Longitudinal Phase Space Manipulation at the LCLS Using Neural Networks and Bayesian Optimization

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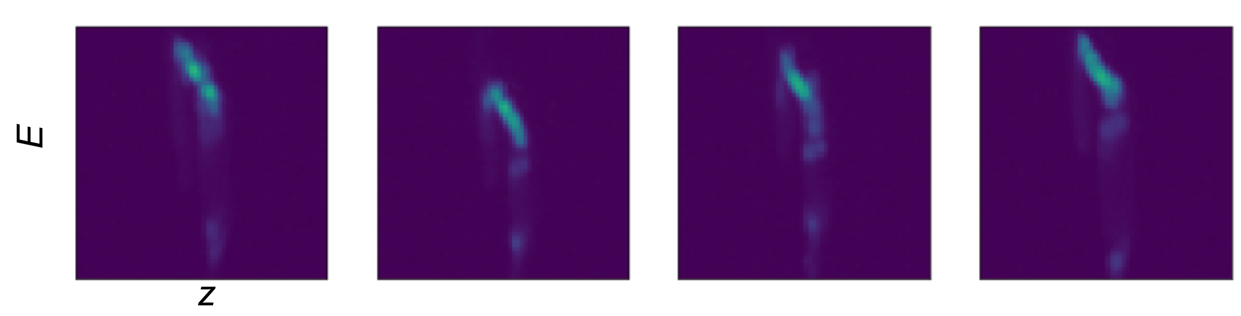
Background and Motivation

Numerous scientific users visit the LCLS each year with requests for custom photon beam parameters (with different associated longitudinal phase space distributions for the electron beam).

To do automatic tuning, we **need a suitable metric** that specifies the difference between an observed and target longitudinal phase space (LPS) distribution

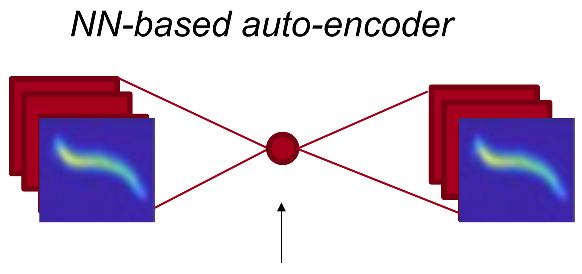


Shot-to-shot fluctuation in LPS for one setting combination

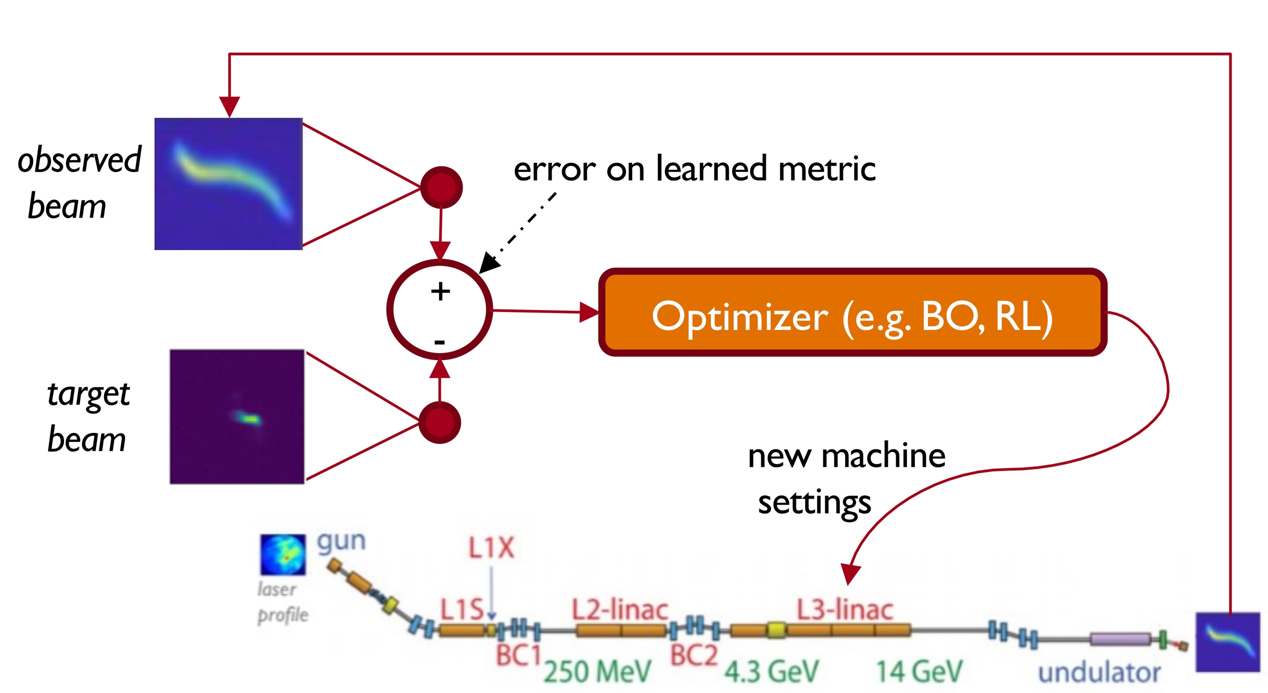
Finding a good metric for longitudinal phase space images at LCLS can be difficult:

