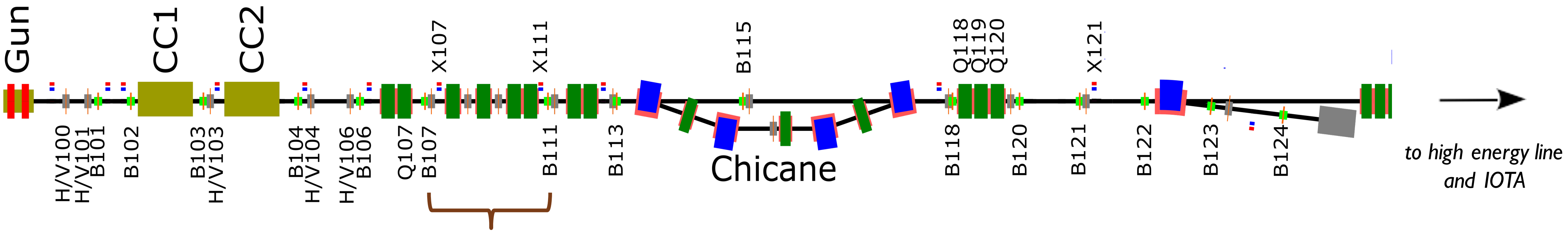
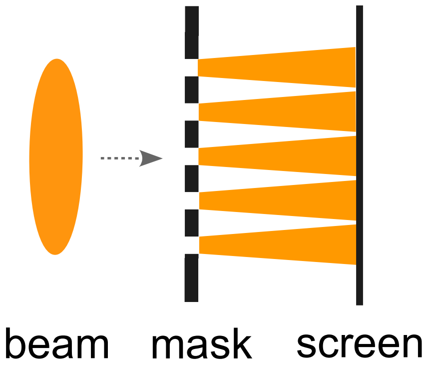
Experience with a Virtual Multi-Slit Phase Space Diagnostic at Fermilab's FAST Facility

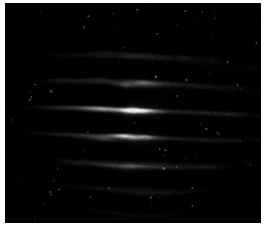
Auralee Edelen
SLAC National Accelerator Laboratory

AI@SLAC Seminar
27 August, 2018

Fermilab's FAST Facility







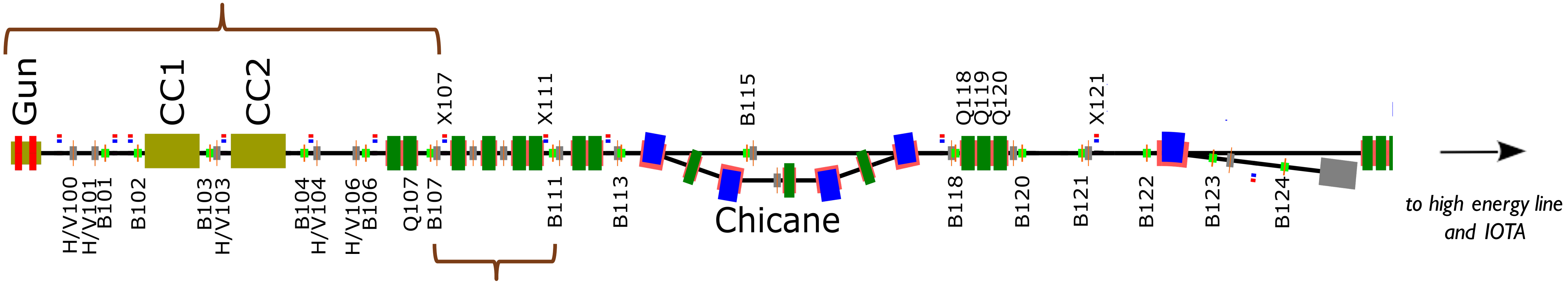
fit to obtain subset of phase space parameters

