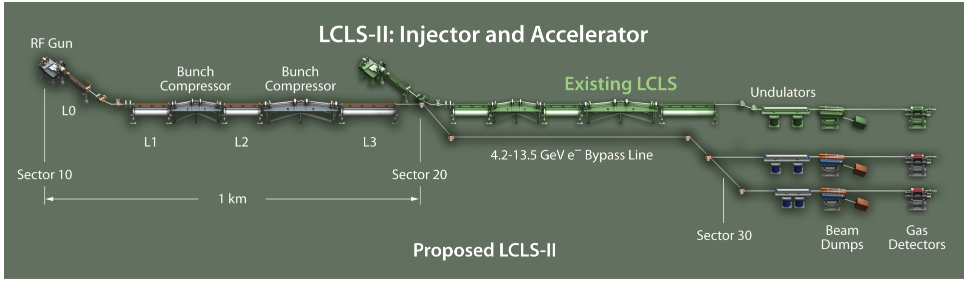
Adaptive Machine Learning for Particle Accelerators

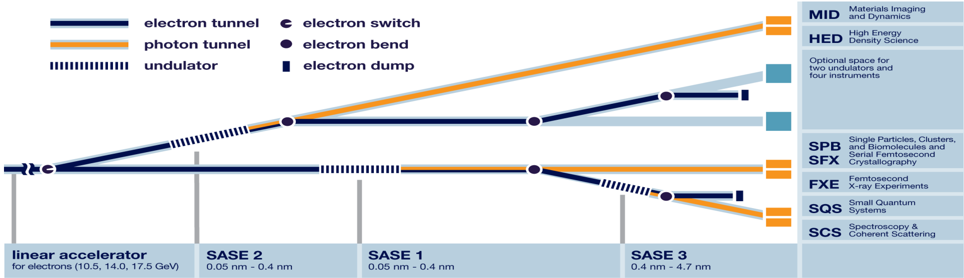
Alexander Scheinker

ICALEPCS 2019 ML Workshop

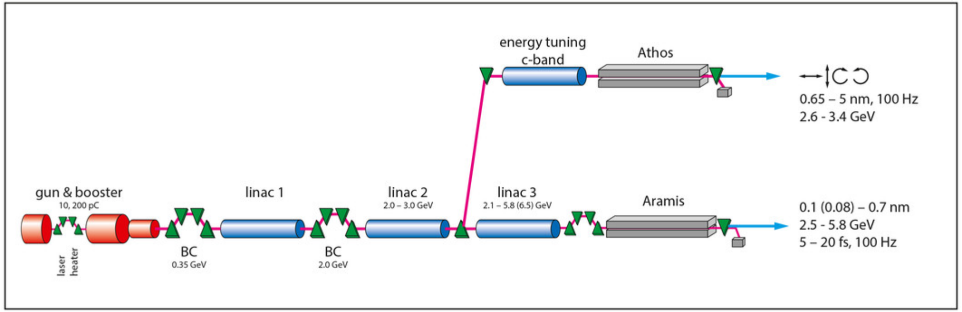
Los Alamos
NATIONAL LABORATORY
EST. 1943



LCLS/LCLS-II



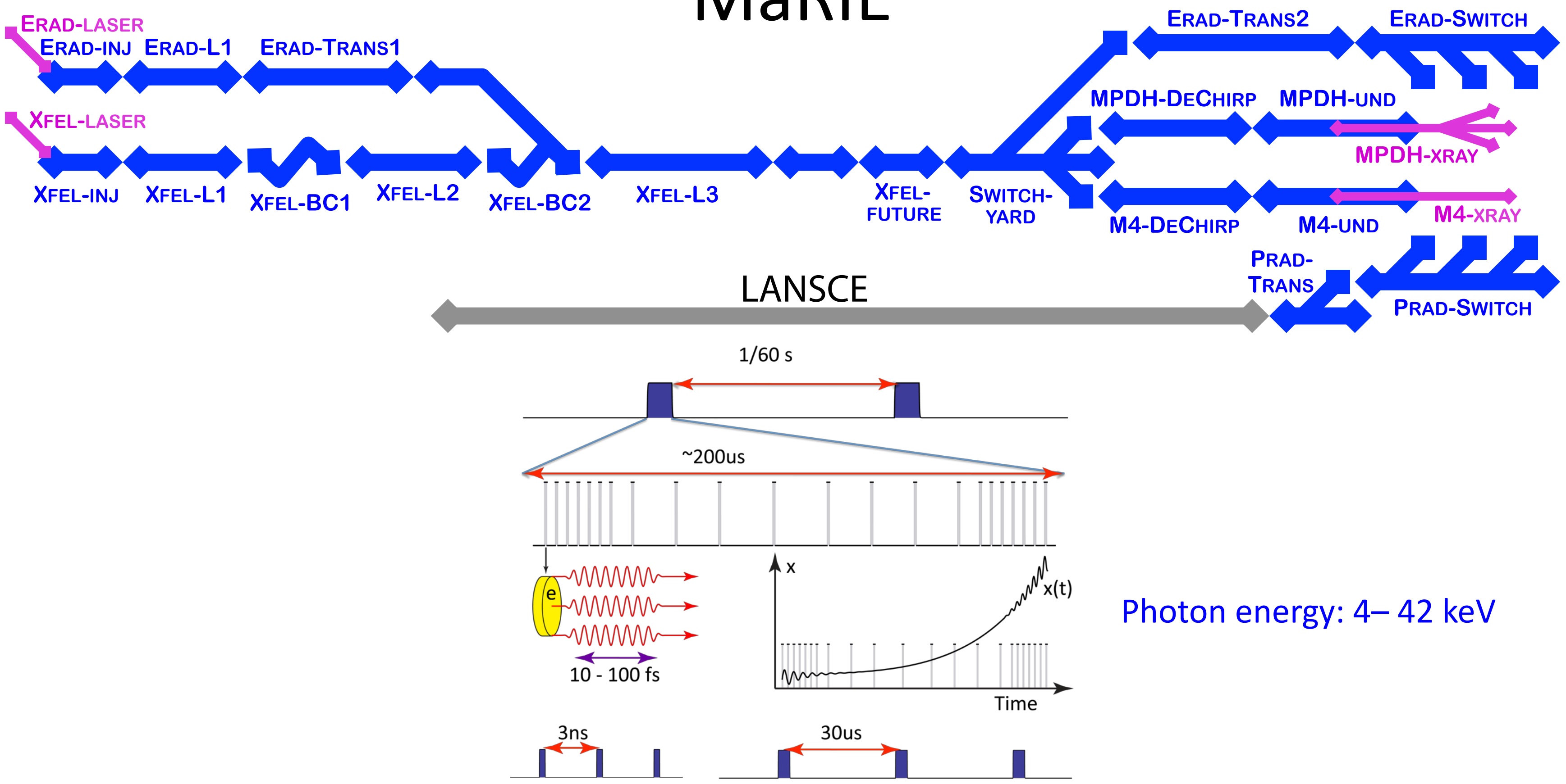
EuXFEL



Swiss XFEL

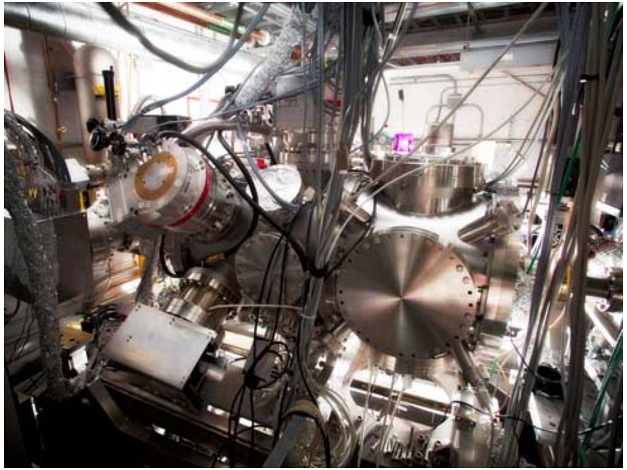
0.6 fs pulses!

MaRIE



Photon energy: 4– 42 keV

AMO



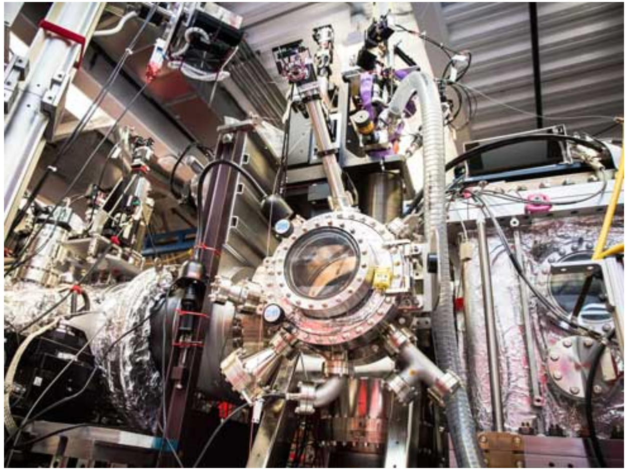
Atomic, Molecular & Optical Science

Soft X-rays for intense ultra short pulses. Gaseous targets of atoms, molecules, and nanoscale objects: protein crystals or viruses.

Photon energy: 0.48 – 2 keV
Pulse duration: 35 – 300 fs
Low charge mode pulse duration: No
Pulse energy: 1 – 20 mJ @ 266 - 800 nm

Max energy adjustment factor: 4.2
Low charge mode: No

CXI



Coherent X-ray imaging

Brilliant hard X-ray pulses for coherent diffractive imaging (CDI). Ultra short pulses for "Diffraction-Before-Destruction" experiments.

Photon energy: 5 – 12 keV
Pulse duration: 40 – 300 fs
Low charge mode pulse duration: <10 fs
Pulse energy: 1 – 3 mJ

Max energy adjustment factor: 2.4
Low charge mode: Yes

MEC

Matter in Extreme Conditions

High peak brightness, ultra short pulses of tunable energy X-rays for studying the transient behavior of matter in extreme conditions.