- Scalar fits → *lose some information and can have artifacts*
- Pixel-by-pixel mean squared error → *requires very precise alignment; hard to distinguish most important feature of beam*
- Spectral similarity index → *not clear this is measuring the right thing for our problems?*
- KL divergence + earth mover distance → *some open questions about robustness + computational efficiency* (*see* https://ml4physicalsciences.github.io/2020/files/NeurIPS_ML4PS_2020_100.pdf)

Approach with a Learned Metric



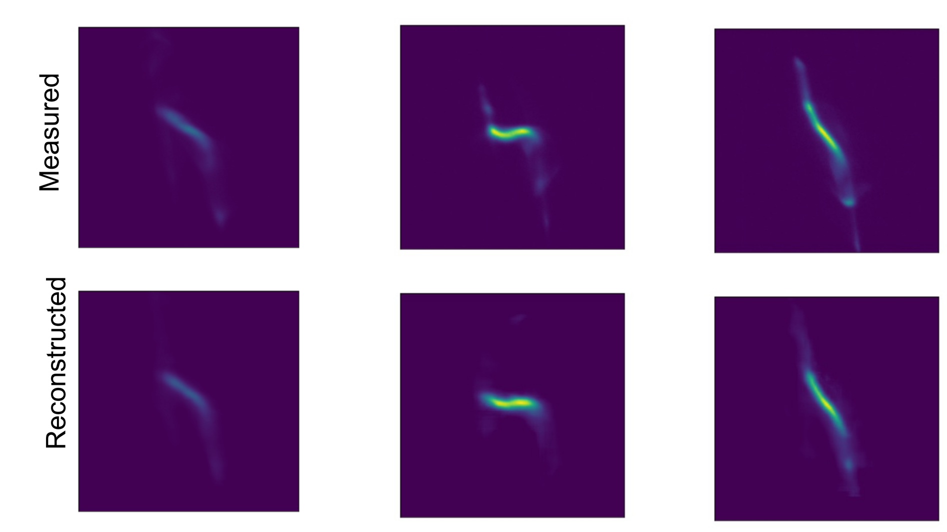
Auto-encoders can reduce high-dimensional data into a low-dimensional representation. This can be used as learned metric for comparing two distributions. In principle this could help ignore irrelevant features/noise and add robustness to cropping/alignment issues.



