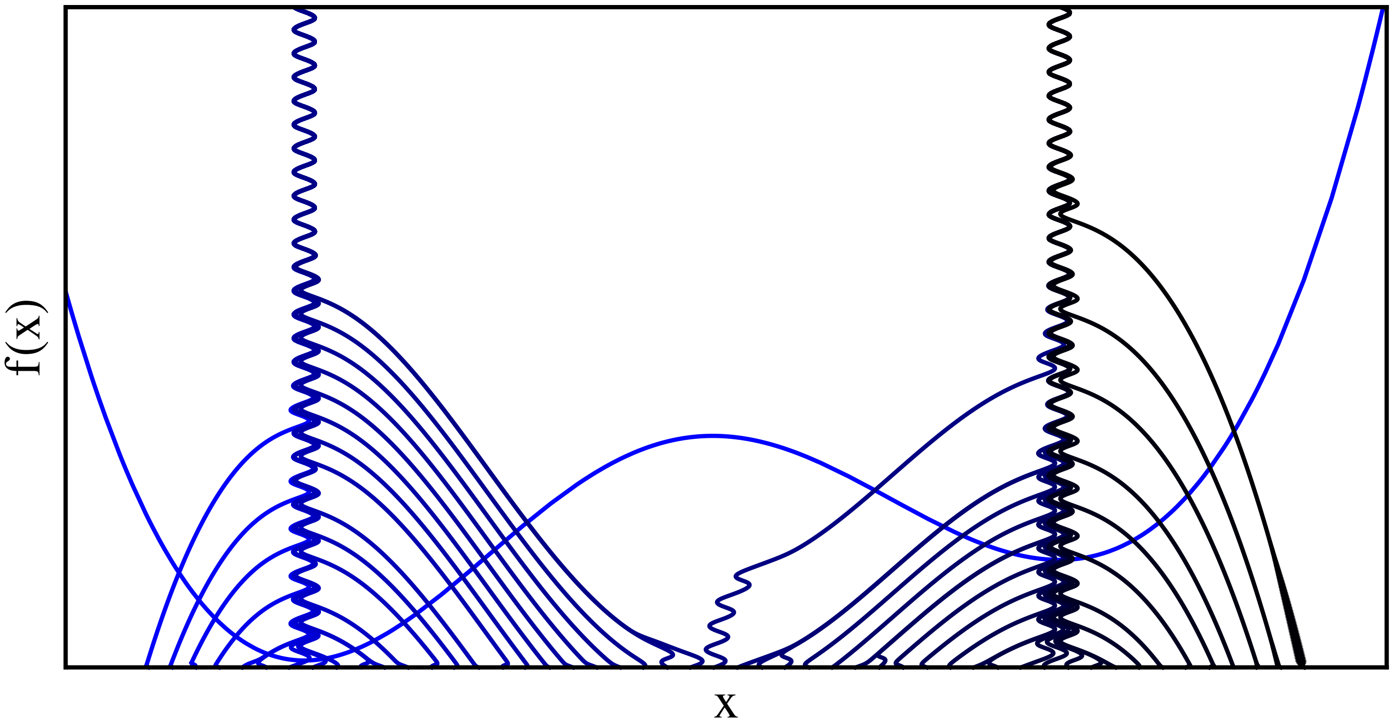

f(x)
x

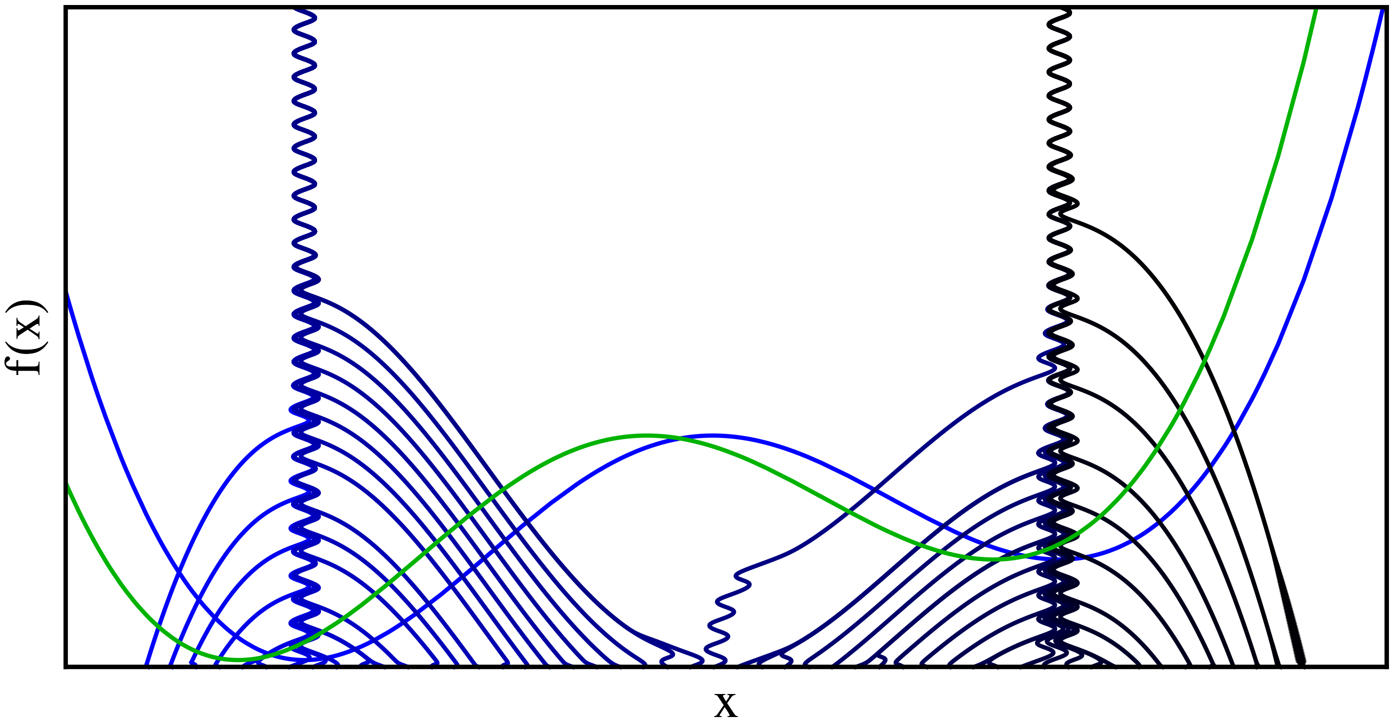


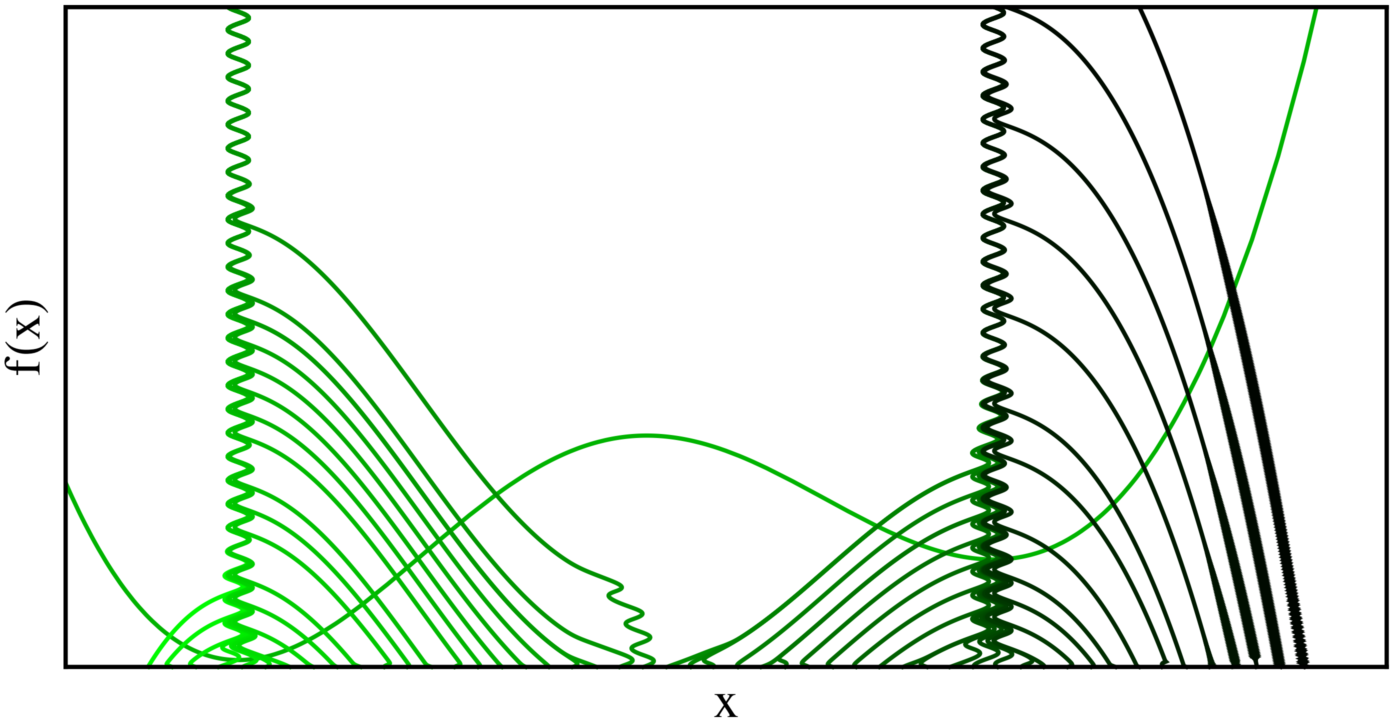
f(x)
x

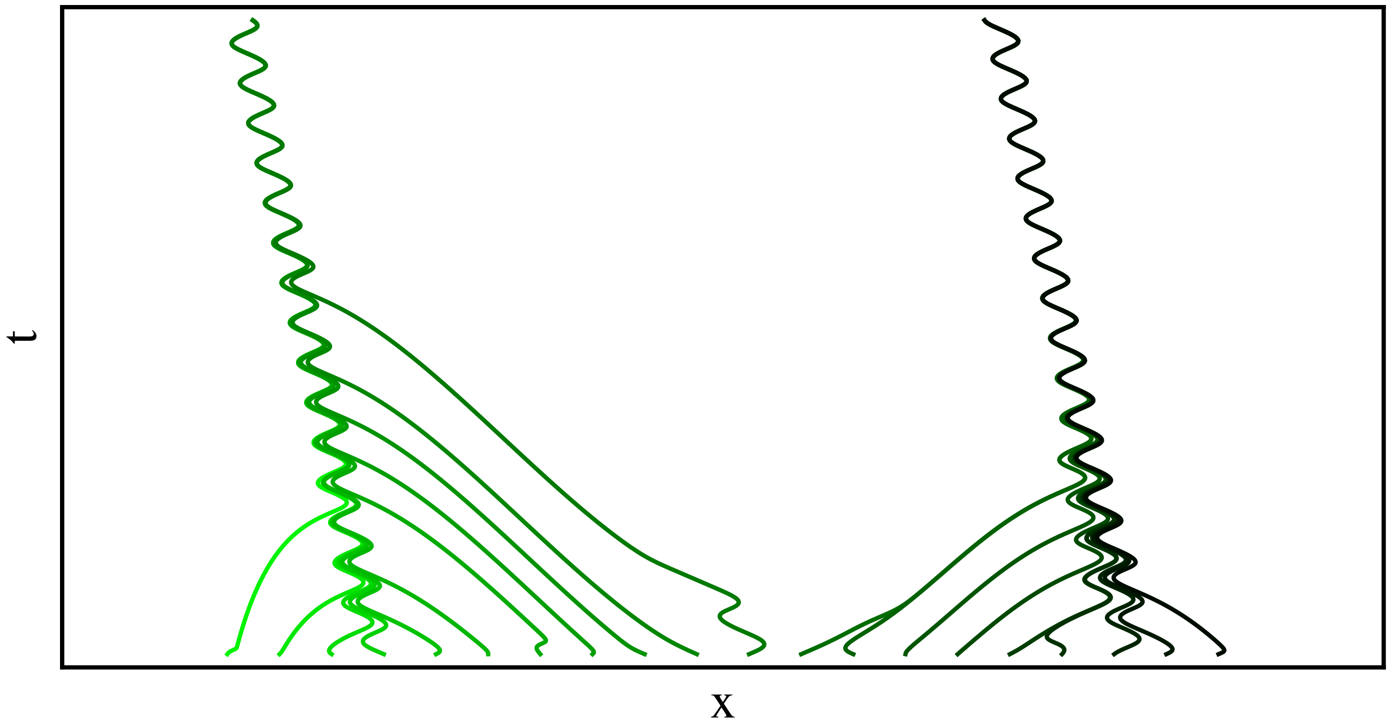


f(x)
x


f(x)
x

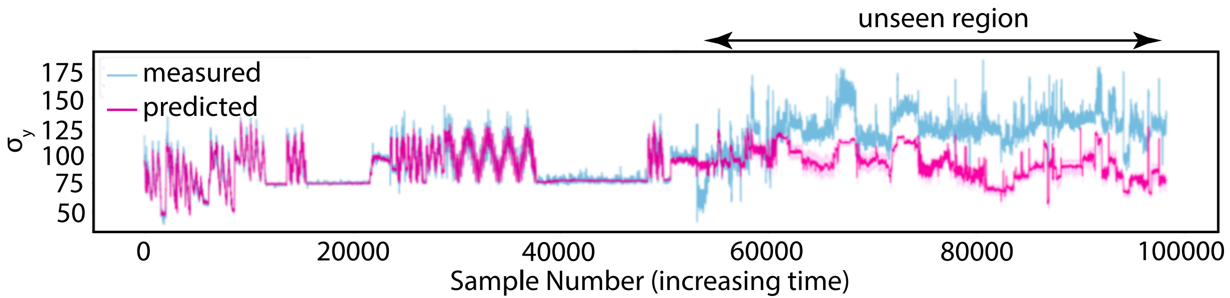

f(x)
x


f(x)
x



t
x

Need for robust machine learning techniques for time-varying systems

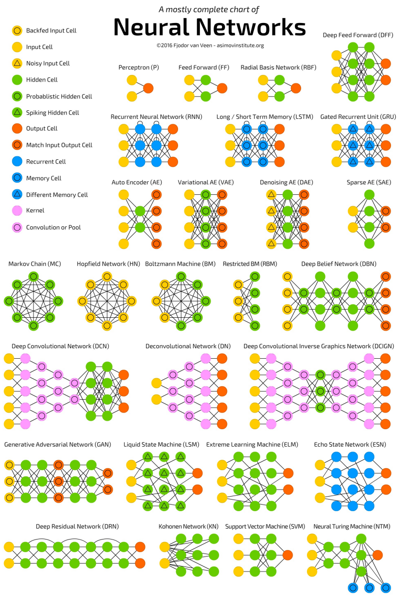


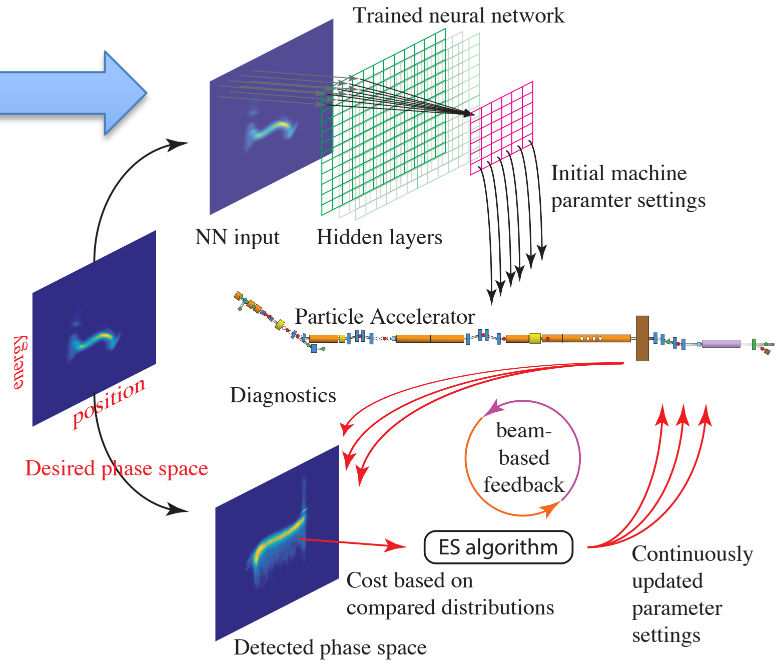
LCLS: time-varying system shows limitations of traditional ML approaches.

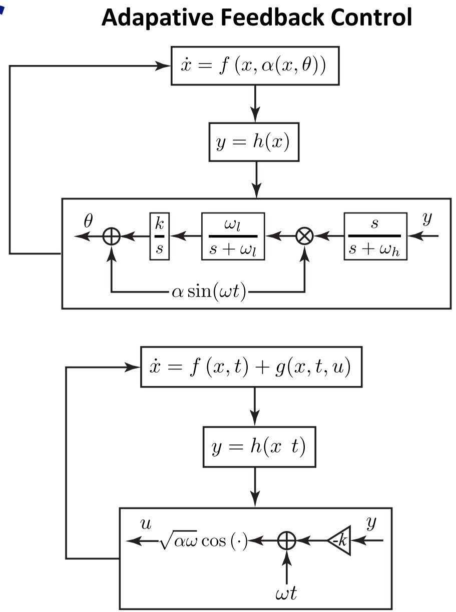
- Neural network predicting σ_y beam size.