Photon energy: 2.5 – 12 keV
Pulse duration: 10 – 300 fs
Low charge mode pulse duration: <10 fs
Pulse energy: 1 – 3 mJ

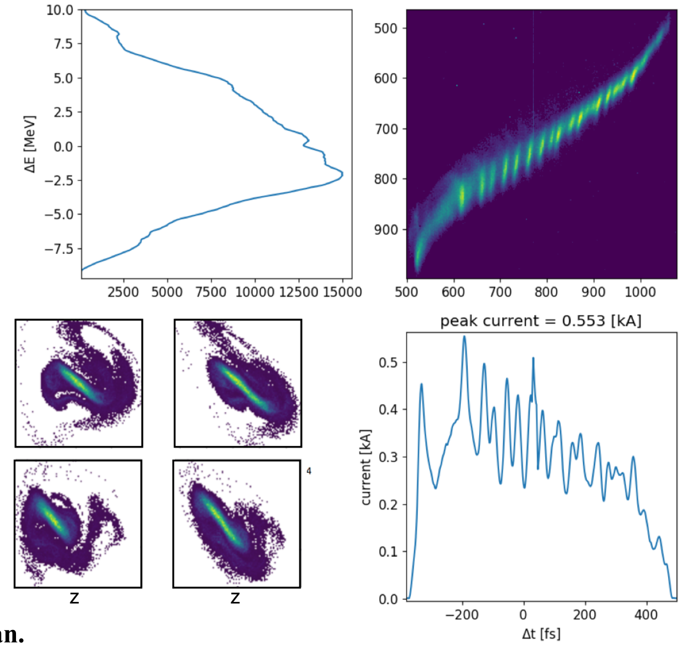
Max energy adjustment factor: 4.8
Low charge mode: Yes

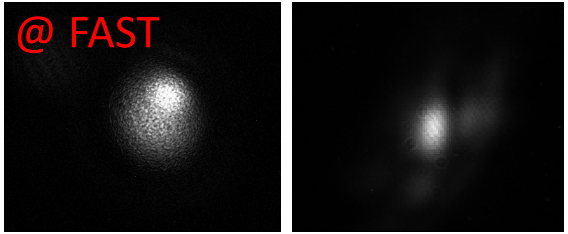
Low charge mode: Lower charge per bunch allows for tighter compression without destroying the electron beam's phase space. Originally studying for accelerating 0.02 nC bunches instead of 1 nC.

Accelerator Tuning Challenges

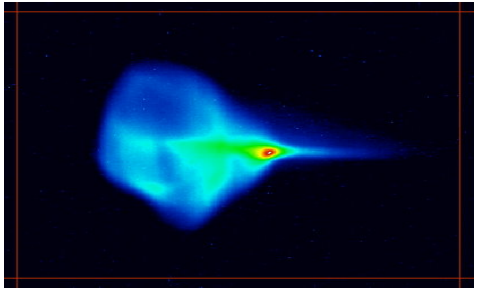
- Dynamics of intense charged particle bunches dominated by:
  - **Components drift unpredictably with time, misalignments**
    - **Uncertain and time varying electron bunch distribution off cathode**
  - **Complex collective effects:**
    - **Wakefields**
    - **Space charge**
    - **Coherent synchrotron radiation**
  - **Limited non-invasive diagnostics**

EuXFEL: µBunch Instabilities



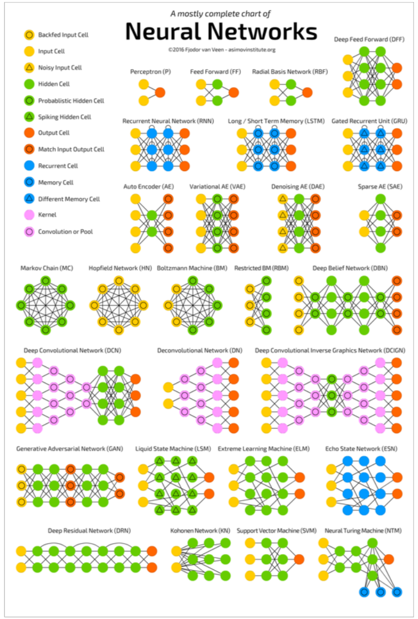


Example images of laser spot
(10 Aug. 2016, 11 Nov. 2017)

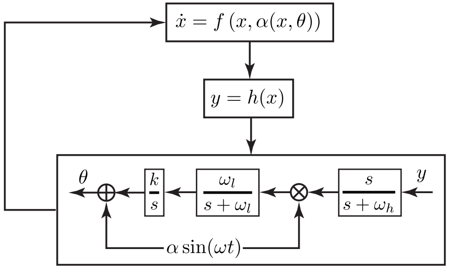


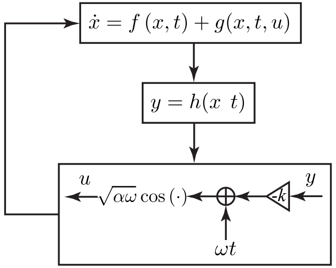
Typical 2D (x,y) beam profile, not a simple Gaussian.

Artificial Intelligence and Adaptive Feedback



Adapative Feedback





Surrogate models
Big data
Global tuning
Anomaly detection

Virtual diagnostics
Real time feedback
Optimization
Phase space tuning

Neural Networks

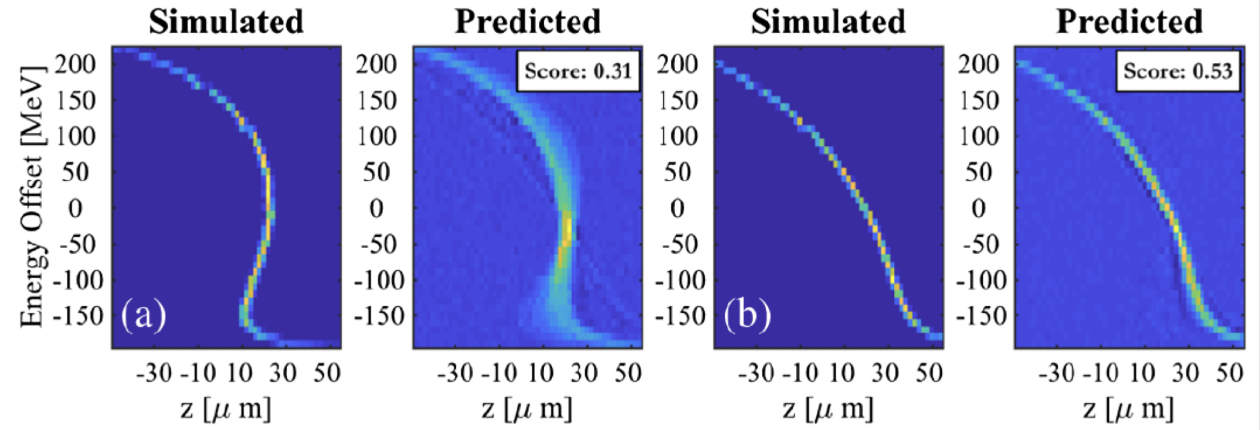
FACET-II Single bunch simulations

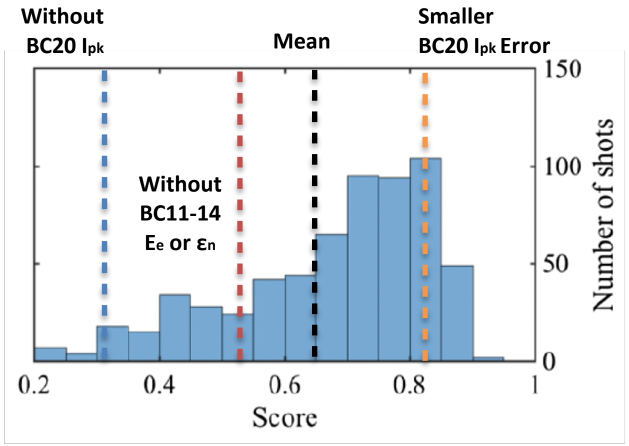
PHYSICAL REVIEW ACCELERATORS AND BEAMS **21**, 112802 (2018)

Machine learning-based longitudinal phase space prediction of particle accelerators

C. Emma,[*,†] A. Edelen,[†] M. J. Hogan, B. O'Shea, G. White, and V. Yakimenko
SLAC National Accelerator Laboratory, Menlo Park, California 94025, USA

(Received 11 September 2018; published 16 November 2018)





- Results for the LPS prediction show similar agreement between NN and simulation.
- Sensitivity study (removing diagnostics from ML input) shows that the most critical diagnostic is the peak current measurement after BC20.

$$\text{score} \equiv R^2 = 1 - \frac{\Sigma_{i,j}(x_{ij}^{\text{true}} - x_{ij}^{\text{predicted}})^2}{\Sigma_{i,j}(x_{ij}^{\text{true}} - \bar{x}^{\text{true}})^2}$$

Slide from: C. Emma

Adaptive Feedback

Extremum Seeking

- Model independent
- Noisy and time varying systems
- Many coupled parameters

$$\begin{bmatrix} \dot{x}_1 \\ \vdots \\ \dot{x}_n \end{bmatrix} = \dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{p}, t) = \begin{bmatrix} f_1(x_1, \ldots, x_n, p_1, \ldots, p_m, t) \\ \vdots \\ f_n(x_1, \ldots, x_n, p_1, \ldots, p_m, t) \end{bmatrix}$$

$$y = V(\mathbf{x}, t) + n(t)$$

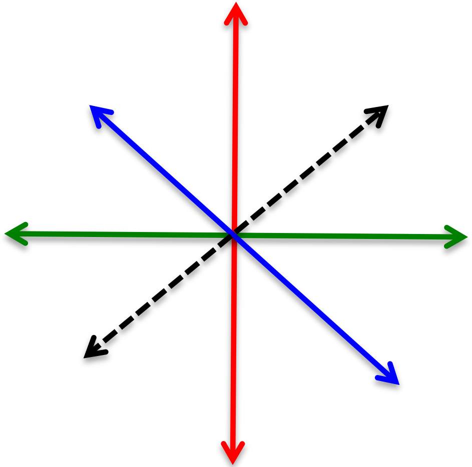
$$\frac{dp_1}{dt} = \sqrt{\alpha\omega_1}\cos(\omega_1 t + ky)$$