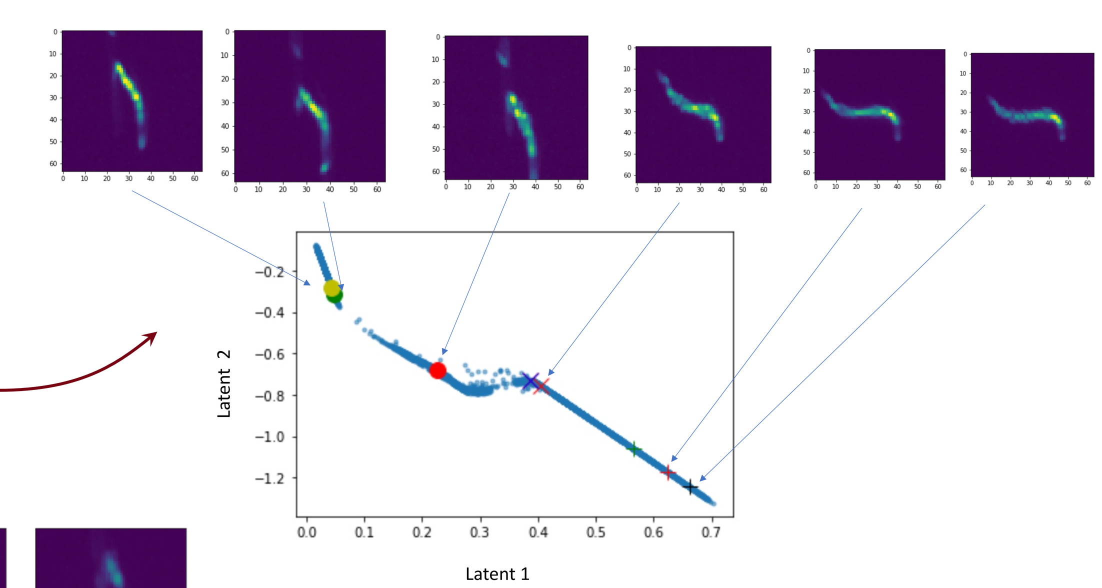
Learned Metric Performance

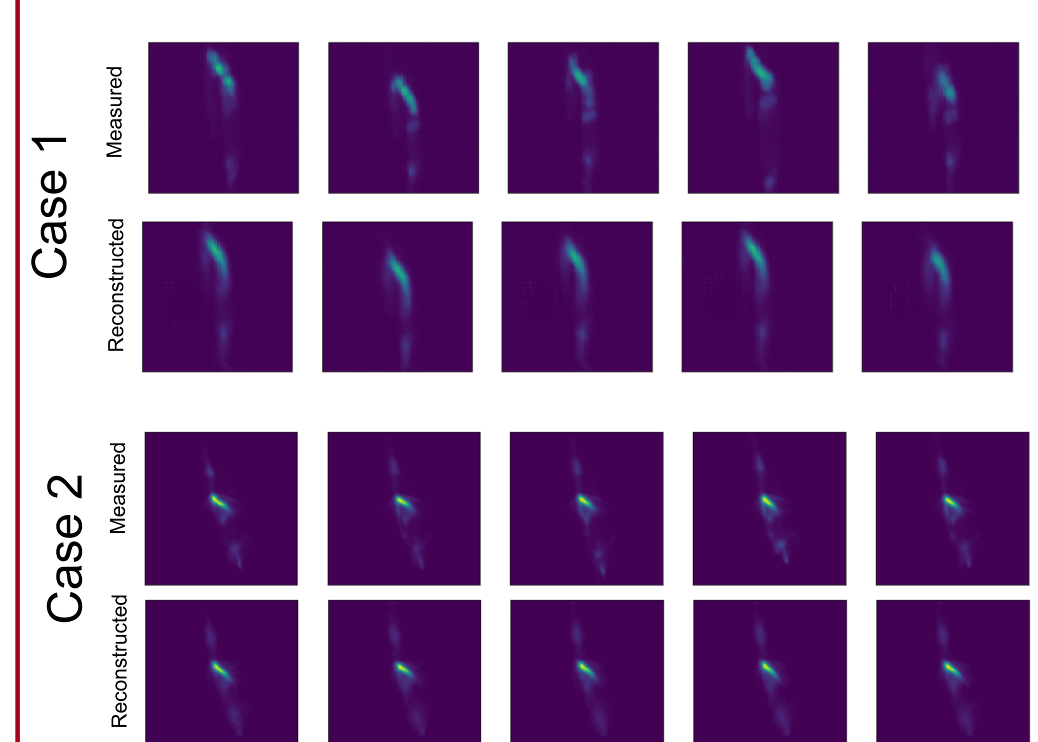
We trained an auto-encoder on a wide variety of measured LPS images and found a two-dimensional latent space was sufficient to capture the major features

A larger latent space enables a higher-fidelity reconstruction (tunable)