Adaptive Machine Learning for Time-Varying Systems

Adaptive Machine Learning for Time Varying Systems







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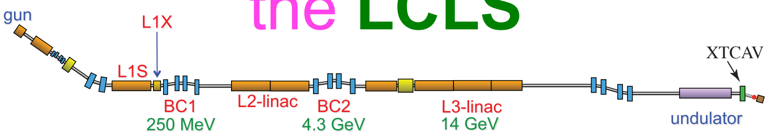
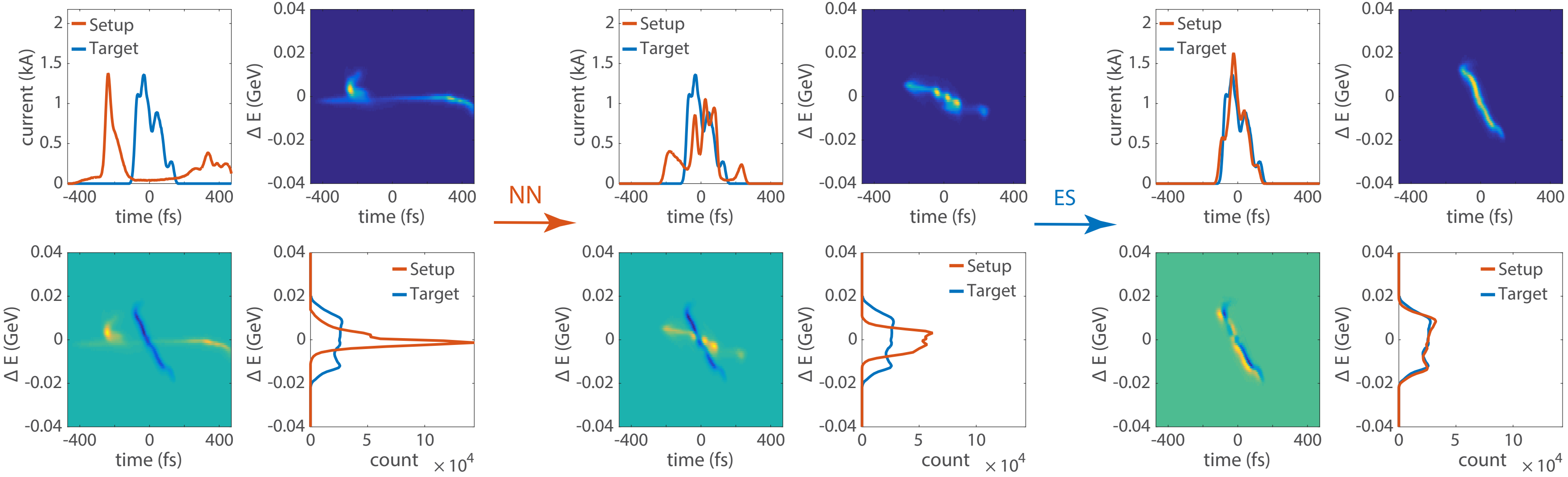
Adaptive ML for automatic longitudinal phase space control at the **LCLS**



$$C = \int_{-\Delta L}^{\Delta L} \int_{-\Delta E}^{\Delta E} |\hat{\rho}(z, E) - \rho(z, E)| \, dE dz$$



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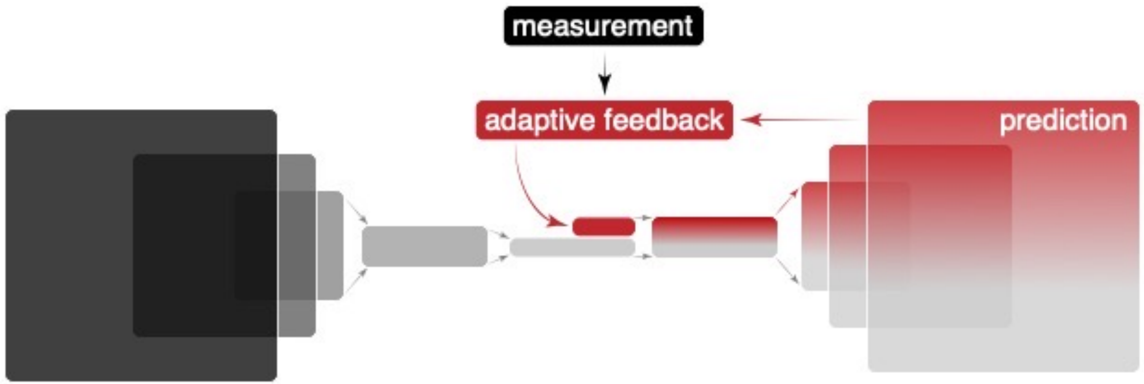
Adaptive Machine Learning (AML) for Time-Varying Systems – Adaptively Tuning the Latent Space