$$\frac{dp_2}{dt} = \sqrt{\alpha\omega_2}\cos(\omega_2 t + ky)$$

$$\frac{dp_3}{dt} = \sqrt{\alpha\omega_3}\cos(\omega_3 t + ky)$$

$$\vdots$$

$$\frac{dp_m}{dt} = \sqrt{\alpha\omega_m}\cos(\omega_m t + ky)$$



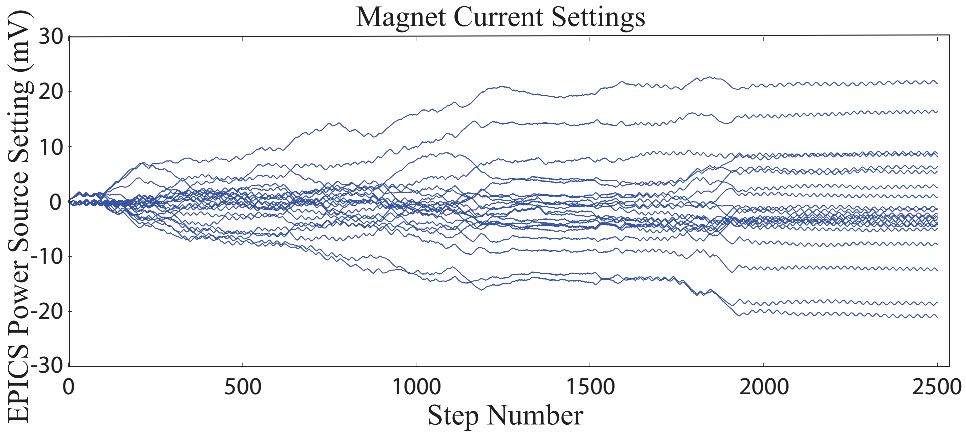
$$\frac{d\mathbf{p}}{dt} = -\frac{k\alpha}{2}\left(\nabla_{\mathbf{p}} V(\mathbf{x}, t)\right)^T$$

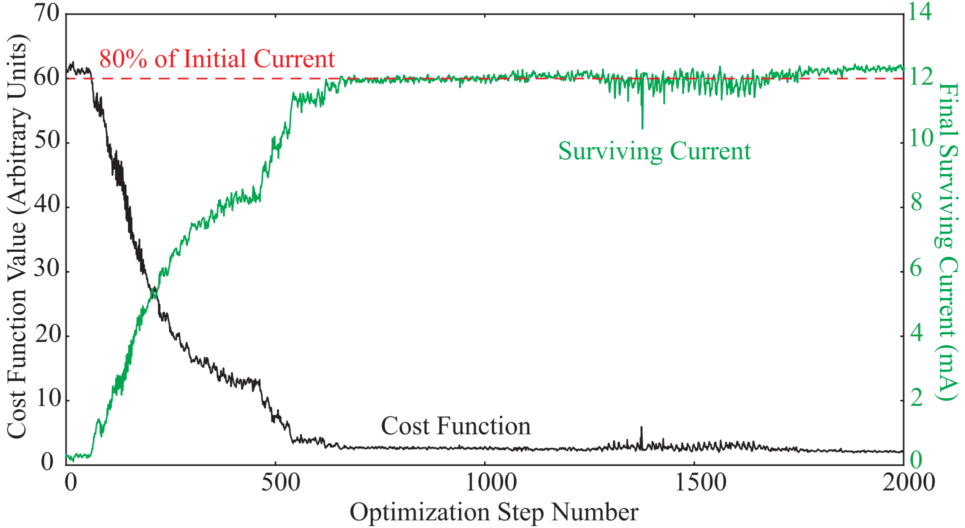
On average, the system performs minimizes the **unknown, time-varying** function V(x,t)

Allows simultaneous tuning of ALL parameters in parallel.

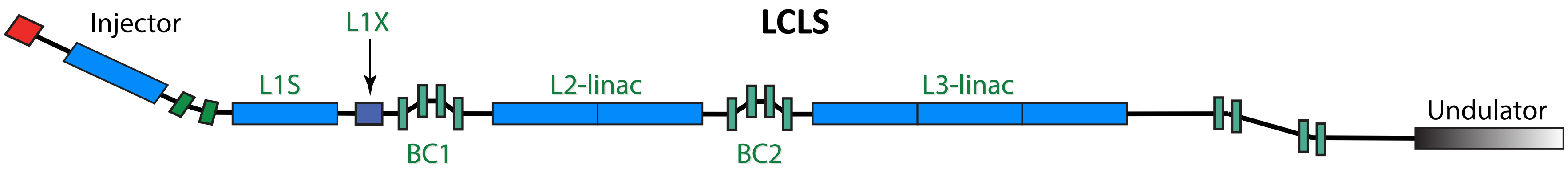
$$\omega_i = \omega r_i, \;\; r_i \neq r_j \implies \text{for any } t > 0$$

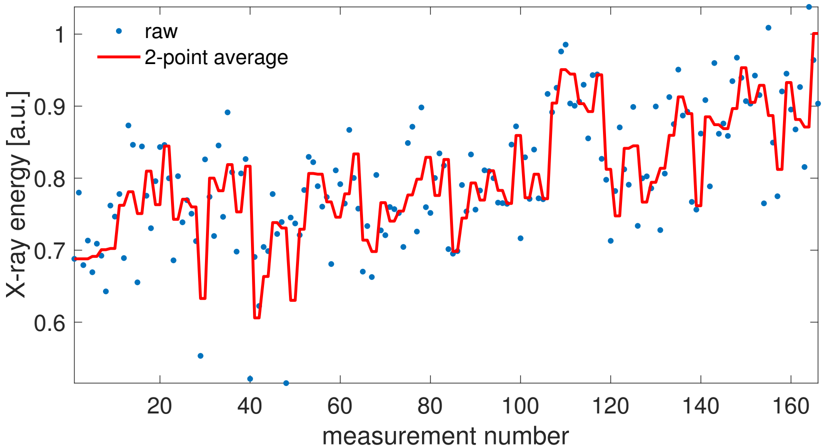
$$\lim_{\omega \to \infty} \langle \cos(\omega_i t), \cos(\omega_j t) \rangle = \lim_{\omega \to \infty} \int_0^t \cos(\omega_i \tau)\cos(\omega_j \tau)\, d\tau = 0$$

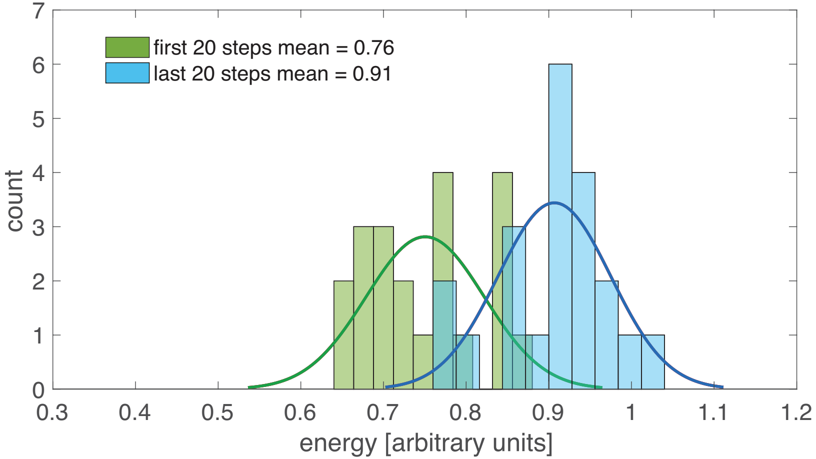


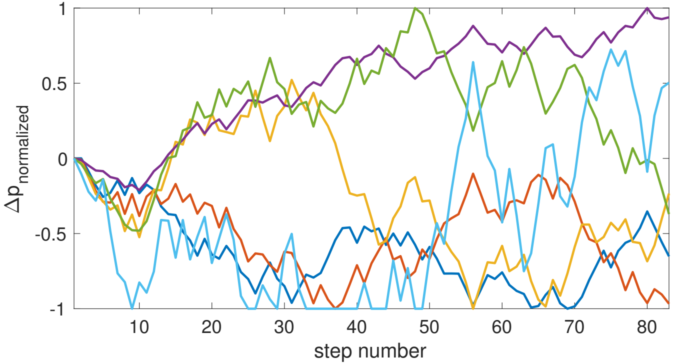


A. Scheinker et al, *2013*.

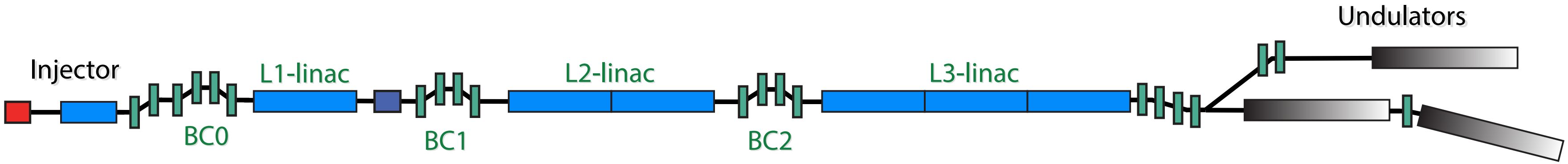




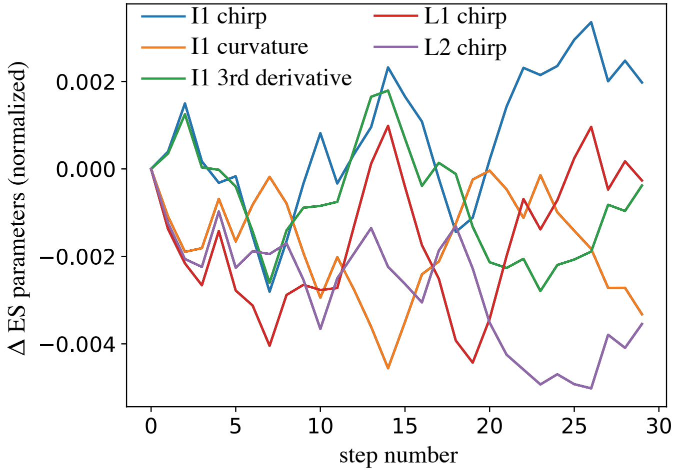


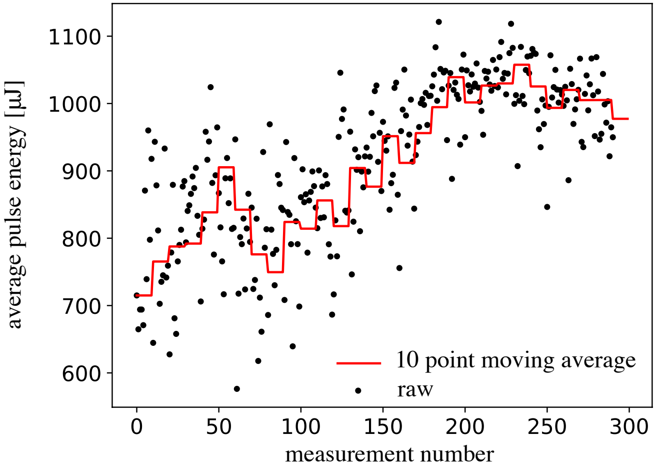


A.Scheinker *et al*. "Model-independent tuning for maximizing free electron laser pulse energy." *Physical Review Accelerators and Beams*, vol. 22, no. 8, 082802, 2019.