The two latent space features roughly encode the bunch length and chirp



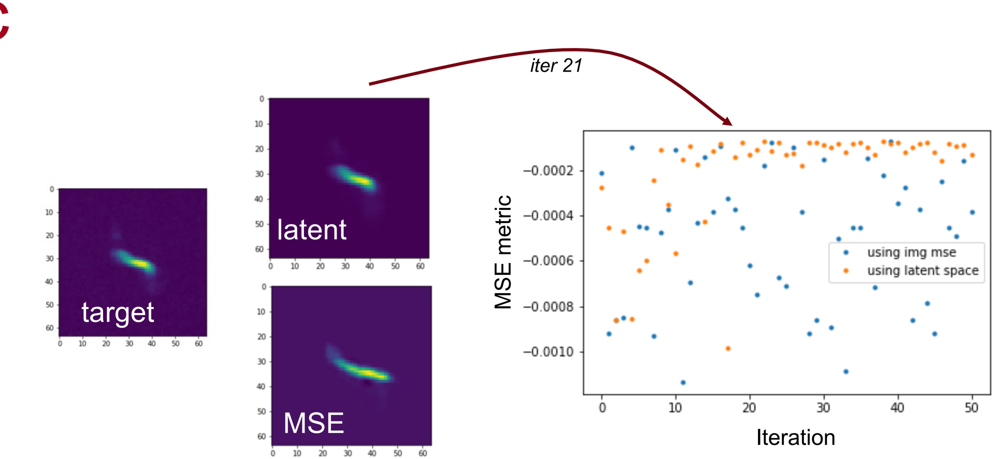


Shot-to-shot fluctuations in the measurement and reconstructions are shown at left

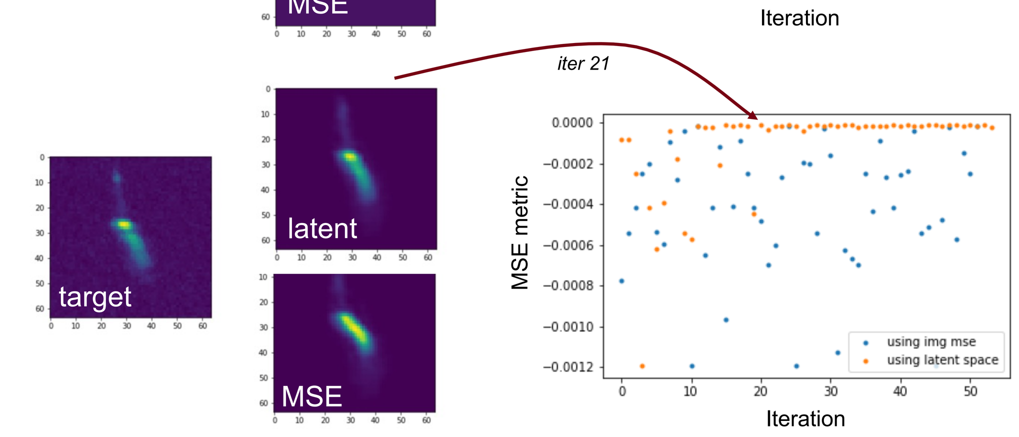
→ reconstruction indicates irrelevant fluctuating features are mostly washed out