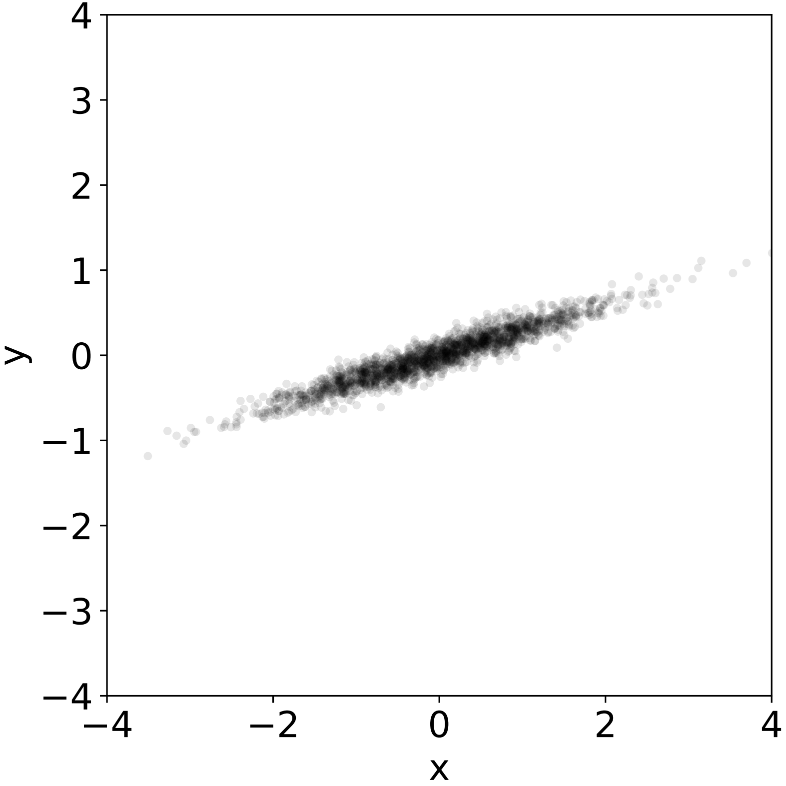
General approach for any complex time-varying system

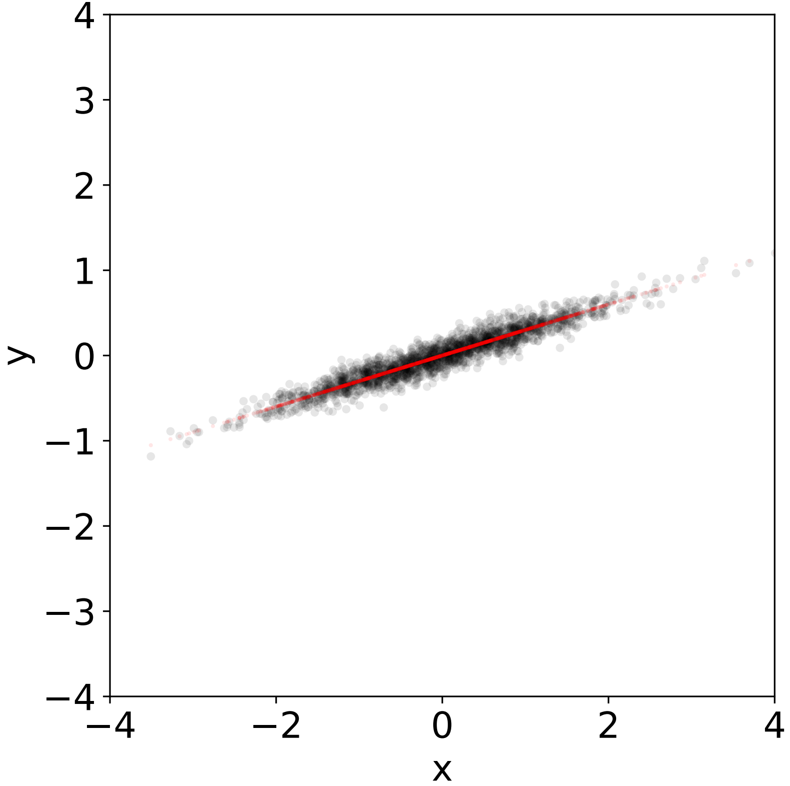


A. Scheinker, et al. "Adaptive deep learning for time-varying systems with hidden parameters: Predicting changing input beam distributions of compact particle accelerators." *arXiv preprint arXiv:2102.10510*. 2021

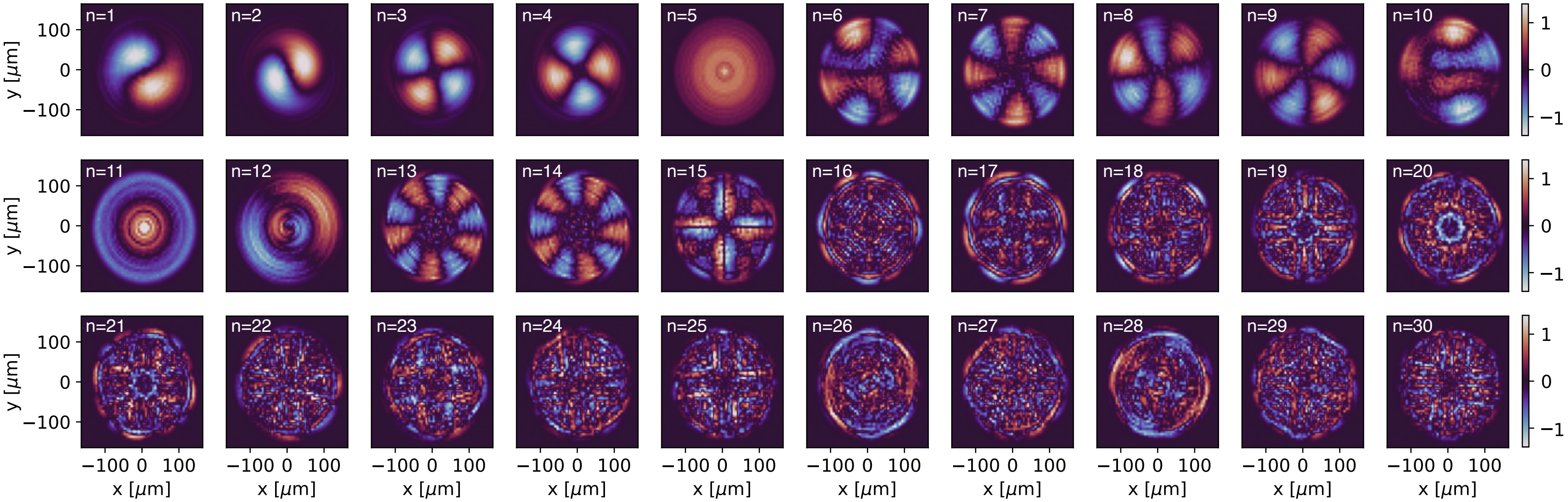
A. Scheinker, et al. "Adaptive Latent Space Tuning for Non-Stationary Distributions." *arXiv preprint arXiv:2105.03584*, 2021.

Principal Component Analysis (PCA)





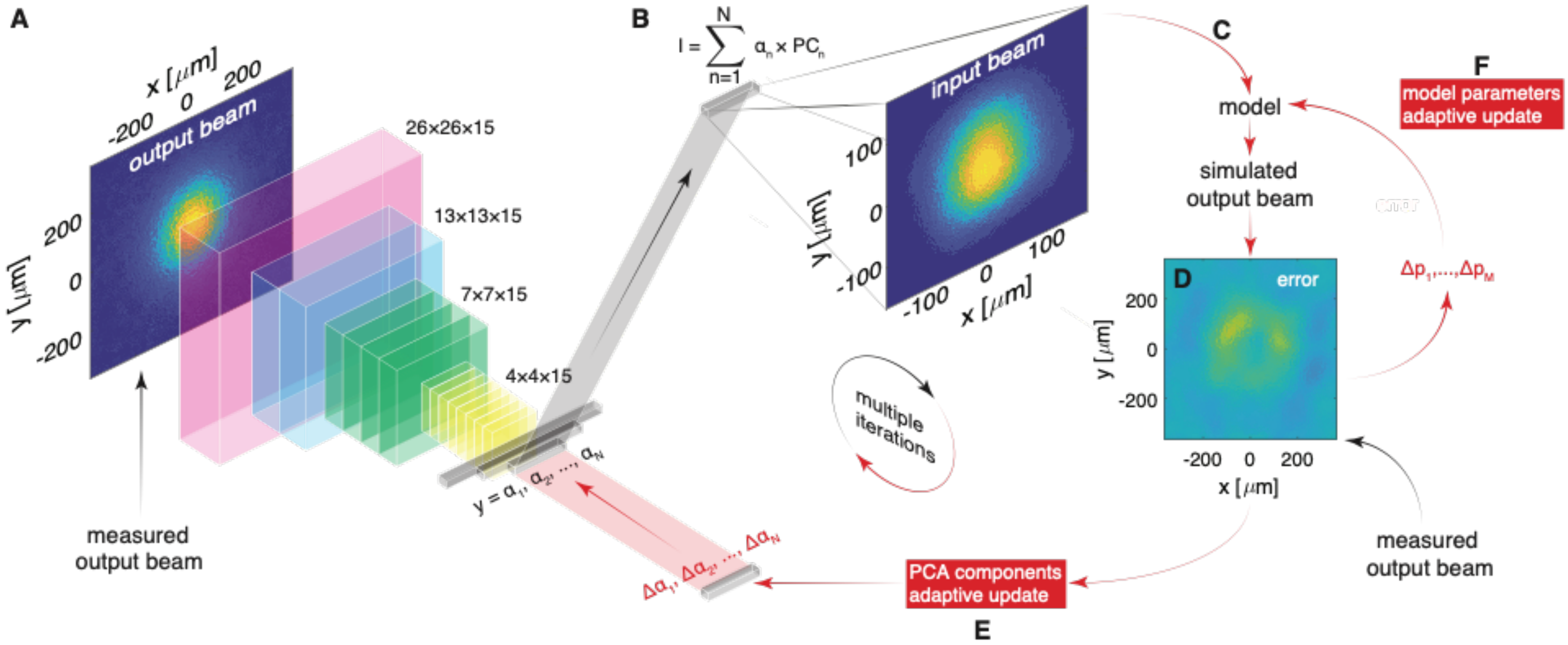
PCA component basis for electron beam.