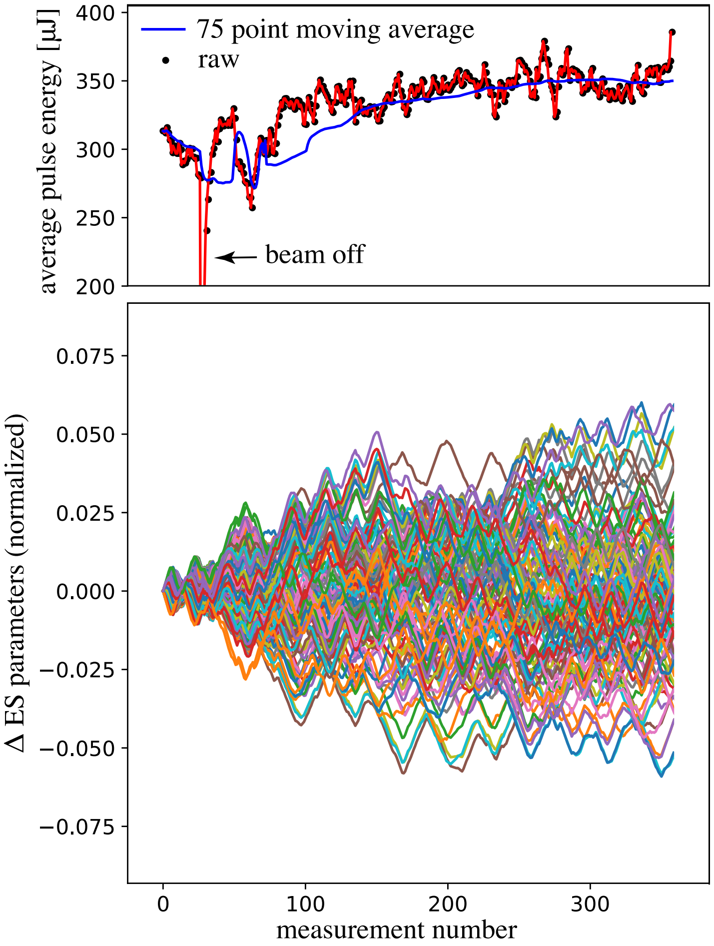
ES at EuXFEL (5 RF parameters: I1 chirp, curvature, 3rd derivative, L1 chirp, L2 chirp)





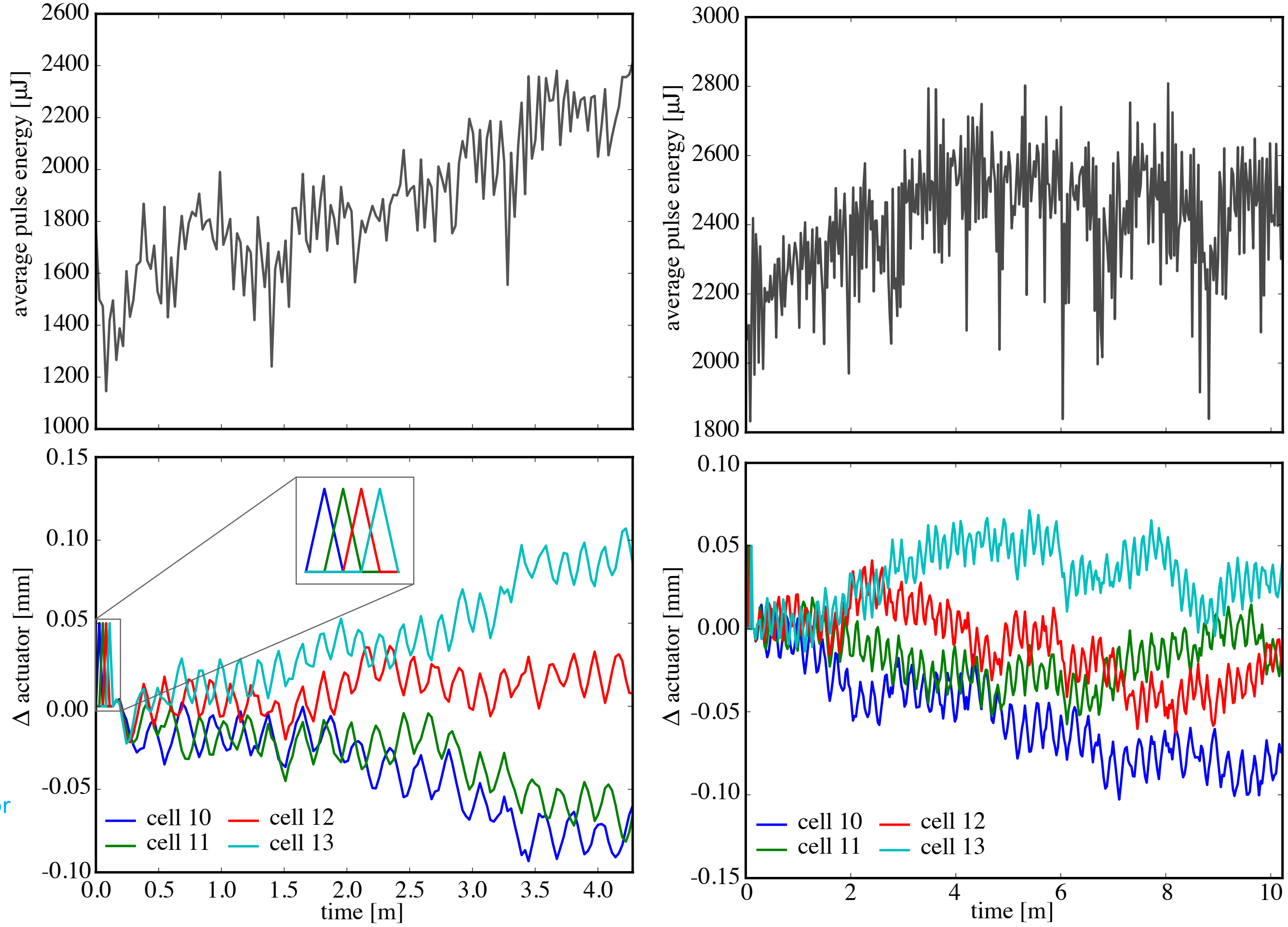
A.Scheinker *et al*. "Model-independent tuning for maximizing free electron laser pulse energy." *Physical Review Accelerators and Beams*, vol. 22, no. 8, 082802, 2019.

ES at EuXFEL (105 parameters = 84 air coils + 21 phase gaps)



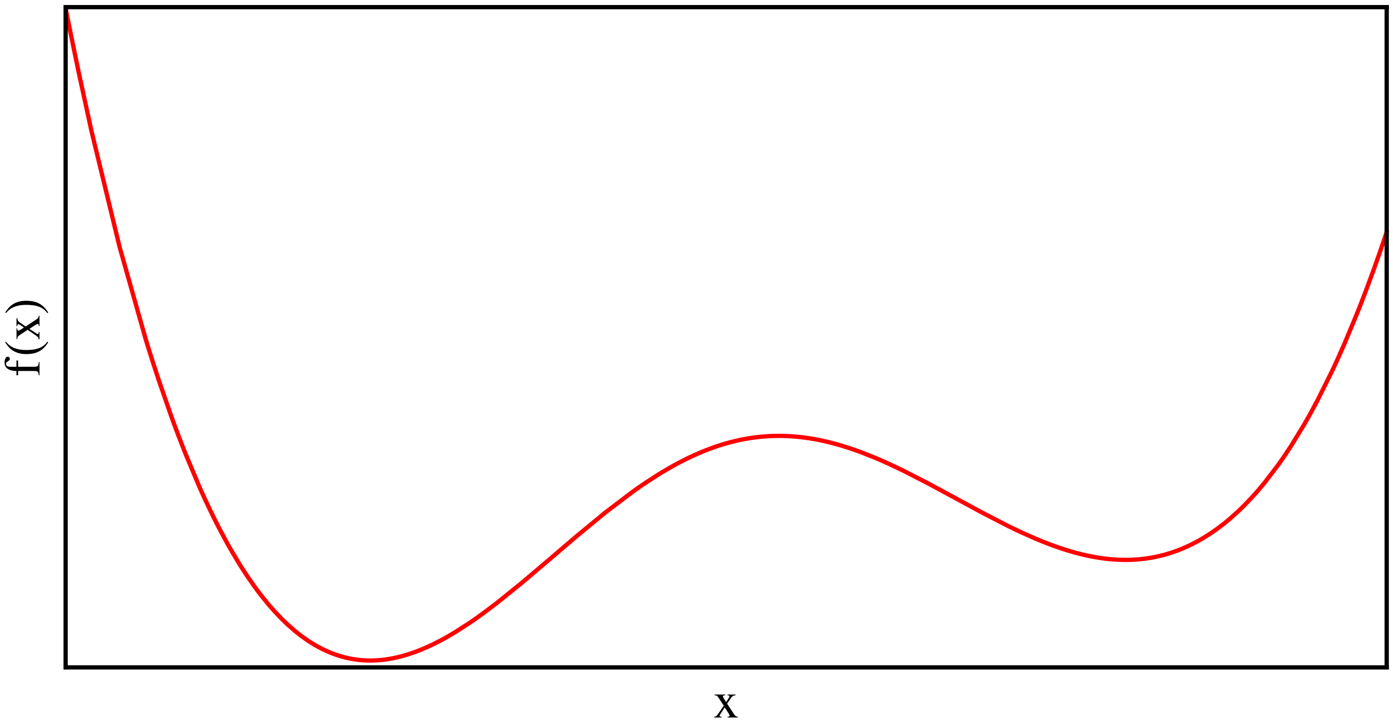
A.Scheinker *et al*. "Model-independent tuning for maximizing free electron laser pulse energy." *Physical Review Accelerators and Beams*, vol. 22, no. 8, 082802, 2019.