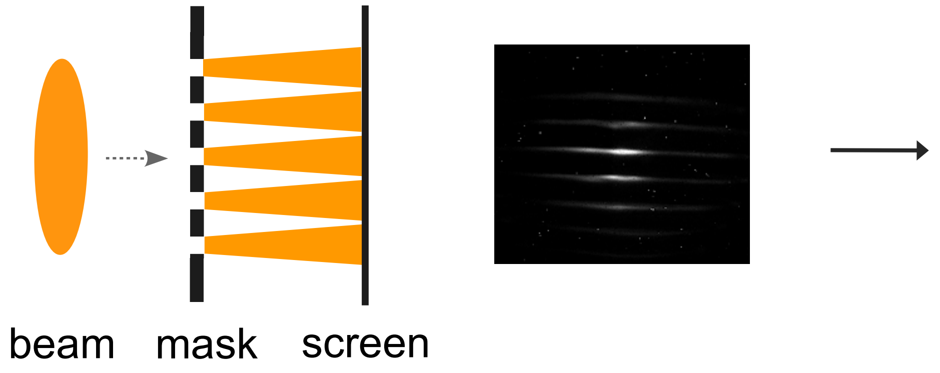
$\langle y^2 \rangle$
$\langle yy' \rangle$
$\langle y'^2 \rangle$

Multi-slit phase space measurement takes 10-15 seconds
For studies, often want both an upstream and downstream measurement

Fermilab's FAST Facility

Generally consistent machine configuration (changing settings only)





fit to obtain subset of phase space parameters $\langle y^2 \rangle$ $\langle yy' \rangle$ $\langle y'^2 \rangle$

Multi-slit phase space measurement takes 10-15 seconds

For studies, often want both an upstream and downstream measurement

→ *can we get an online prediction of what the upstream intercepting diagnostic would show?*

Virtual Diagnostics

Predict what the output of a diagnostic would look like when it is unavailable

Virtual Diagnostics

Predict what the output of a diagnostic would look like when it is unavailable

fast-executing physics-based simulation

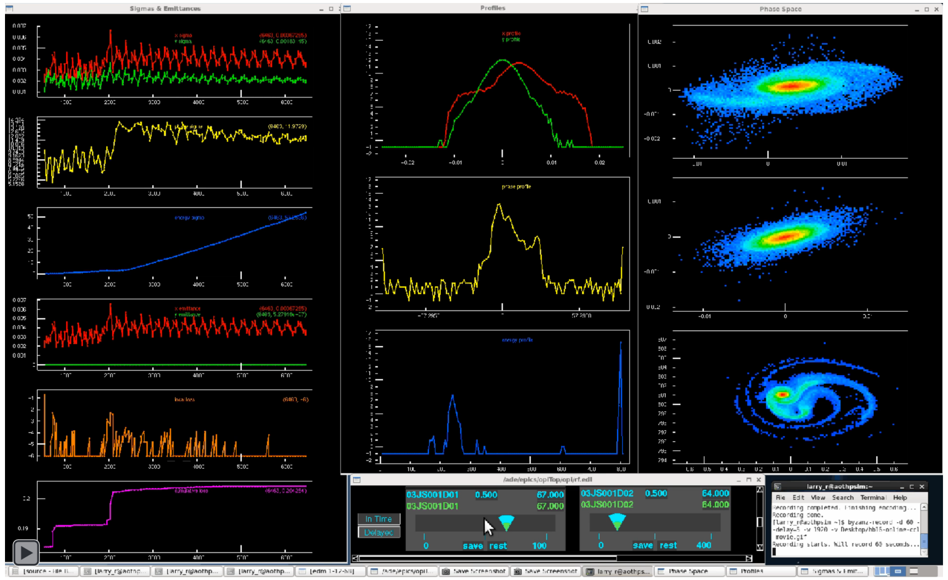
measured machine inputs → Online Model → Real-time prediction of beam characteristics or explicit diagnostic output

Virtual Diagnostics

Predict what the output of a diagnostic would look like when it is unavailable

fast-executing physics-based simulation

measured machine inputs → Online Model → Real-time prediction of beam characteristics or explicit diagnostic output



e.g. GPU-accelerated HPSim at LANSCE (based on PARMILA)