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

Scheinker, A., Cropp, F., Paiagua, S., & Filippetto, D. “An adaptive approach to machine learning for compact particle accelerators.” *Scientific Reports* **11,** 19187, 2021.
https://doi.org/10.1038/s41598-021-98785-0

AML for adaptive inverse physics models



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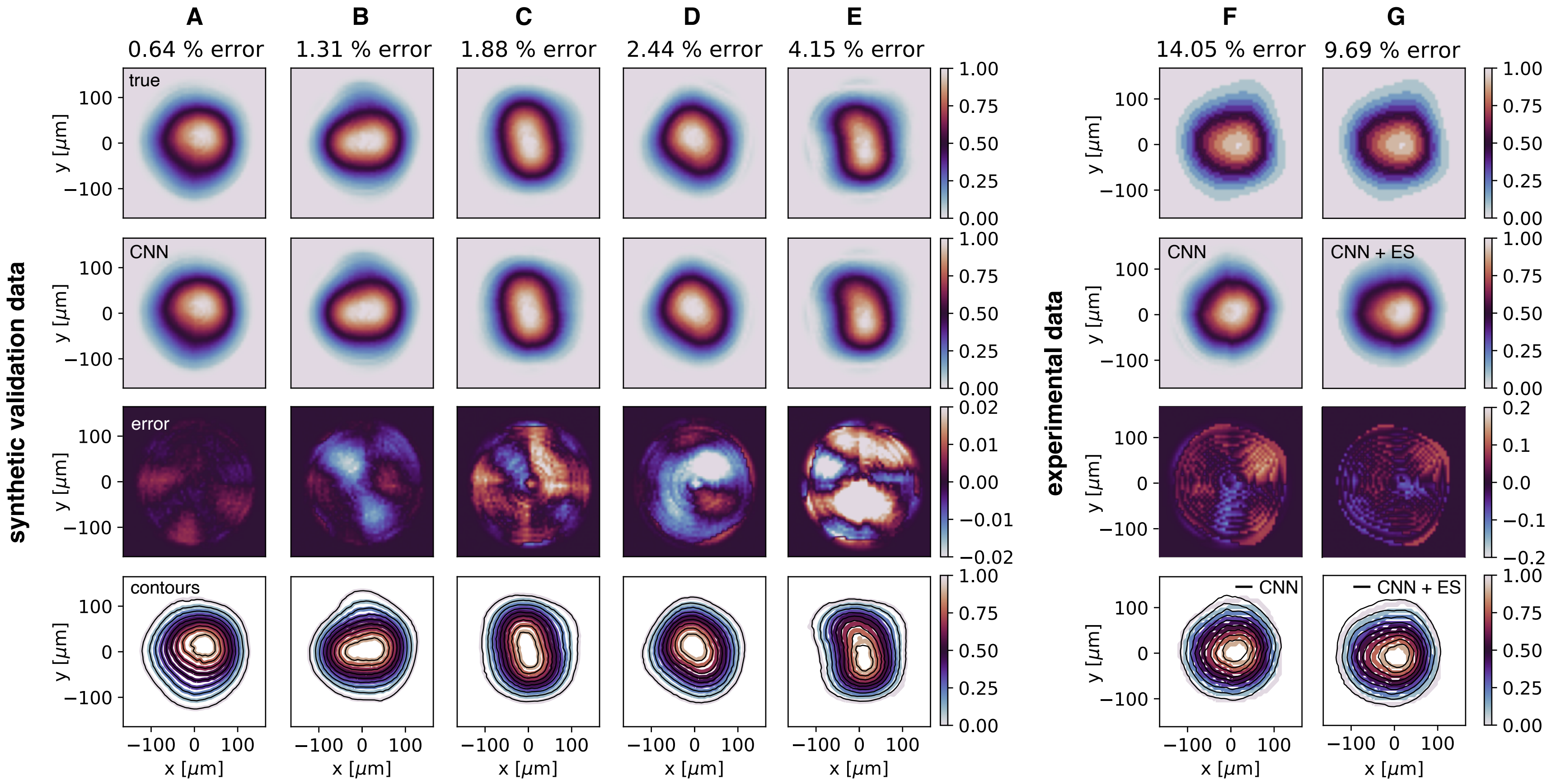

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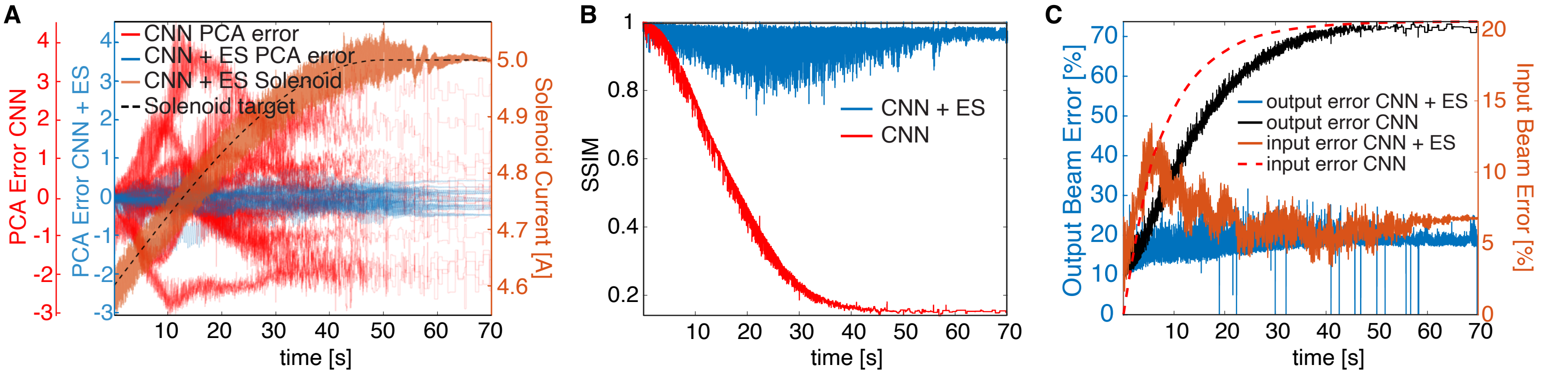

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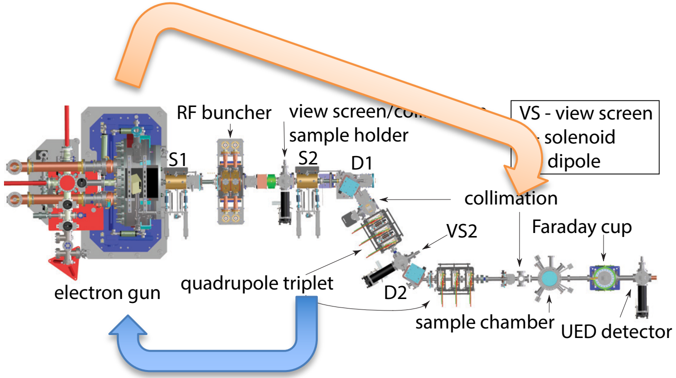

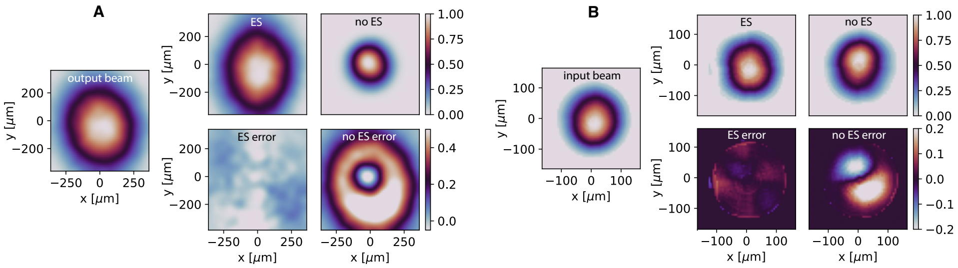

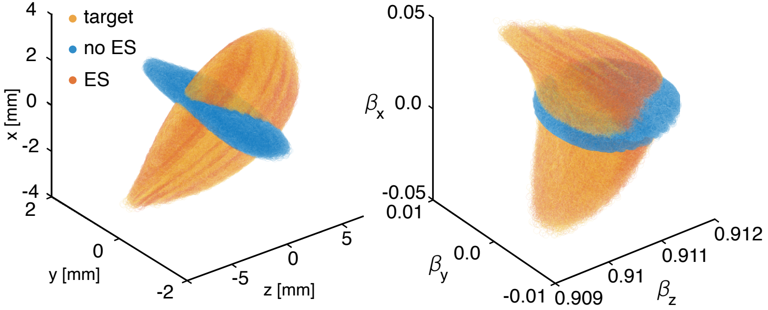

Scheinker, A., Cropp, F., Paiagua, S., & Filippetto, D. "An adaptive approach to machine learning for compact particle accelerators." *Scientific Reports* **11,** 19187, 2021.
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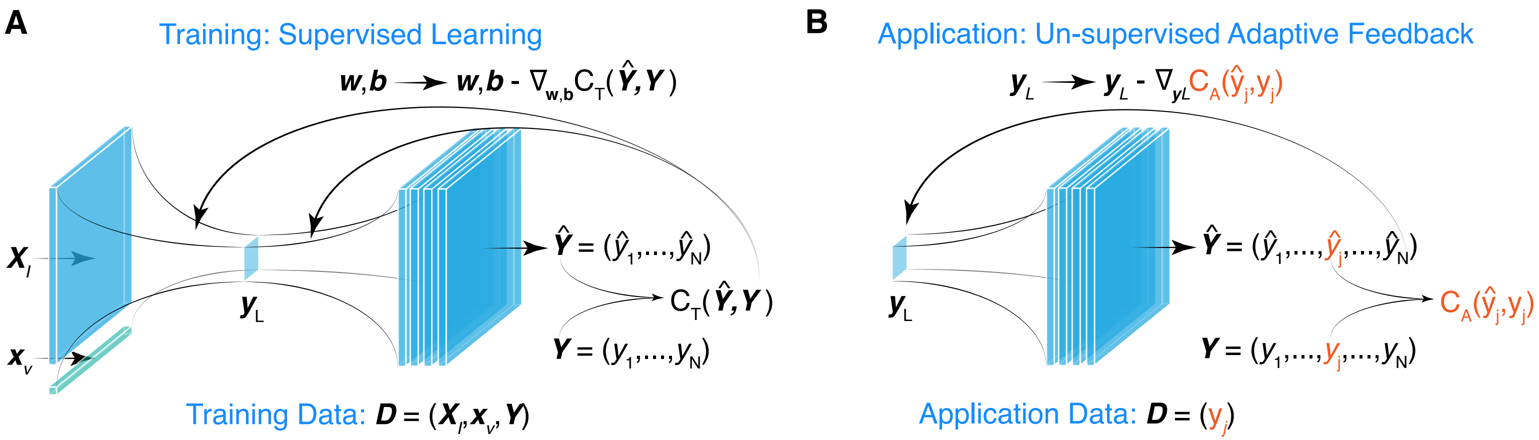
Encoder-decoder generative CNN for nonlinear data compression: Low-dimensional latent space tuning



A. Scheinker. "Adaptive machine learning for time-varying systems: Low dimensional latent space tuning." arXiv:2107.06207