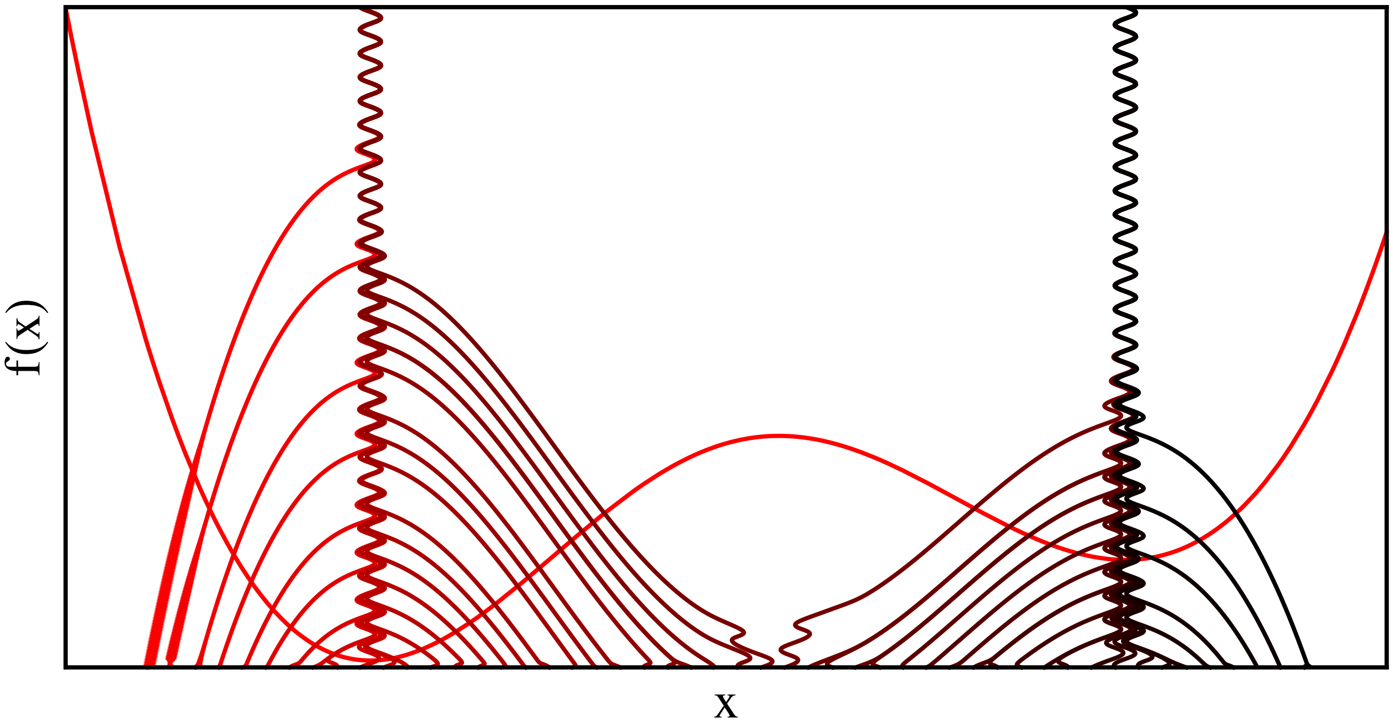
ES Implemented as optimizer in OCELOT



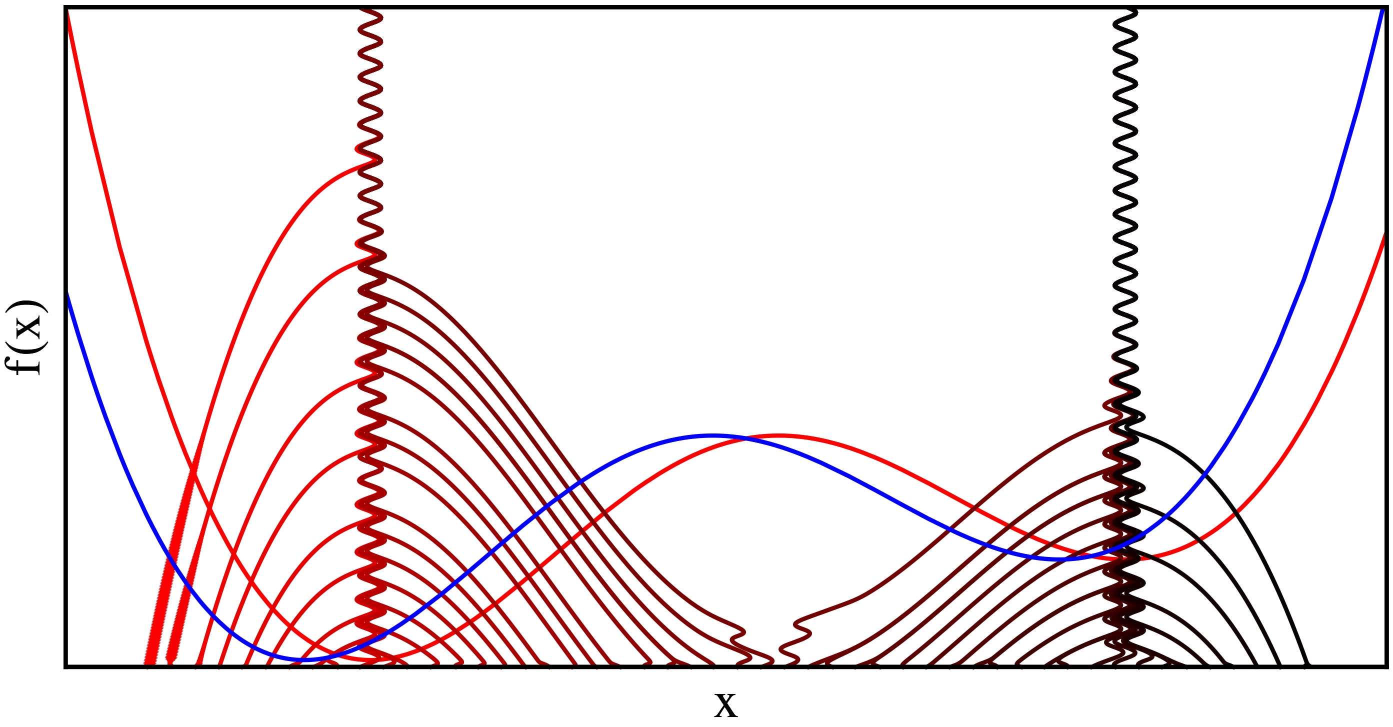
A.Scheinker *et al*. “Model-independent tuning for maximizing free electron laser pulse energy." *Physical Review Accelerators and Beams*, vol. 22, no. 8, 082802, 2019.