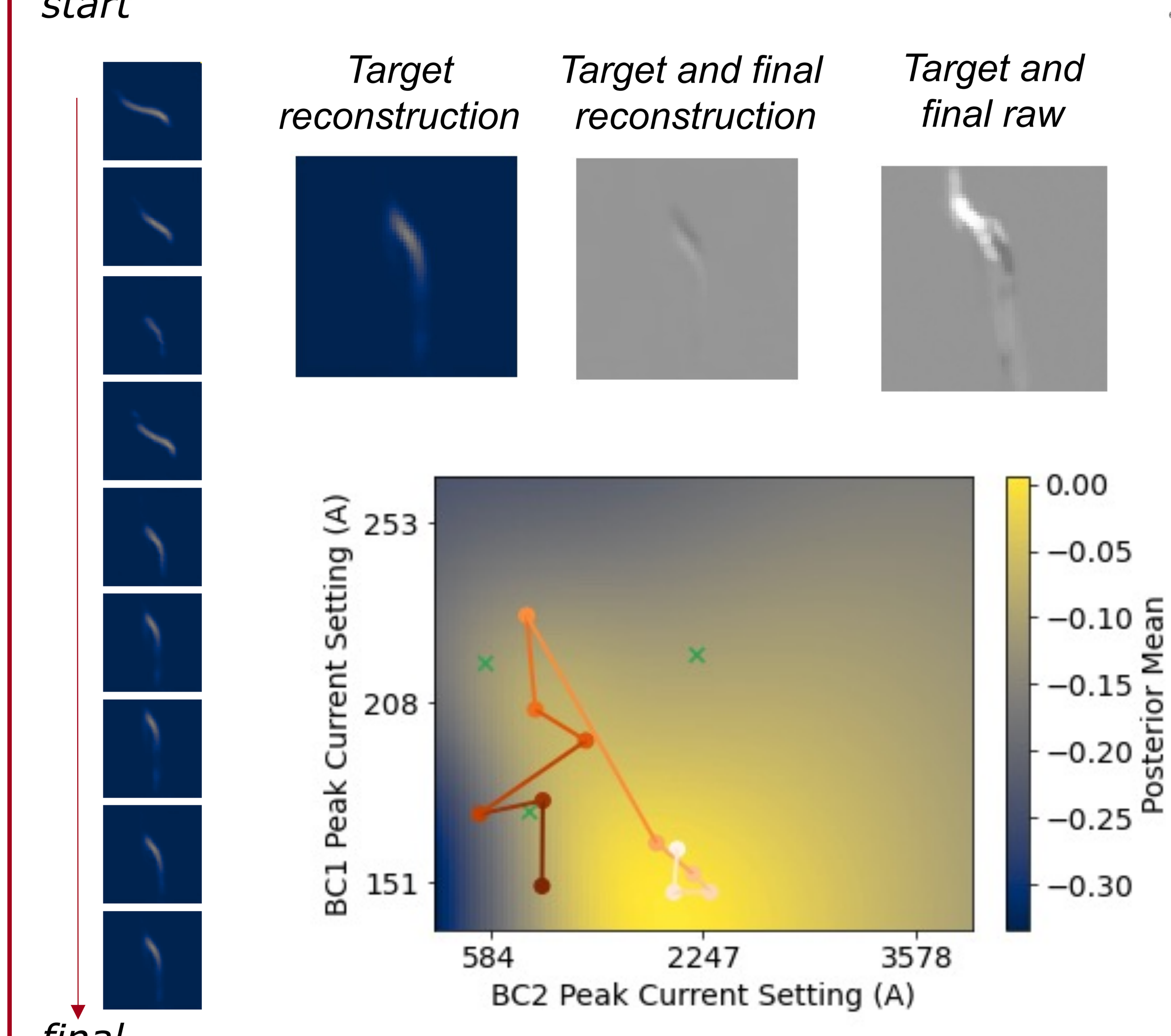
Tuning with Learned Metric

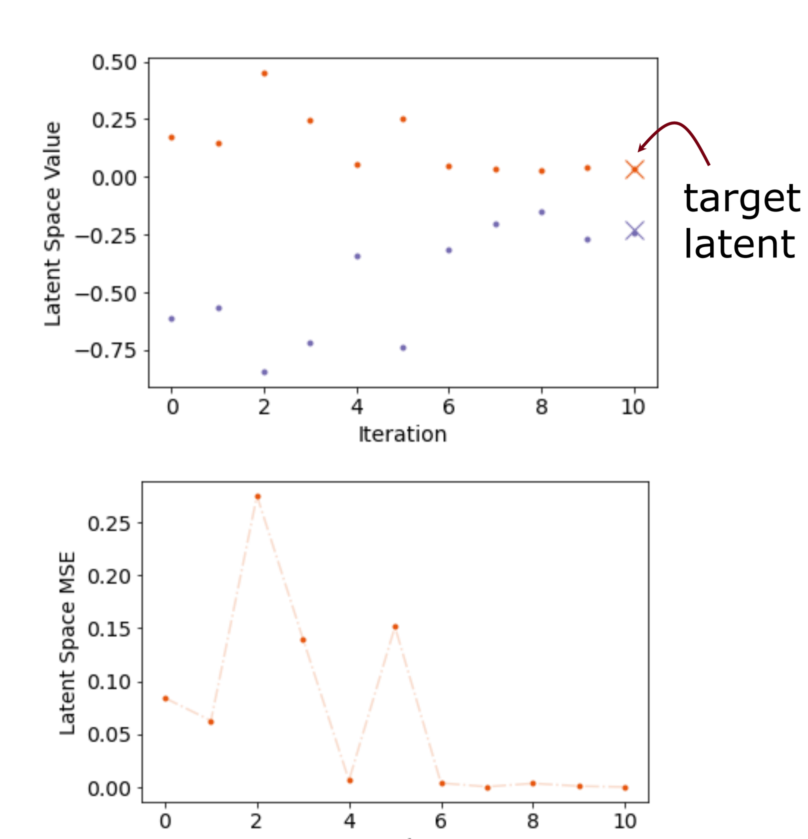
Here we adjust the BC1 and BC2 peak current settings (the main variables used by operations) with Bayesian Optimization to reach a target LPS



The latent space metric performs substantially better in tuning than the mean squared error (MSE) metric
→ substantially faster convergence with learned metric







Example from tuning with latent space metric and BO on LCLS

Questions? Contact Auralee Edelen, edelen@slac.stanford.edu