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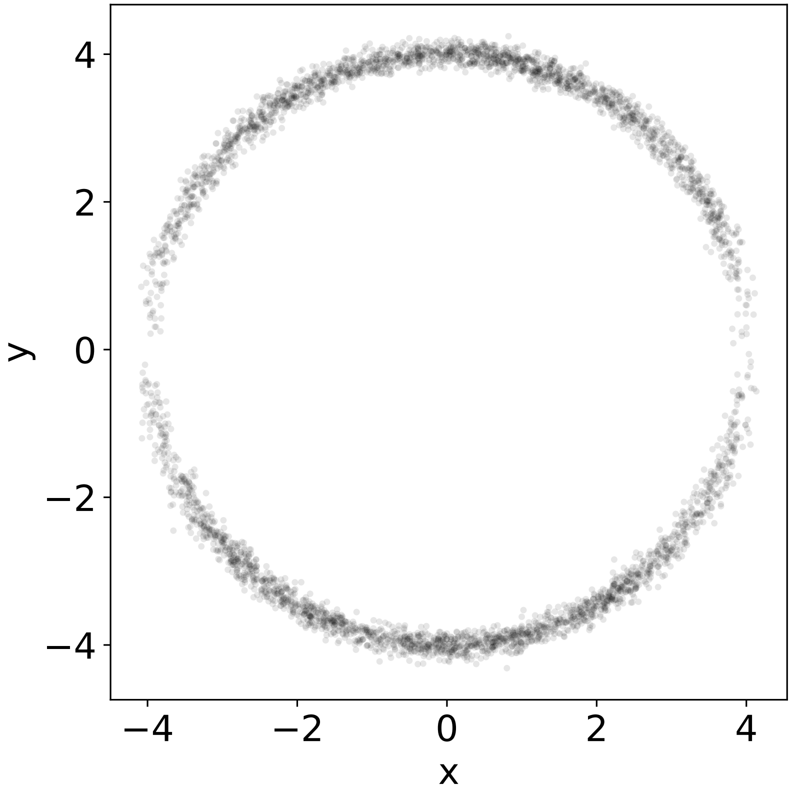
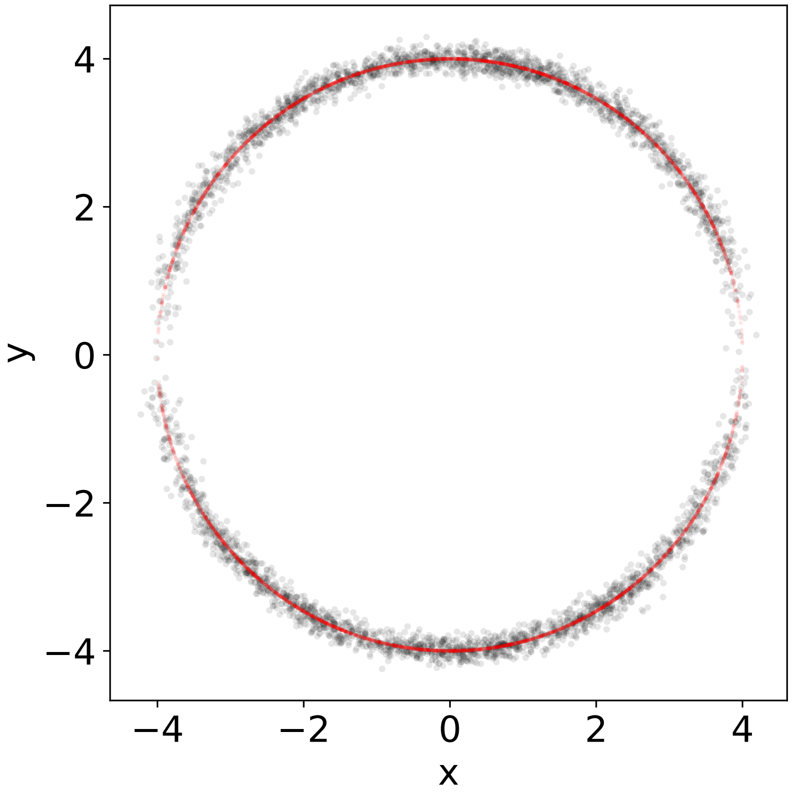
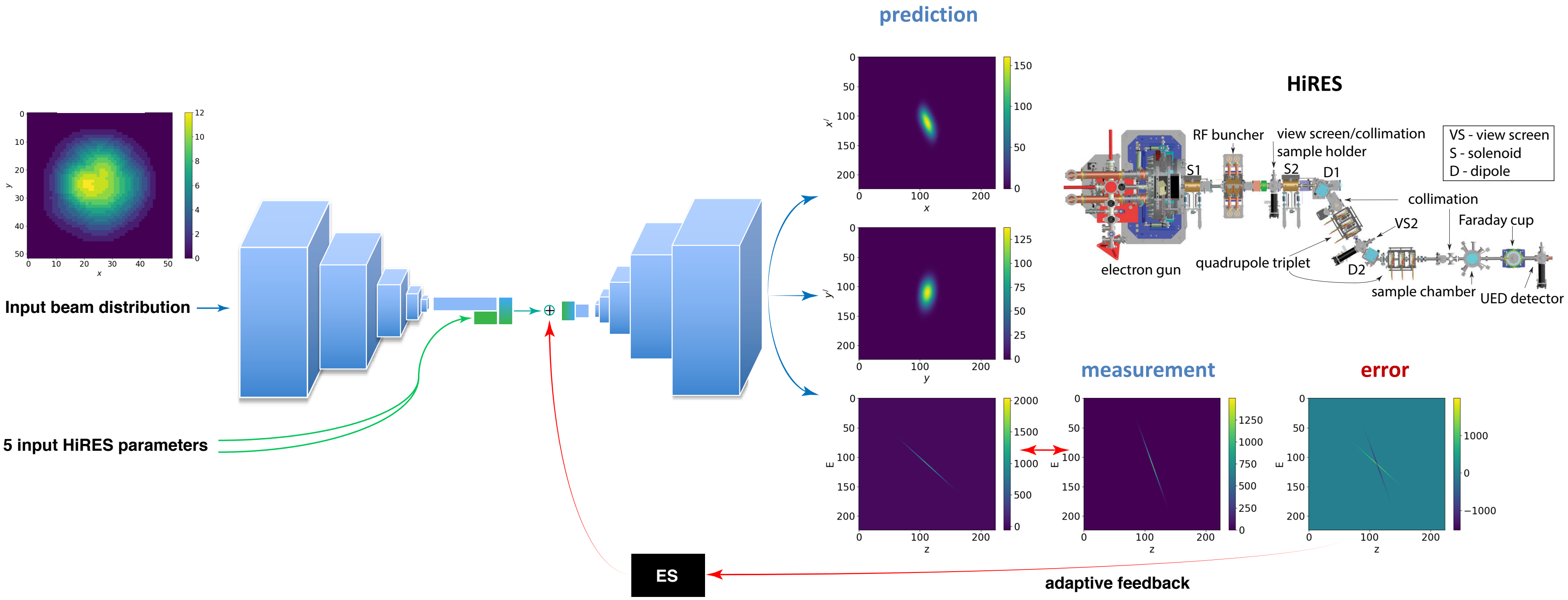
Encoder-decoder CNN for nonlinear data





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



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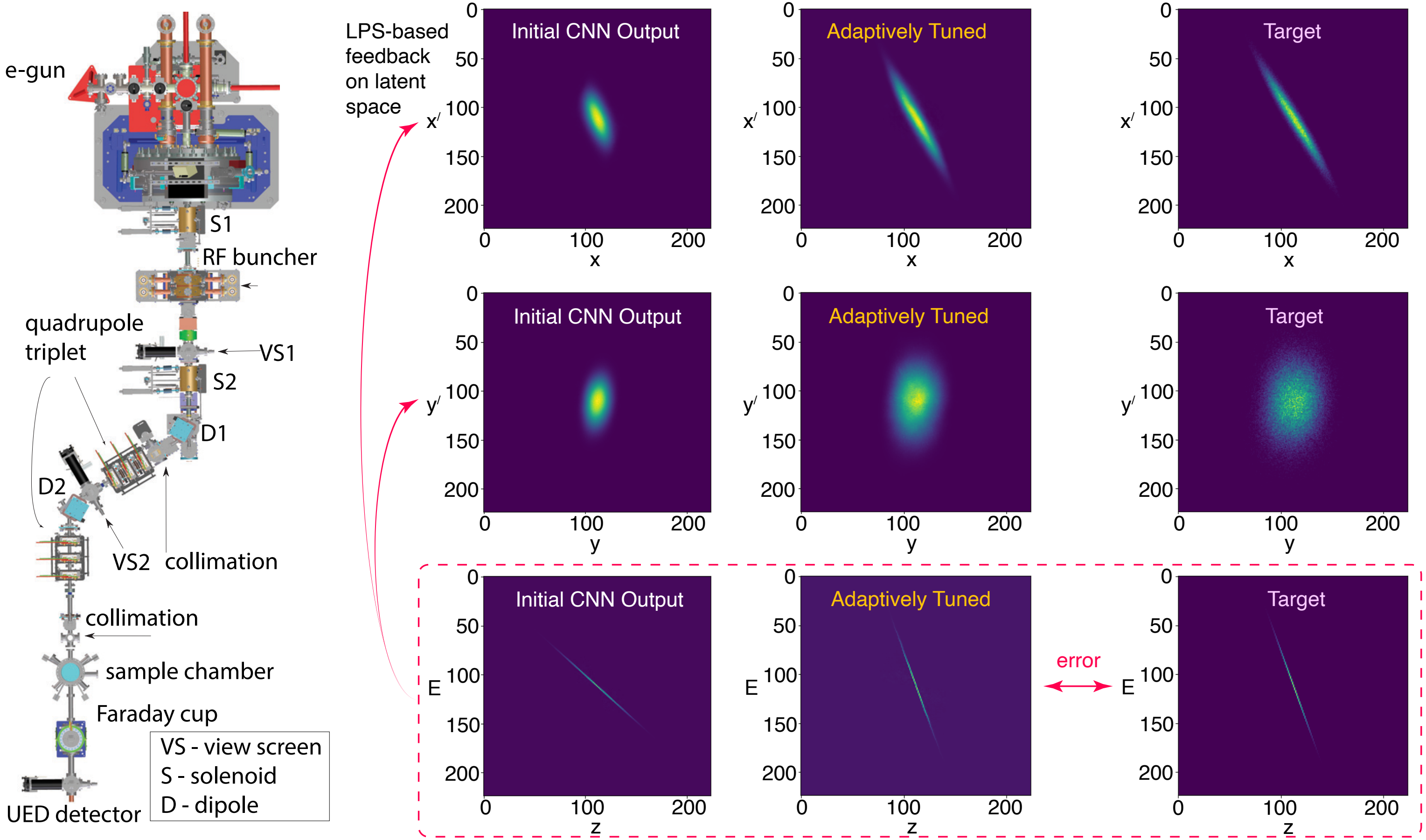
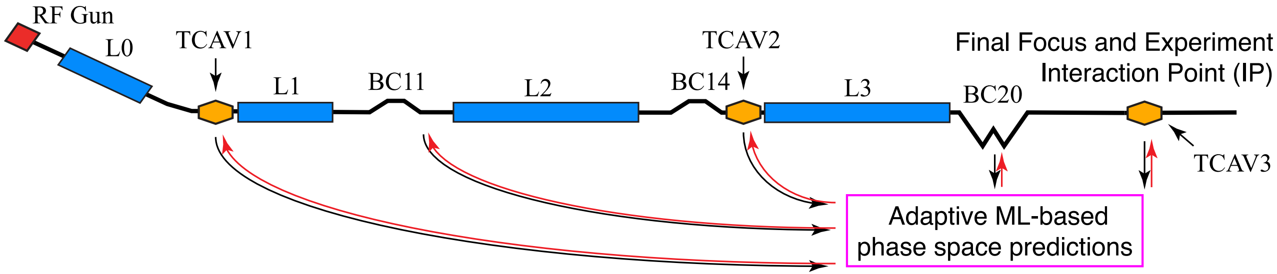


Scheinker, A., Cropp, F., Paiagua, S., & Filippetto, D. (2021). Adaptive deep learning for time-varying systems with hidden parameters: Predicting changing input beam distributions of compact particle accelerators. *arXiv preprint arXiv:2102.10510*.