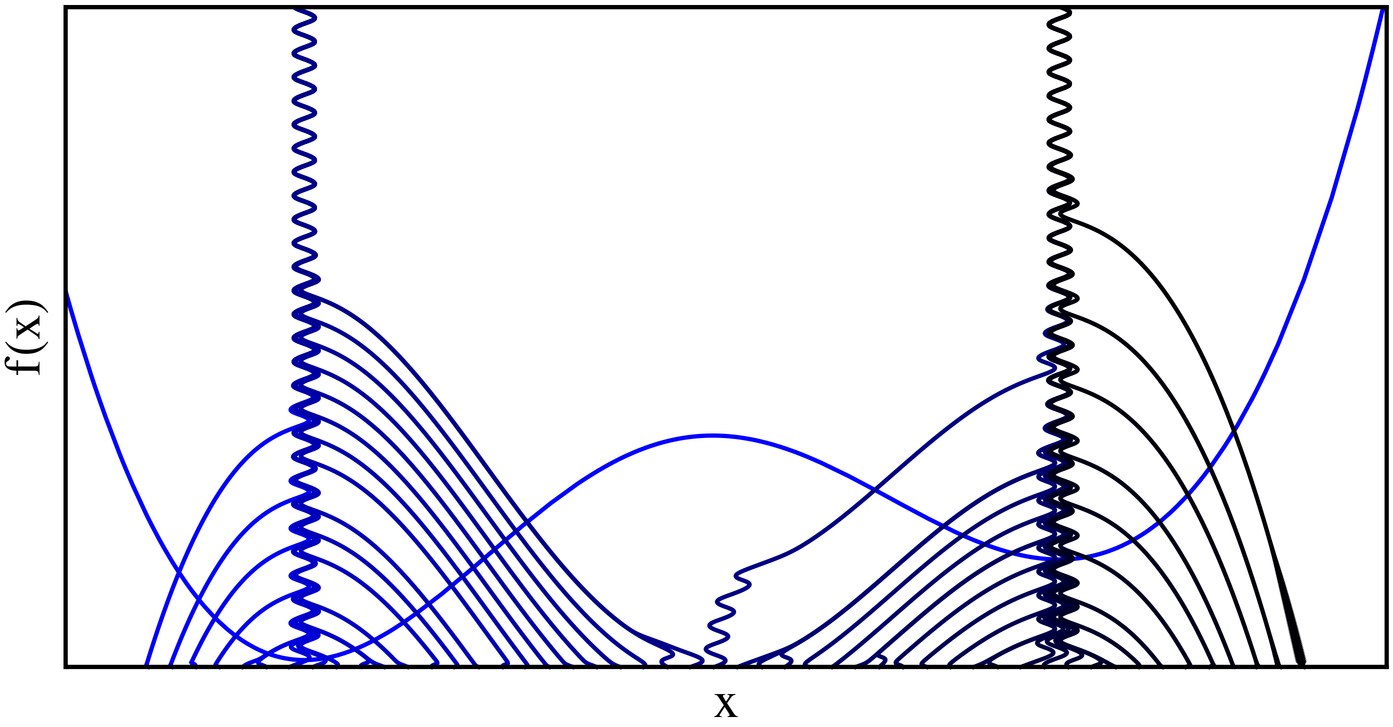
Neural Nets for Changing Systems

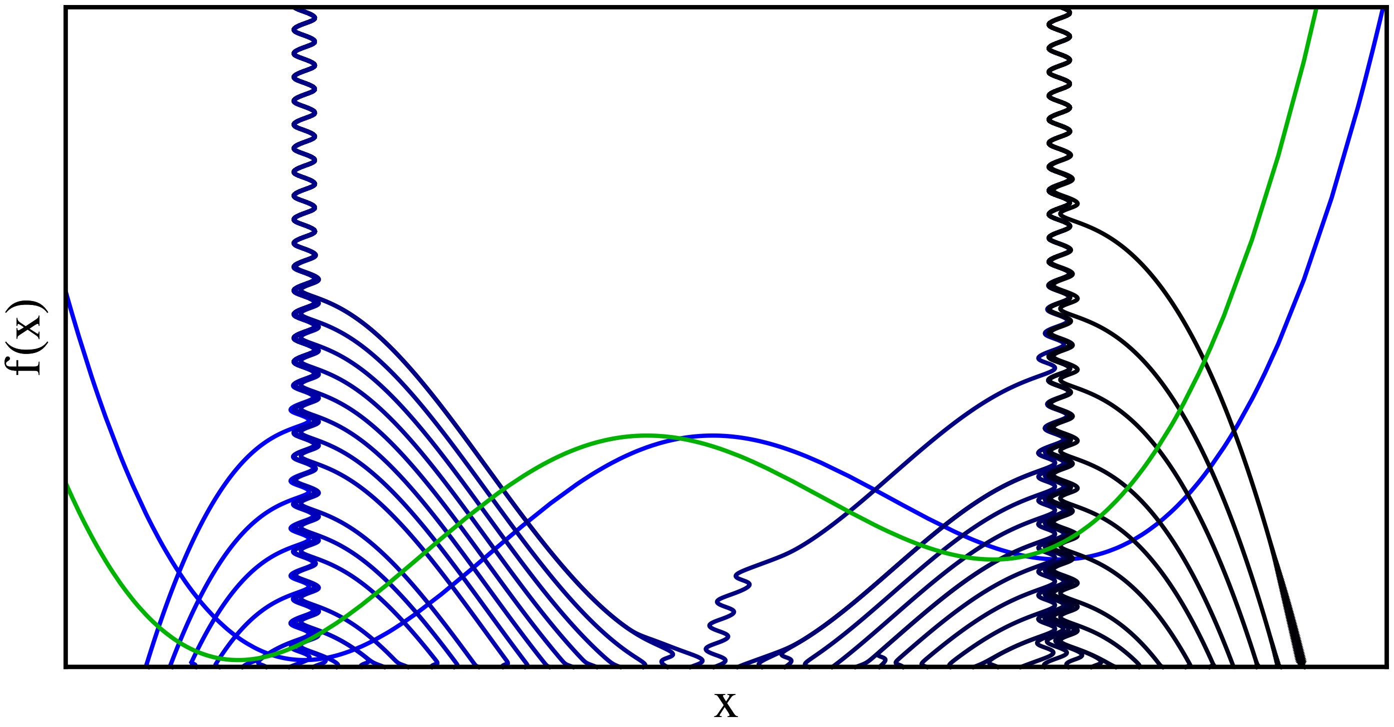

f(x)
x



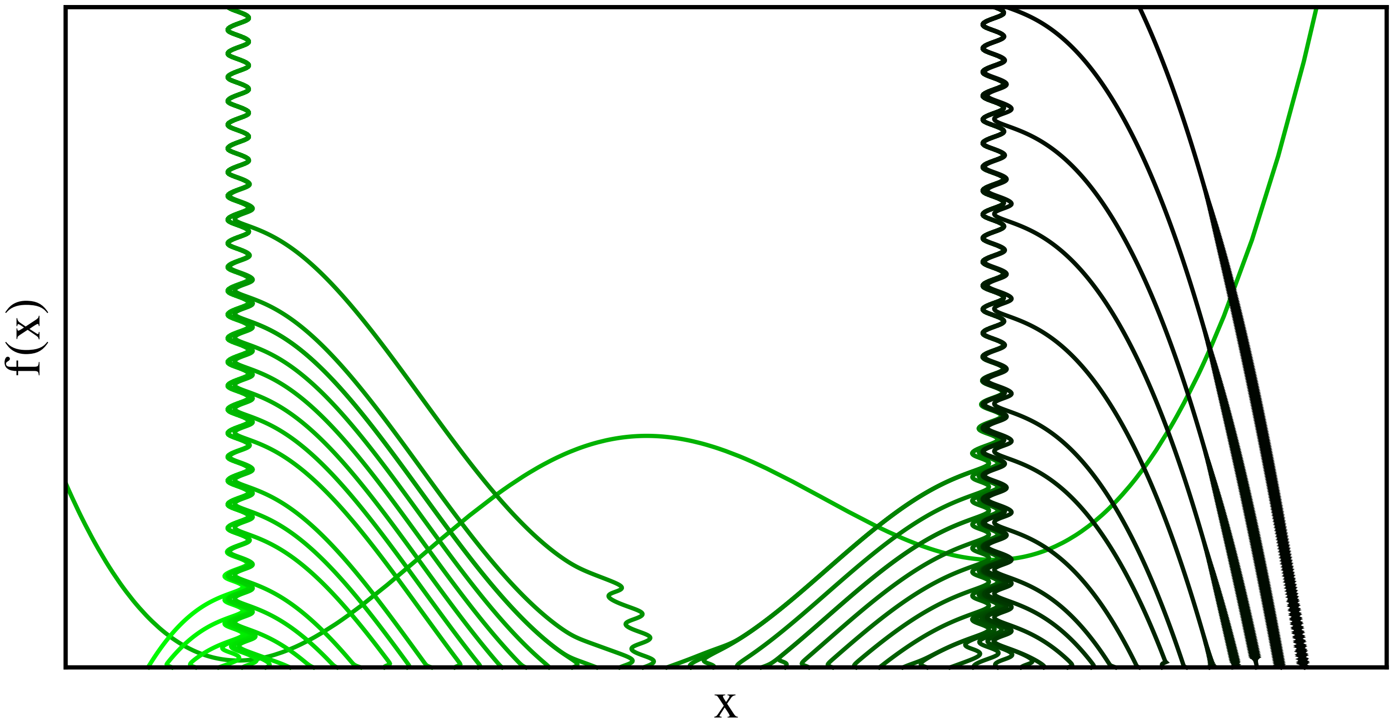
f(x)
x


f(x)
x

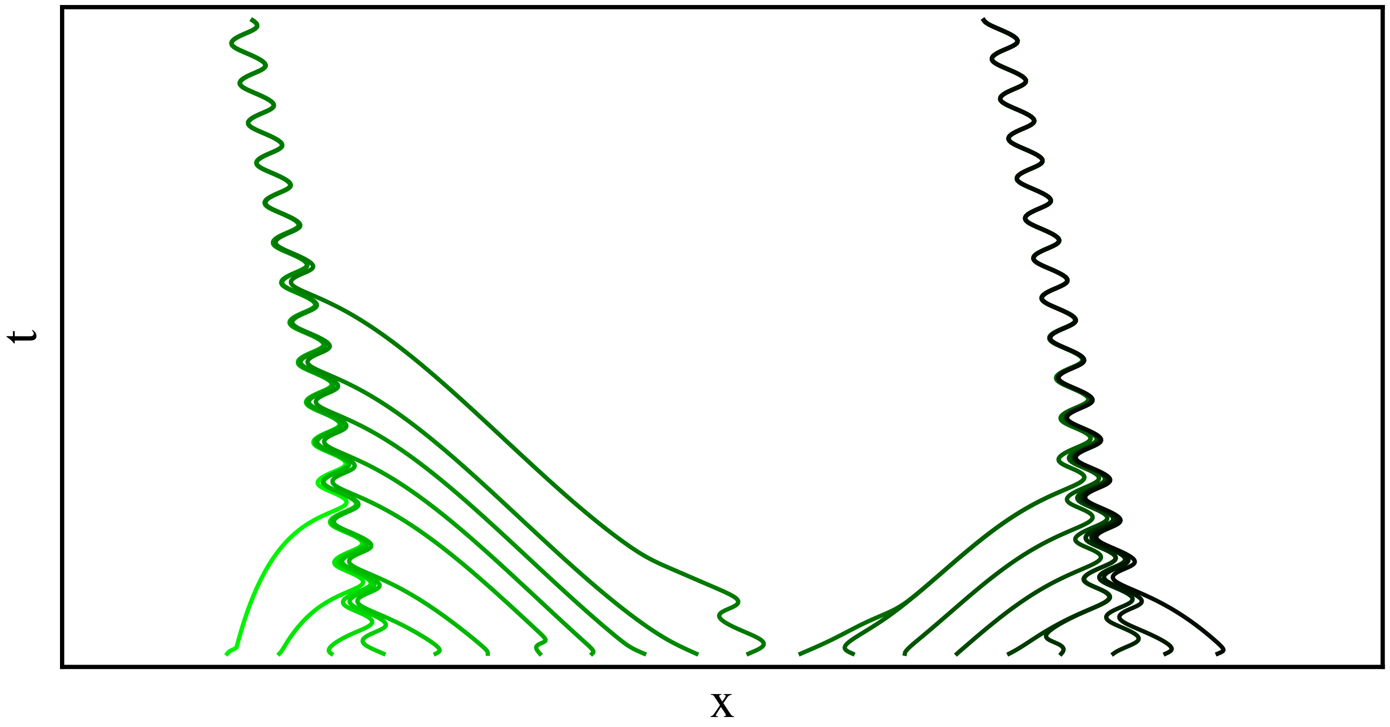

f(x)
x



f(x)
x



f(x)
x

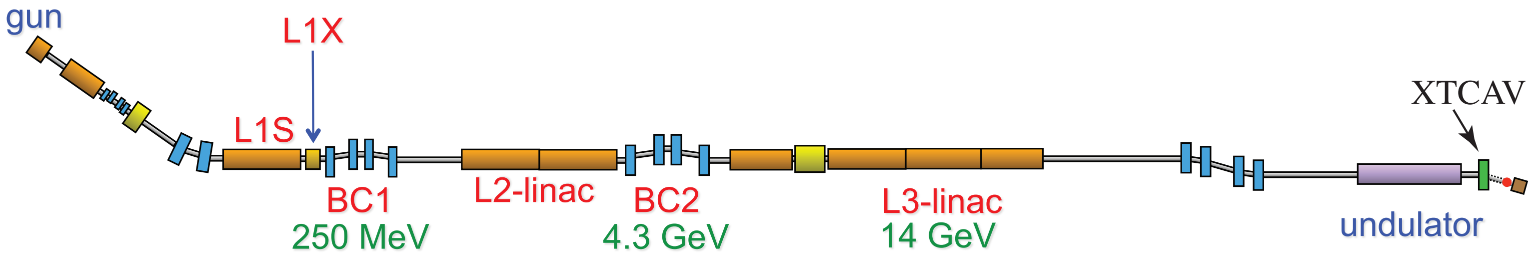


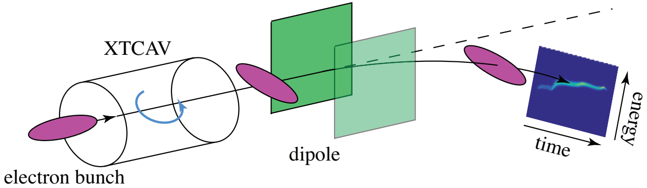
t
x

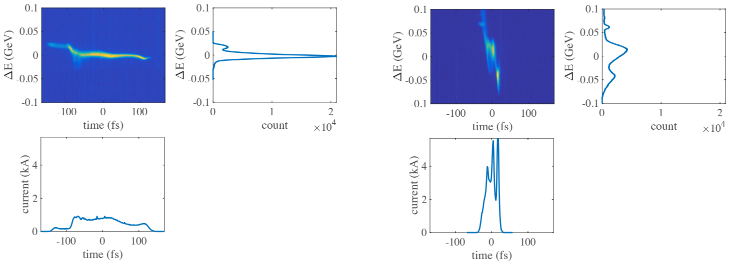
Combining ML and ES

(LANL and SLAC)