Predicting 2D projections of 6D phase space at FACET-II



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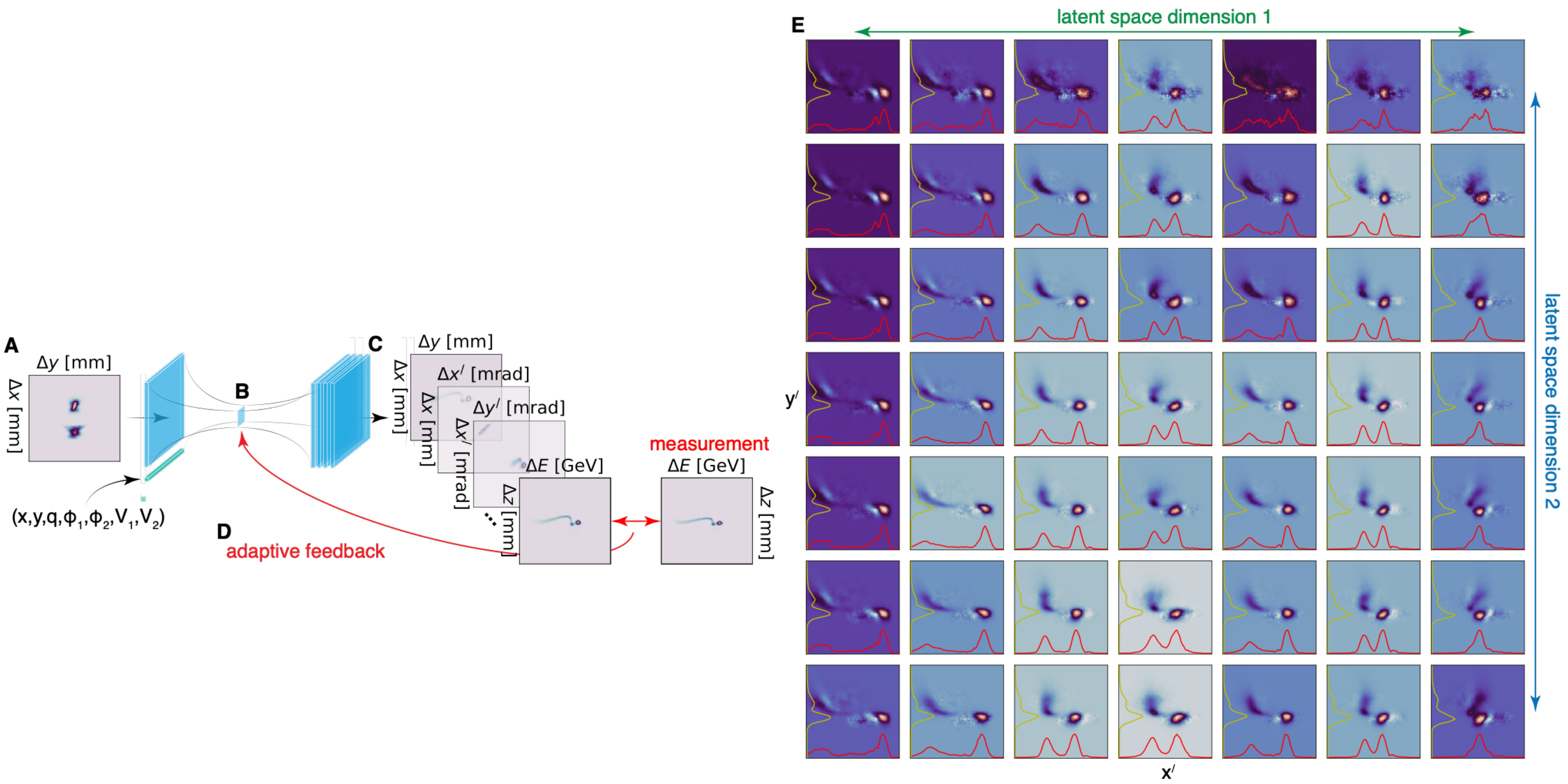

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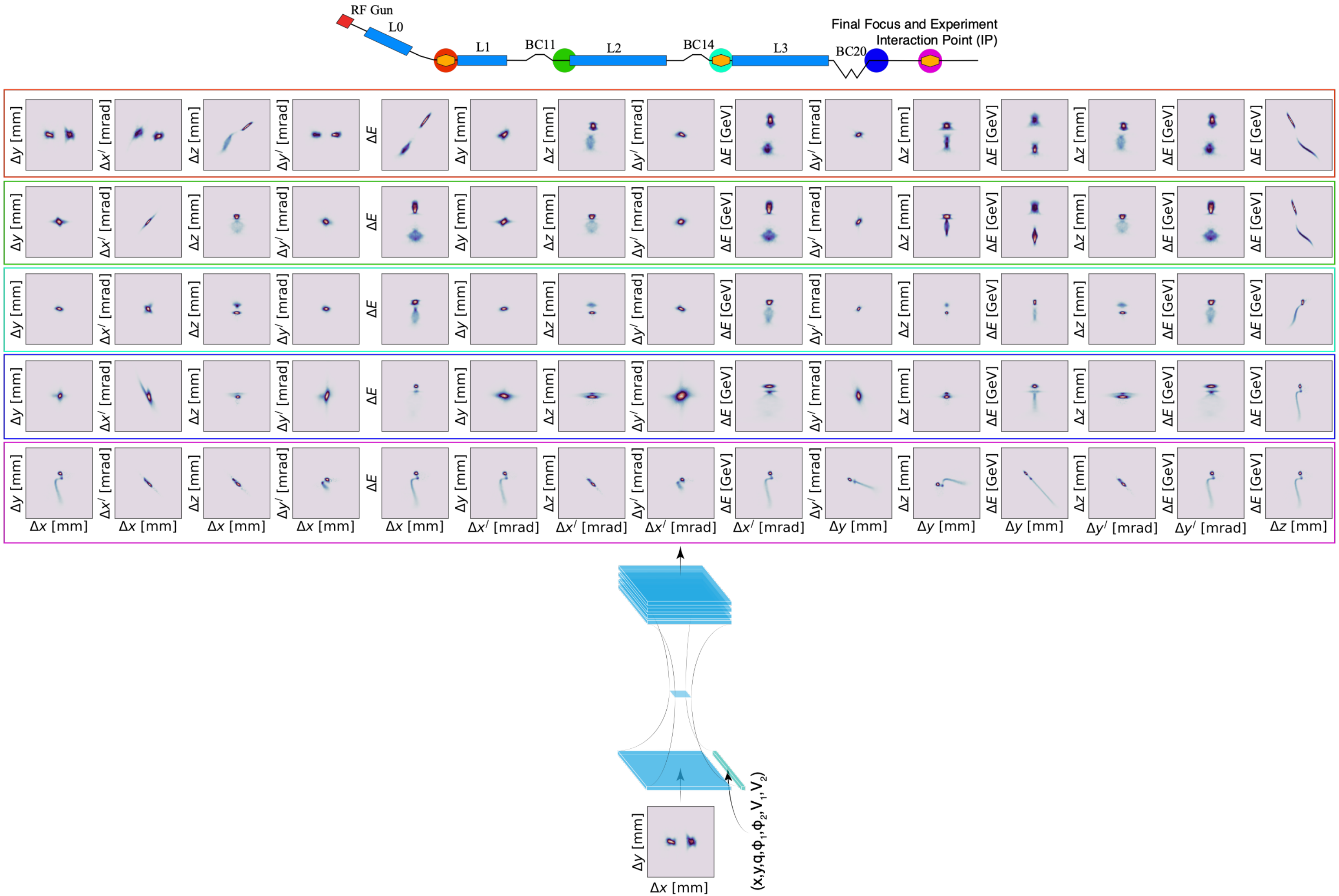
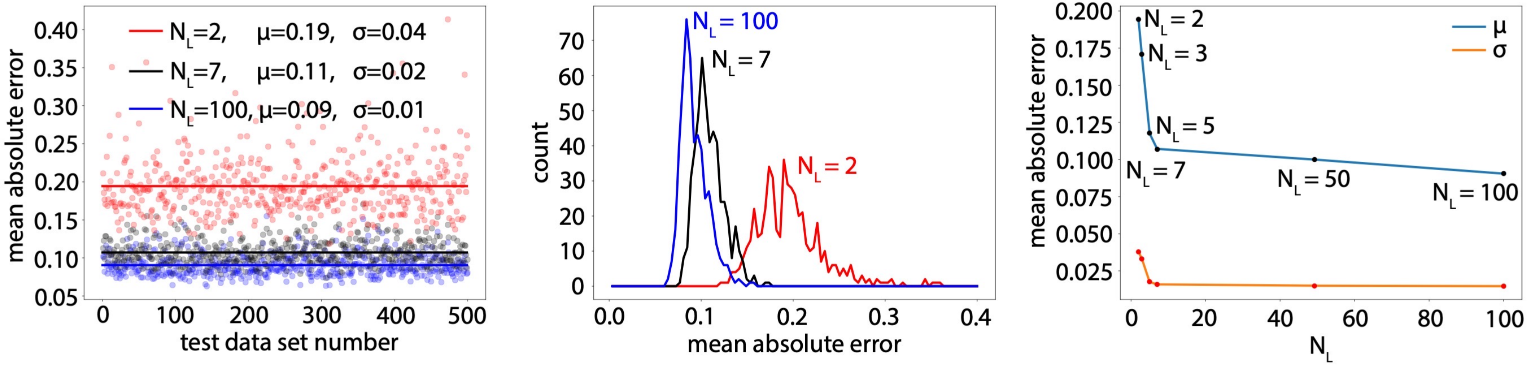


RF Gun
L0
L1
BC11
L2
BC14
L3
BC20
Final Focus and Experiment
Interaction Point (IP)
Δx [mm]
Δx' [mrad]
Δy [mm]
Δy' [mrad]
Δz [mm]
ΔE [GeV]
(x,y,q,Φ1,Φ2,V1,V2)



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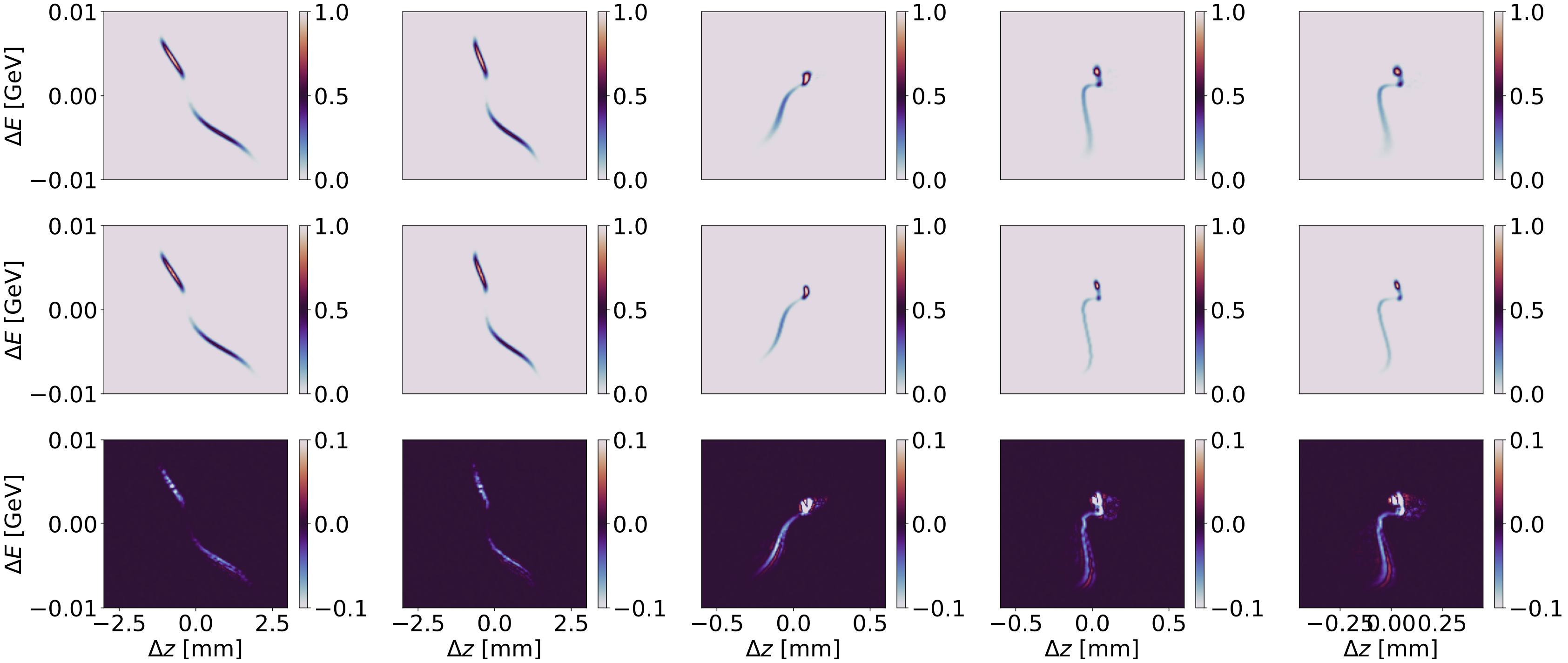

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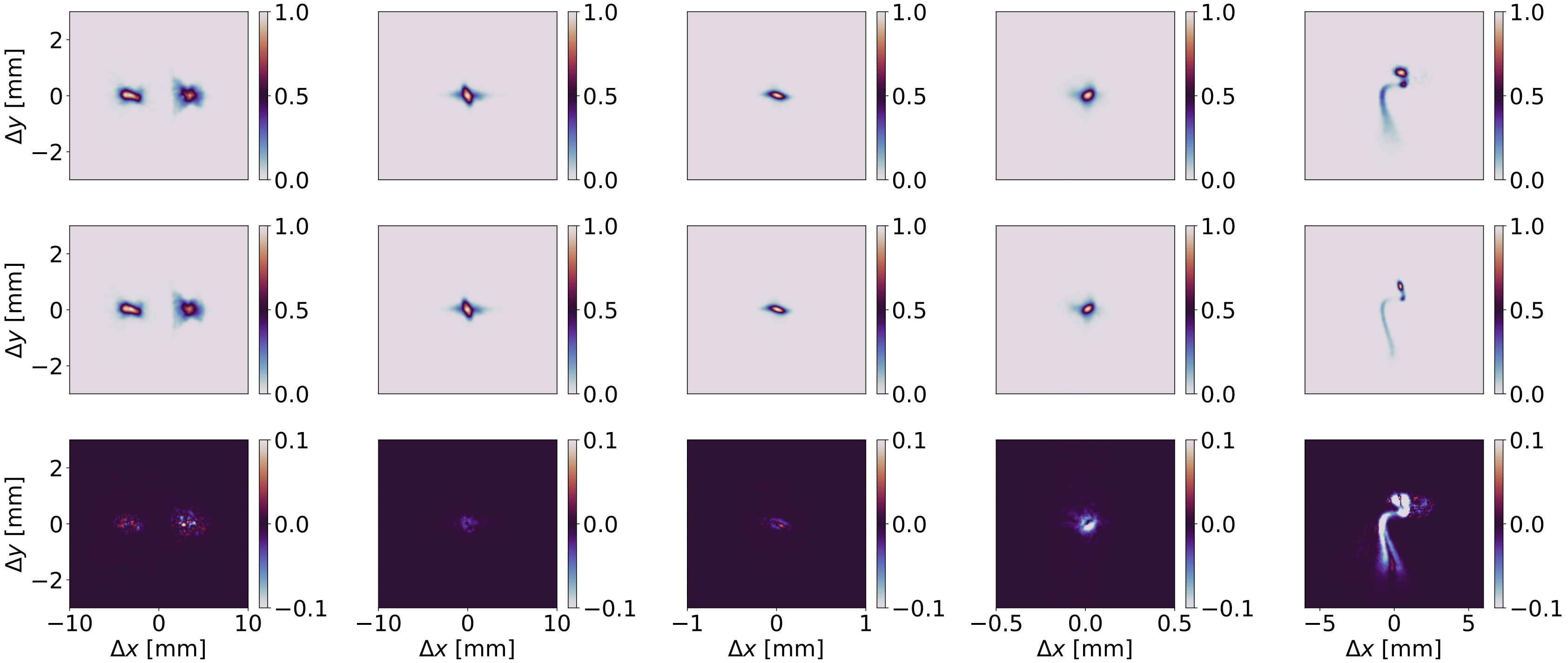

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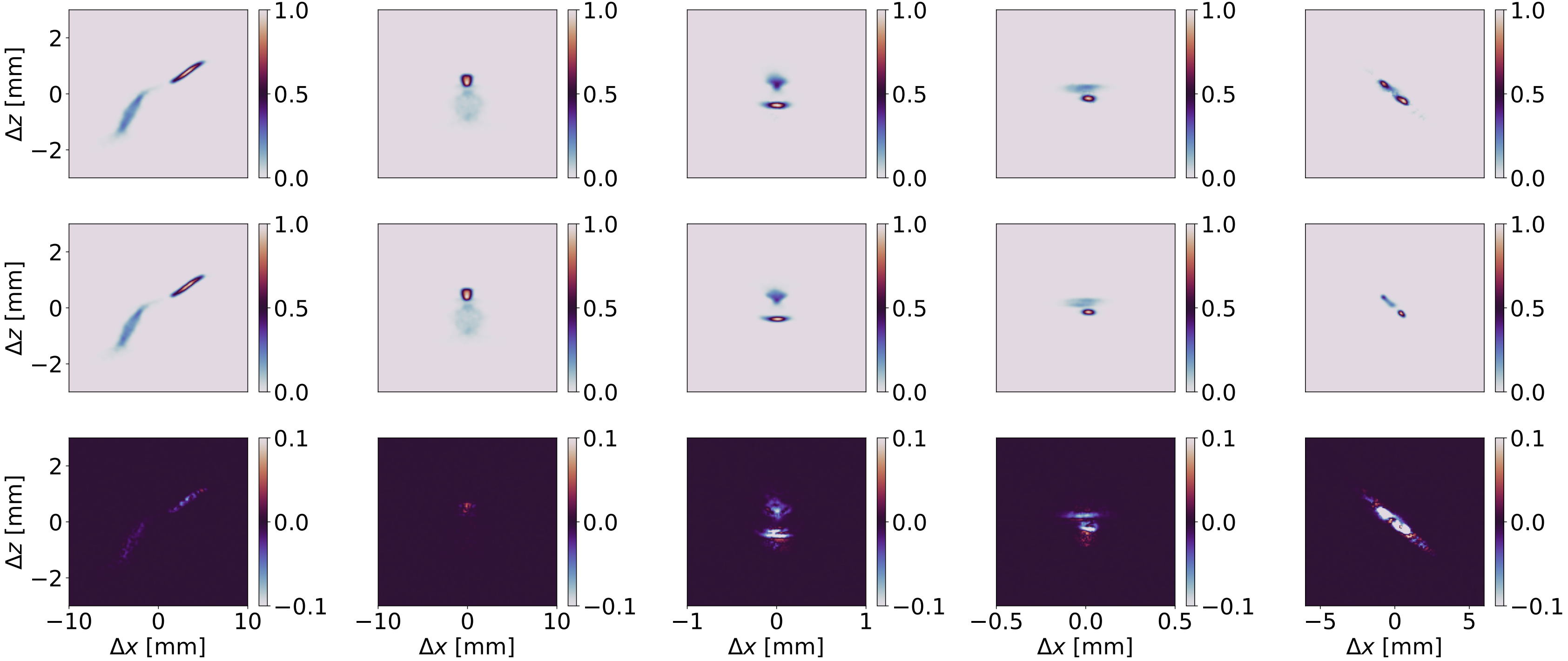

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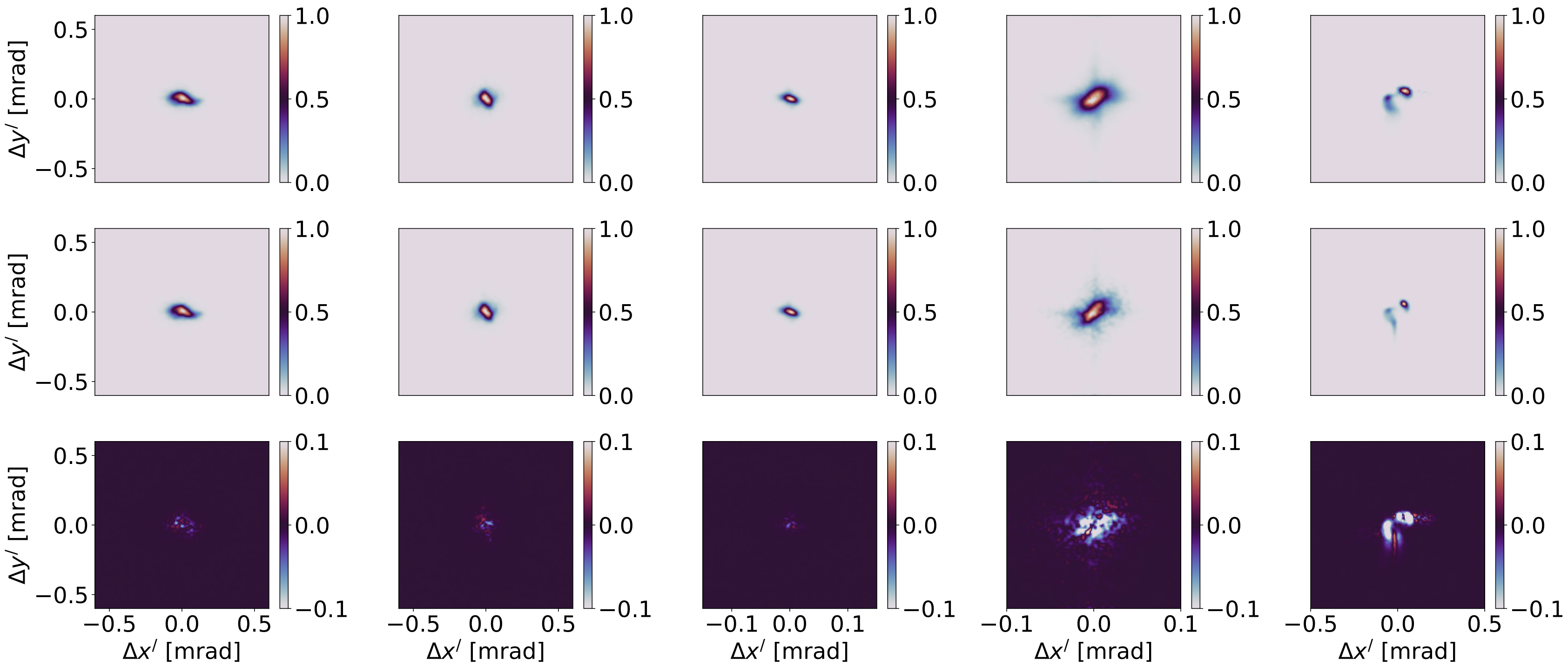