Adaptive Machine Learning for Phase Space Tuning

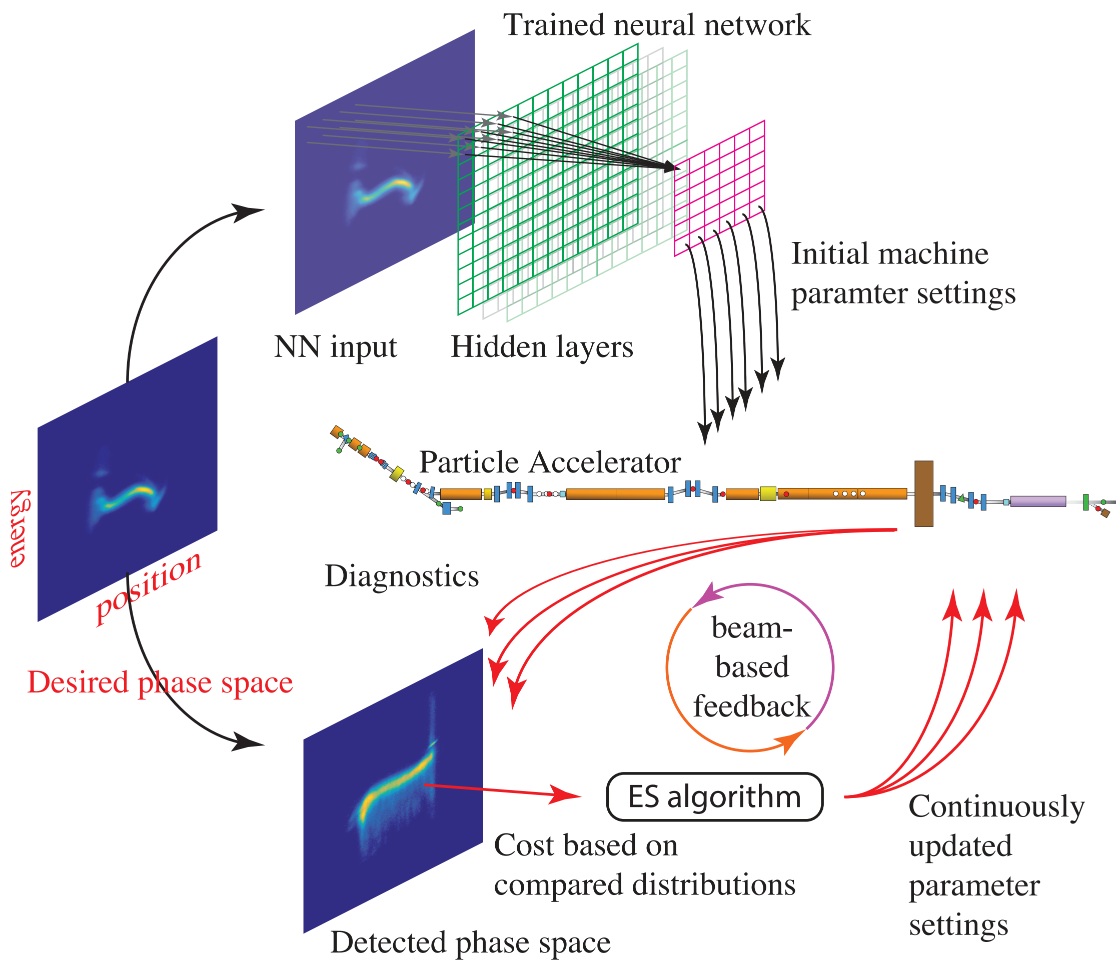




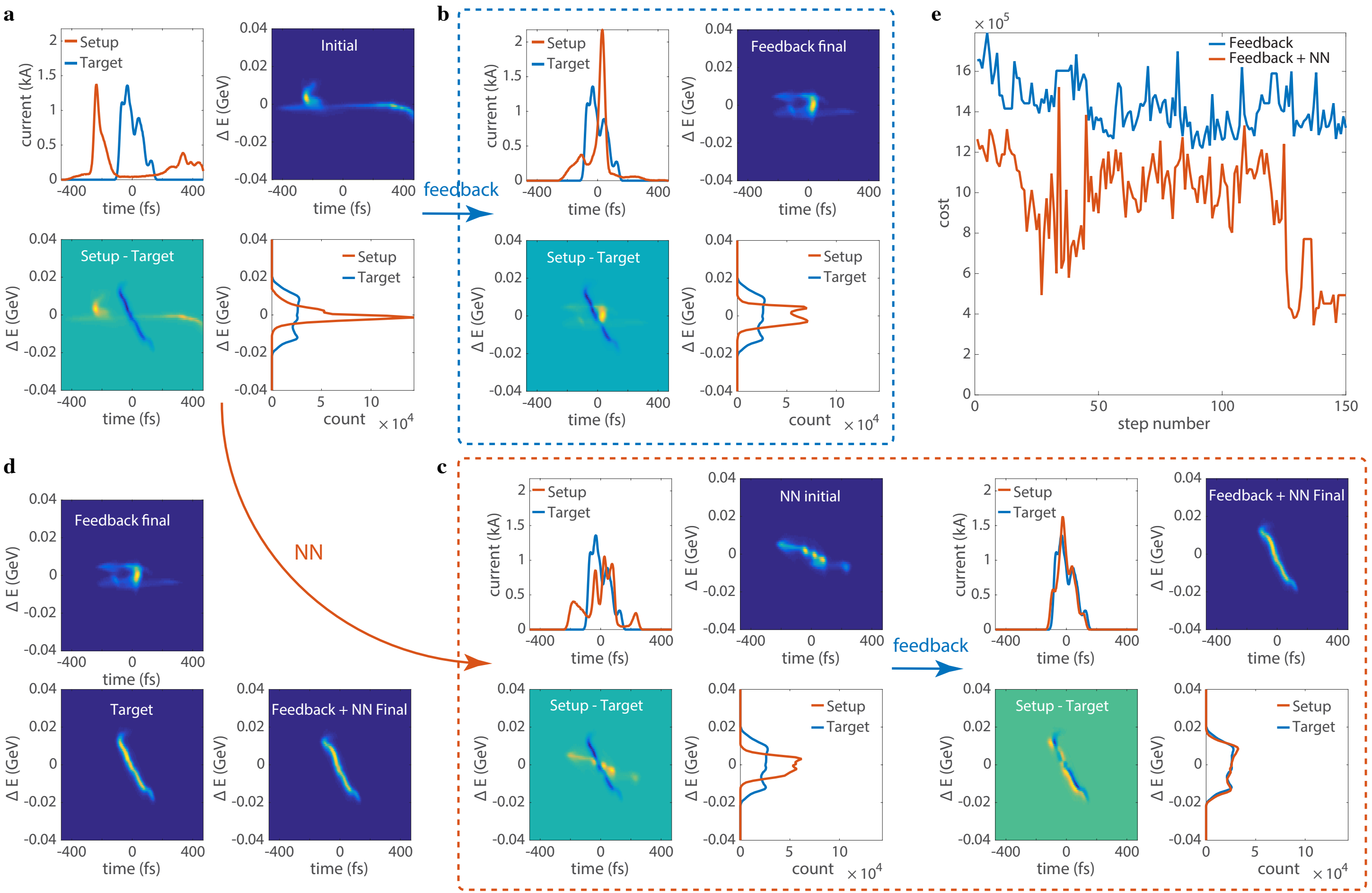


$$C = \int_{-\Delta L}^{\Delta L} \int_{-\Delta E}^{\Delta E} |\hat{\rho}(z, E) - \rho(z, E)| \, dE dz$$

Adaptive Machine Learning for Phase Space Tuning



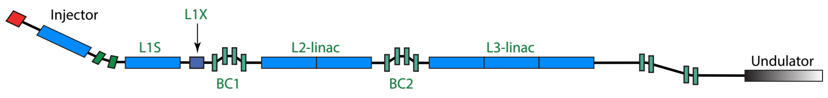
A. Scheinker, A. Edelen, D. Bohler, C. Emma, and A. Lutman, *Phys. Rev. Lett.* **121**, 044801, 2018.