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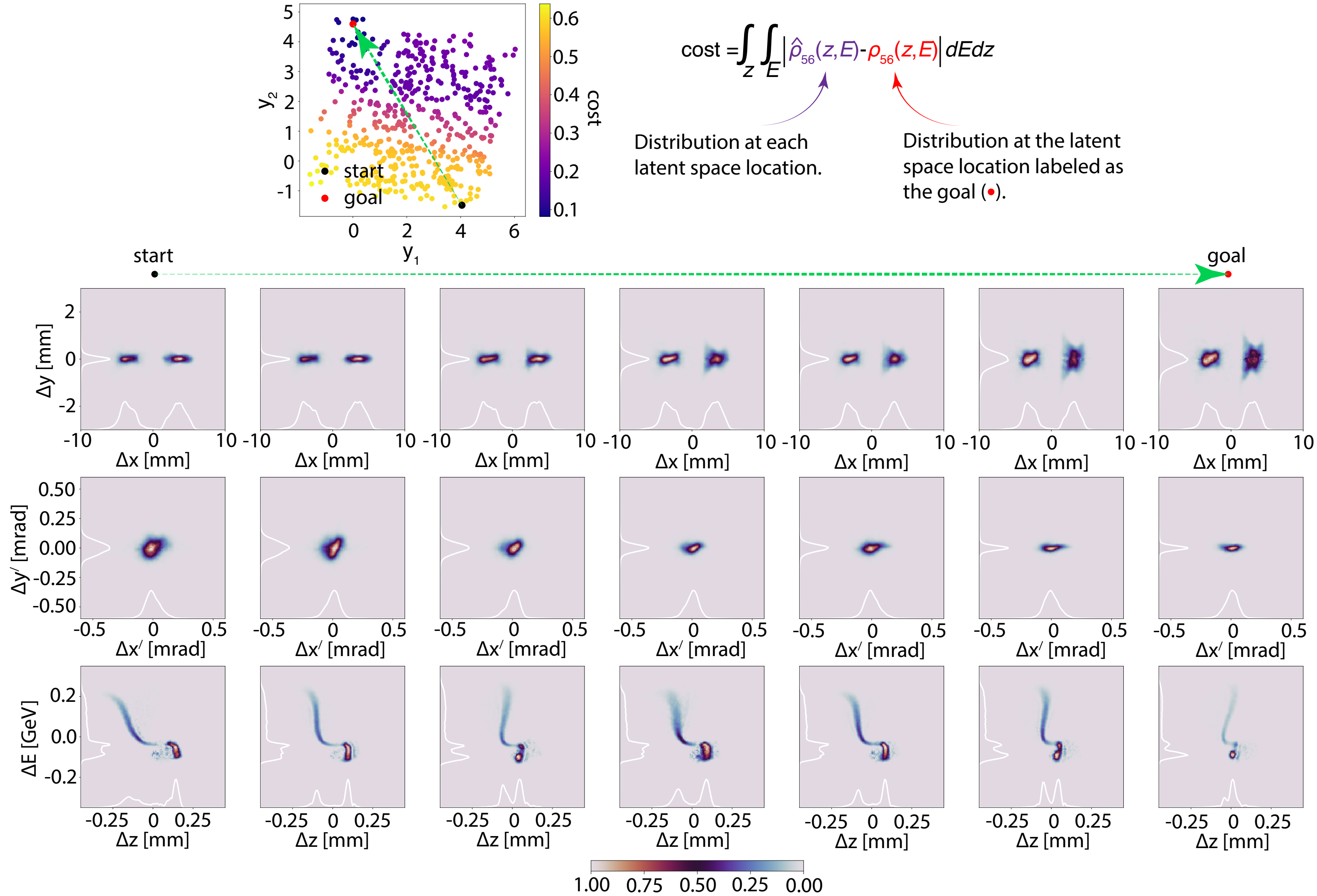
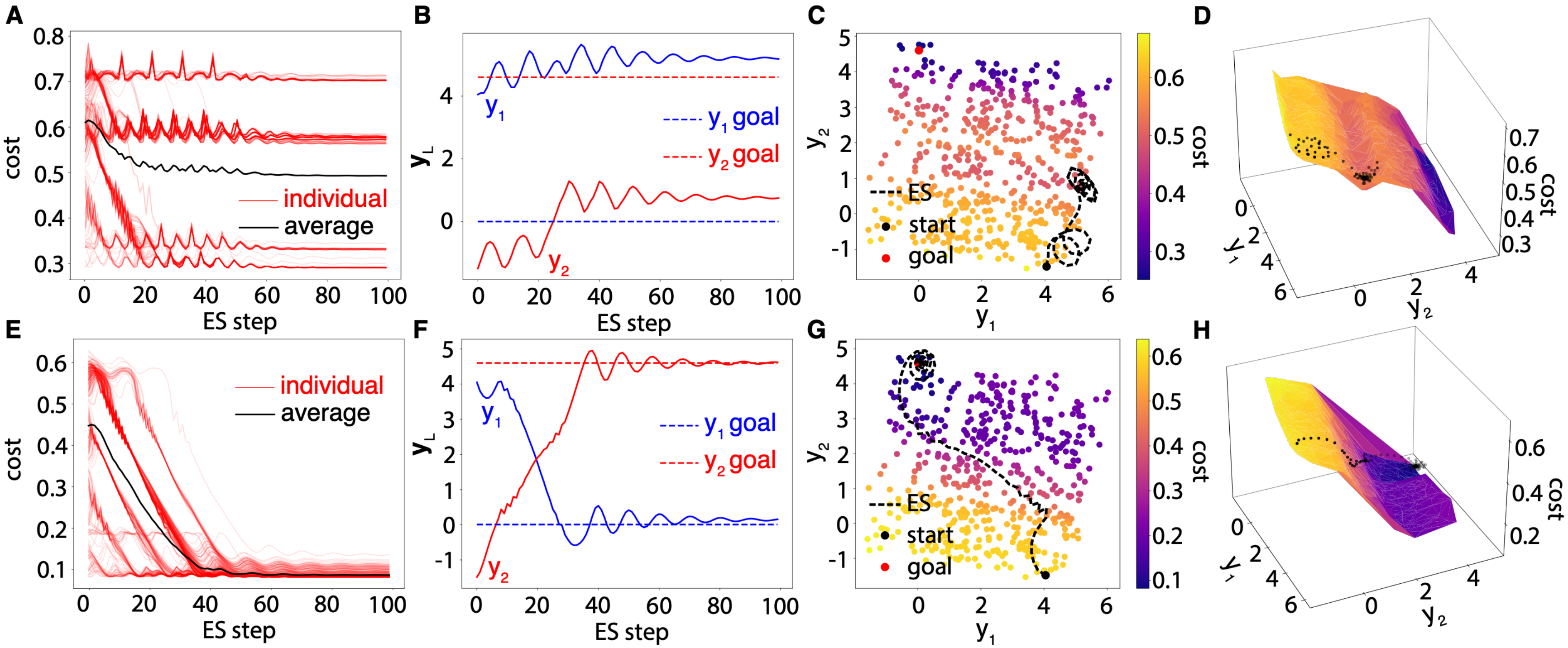


cost = ∫z ∫E |ρ̂56(z,E)-ρ56(z,E)| dEdz
Distribution at each latent space location.
Distribution at the latent space location labeled as the goal (•).
start
goal
y1
y2
cost
start
goal
Δx [mm]
Δy [mm]
Δx′ [mrad]
Δy′ [mrad]
Δz [mm]
ΔE [GeV]
1.00 0.75 0.50 0.25 0.00



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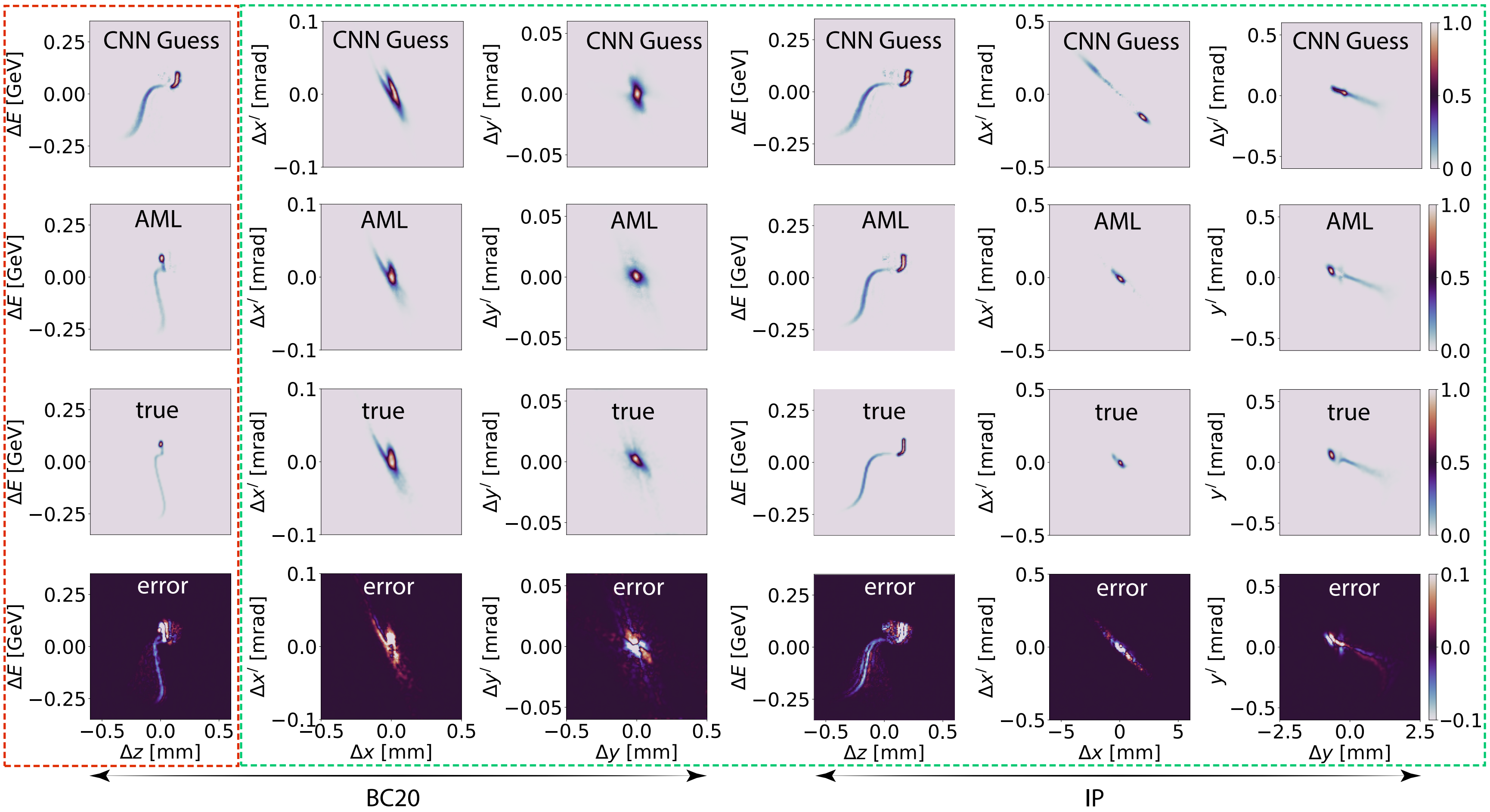
Adaptive Latent Space Tuning



FACET-II Beam Time E325

Automatic tuning for high gain, low energy spread, and low variance PWFA

- Alexander Scheinker
- Spencer Gessner
- Claudio Emma