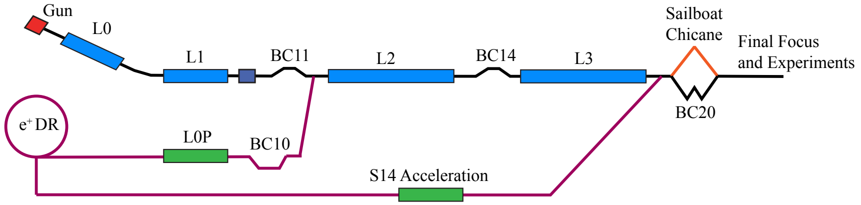


Thanks

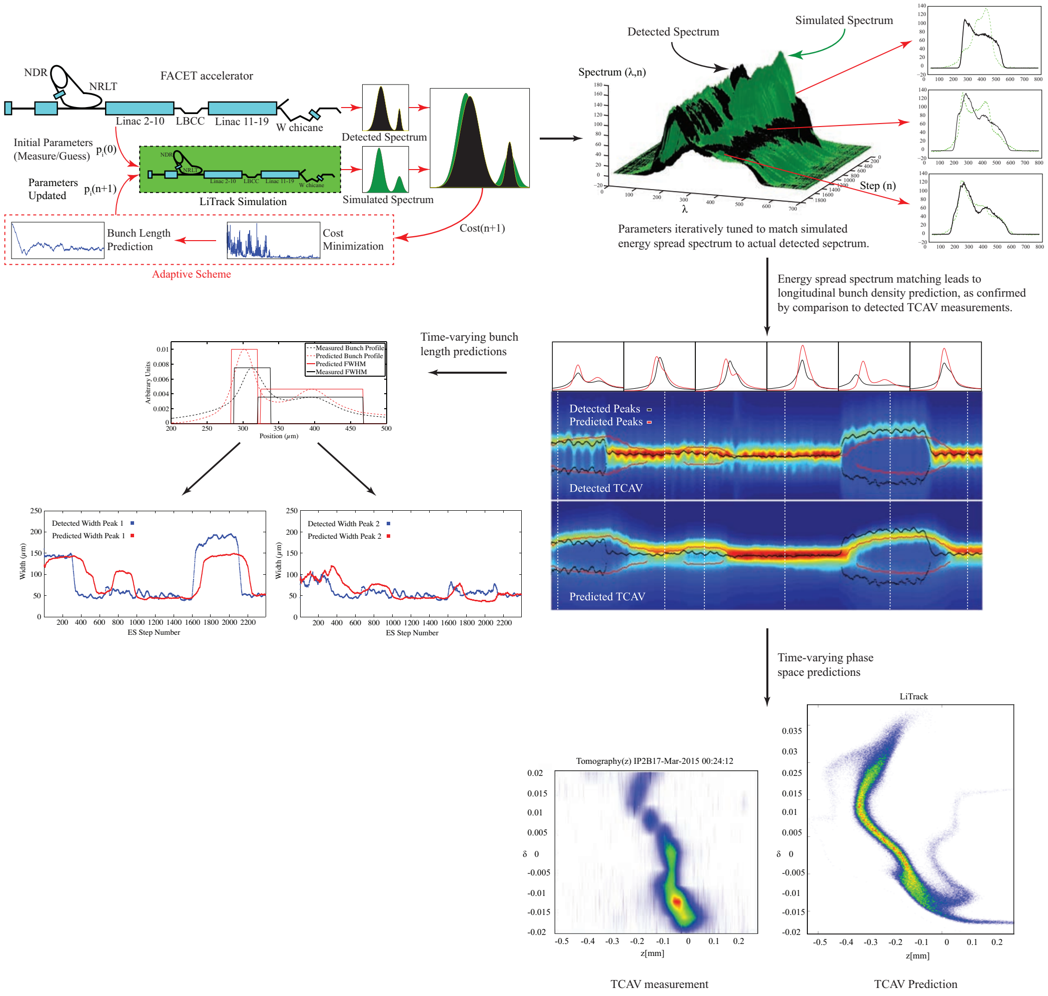
LCLS/FACET/FACET-II

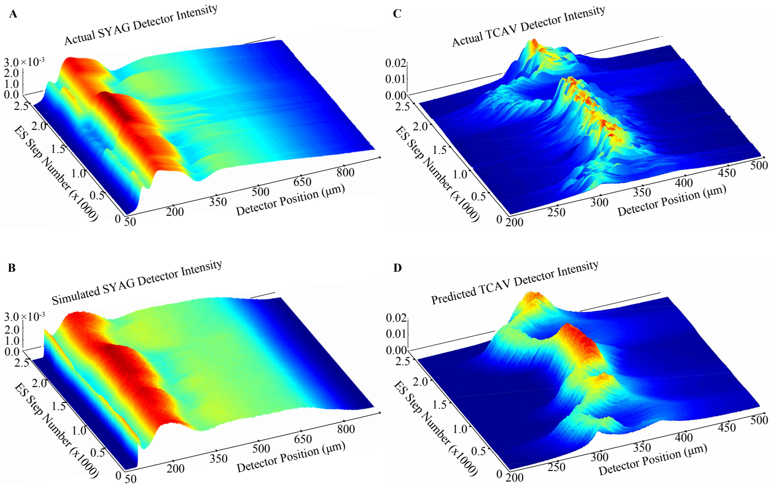
Spencer Gessner
Auralee Edelen
Claudio Emma
Alberto Lutman
Dorian Bohler



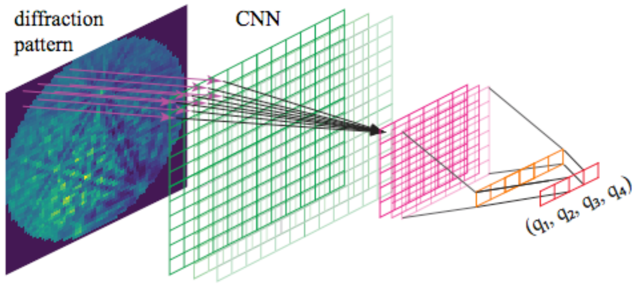


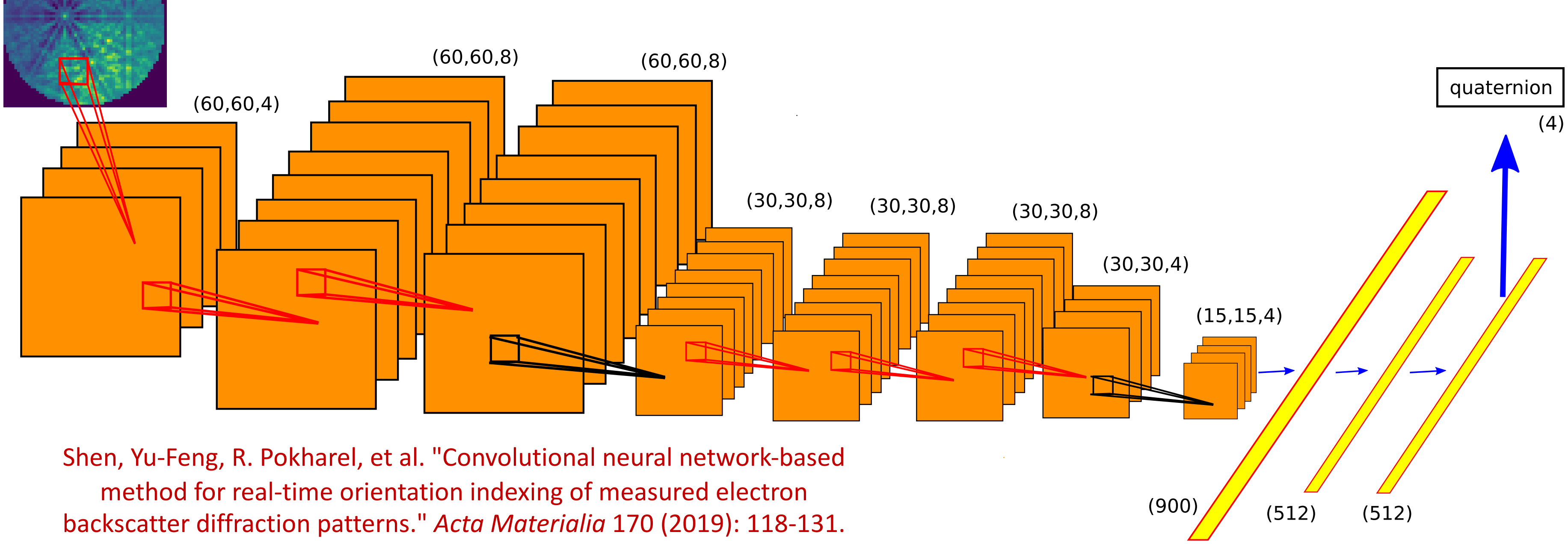
A. Scheinker and S. Gessner, PRAB, 2015.





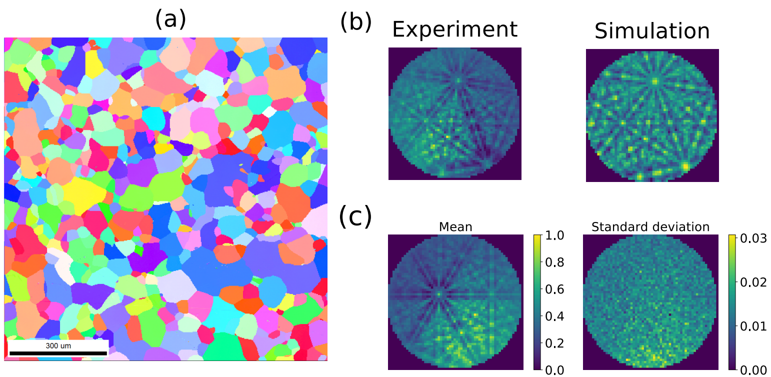
Re-Training and Domain Transfer for Convolutional Neural Network





Shen, Yu-Feng, R. Pokharel, et al. "Convolutional neural network-based method for real-time orientation indexing of measured electron backscatter diffraction patterns." *Acta Materialia* 170 (2019): 118-131.

Used lots of easily available simulation data for initial training, incorporating the physics Knowledge (> 100 K samples).



Shen, Yu-Feng, R. Pokharel, et al. "Convolutional neural network-based method for real-time orientation indexing of measured electron backscatter diffraction patterns." *Acta Materialia* 170 (2019): 118-131.

Transfer learning or layer re-training for experimental applications (~ 1 K experimental data sets).