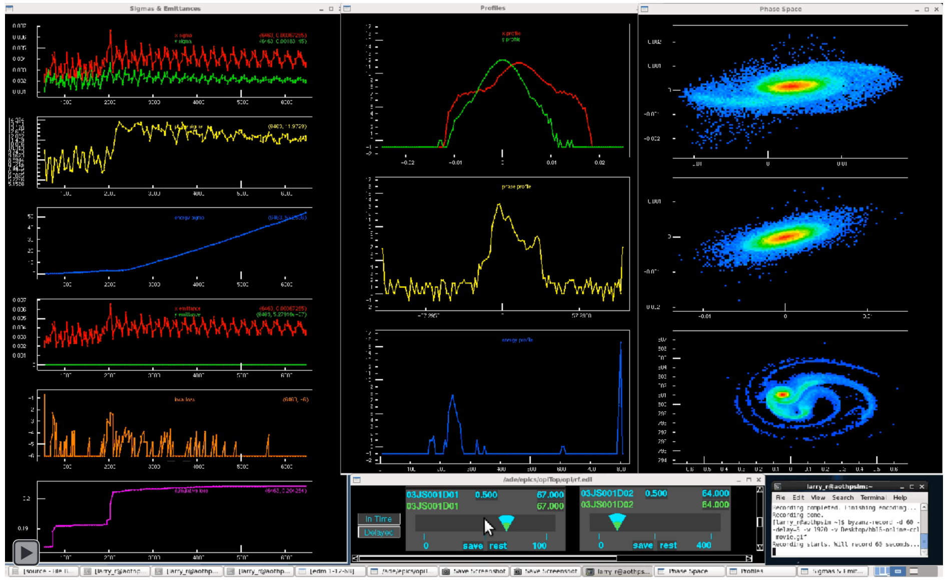
X. Pang, et al., PAC13, MOPMA13
X. Pang and L. Rybarcyk, CPC185, is. 3 (2014)
L. Rybarcyk, et al., IPAC15, MOPWI033
L. Rybarcyk, HB2016, WEPM4Y01

Virtual Diagnostics

Predict what the output of a diagnostic would look like when it is unavailable

fast-executing physics-based simulation

measured machine inputs → Online Model → Real-time prediction of beam characteristics or explicit diagnostic output



e.g. GPU-accelerated HPSim at LANSCE (based on PARMILA)

X. Pang, et al., PAC13, MOPMA13
X. Pang and L. Rybarcyk, CPC185, is. 3 (2014)
L. Rybarcyk, et al., IPAC15, MOPWI033
L. Rybarcyk, HB2016, WEPM4Y01

Challenges with this approach:

Execution often still isn't so fast

Can require HPC resources

Still need a lot of work to get simulation to match the machine closely

One approach: faster modeling codes

Simpler models (tradeoff with accuracy)

analytic calculations — *e. g. J. Galambos, et al., HPPA5, 2007*

Parallelization and GPU-acceleration of existing codes

HPSim/PARMILA — *X. Pang, PAC13, MOPMA13*

elegant — *I.V. Pogorelov, et al., IPAC15, MOPMA035*

Improvements to modeling algorithms

Lorentz-boosted frame — *J.-L.Vay, Phys. Rev. Lett.98 (2007) 130405*

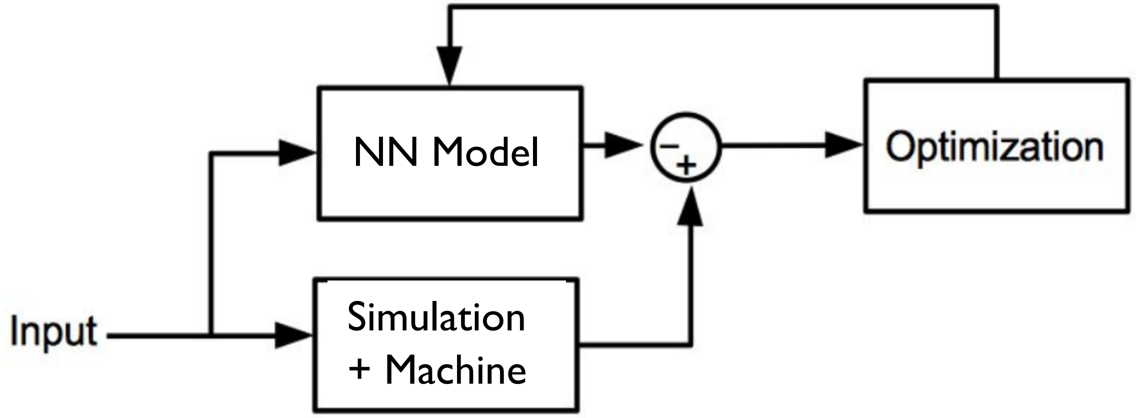
Another approach: machine learning model

Once trained, neural networks can execute quickly

Train on data from slow, high-fidelity simulations

+

Train on measured data



An initial study at Fermilab:

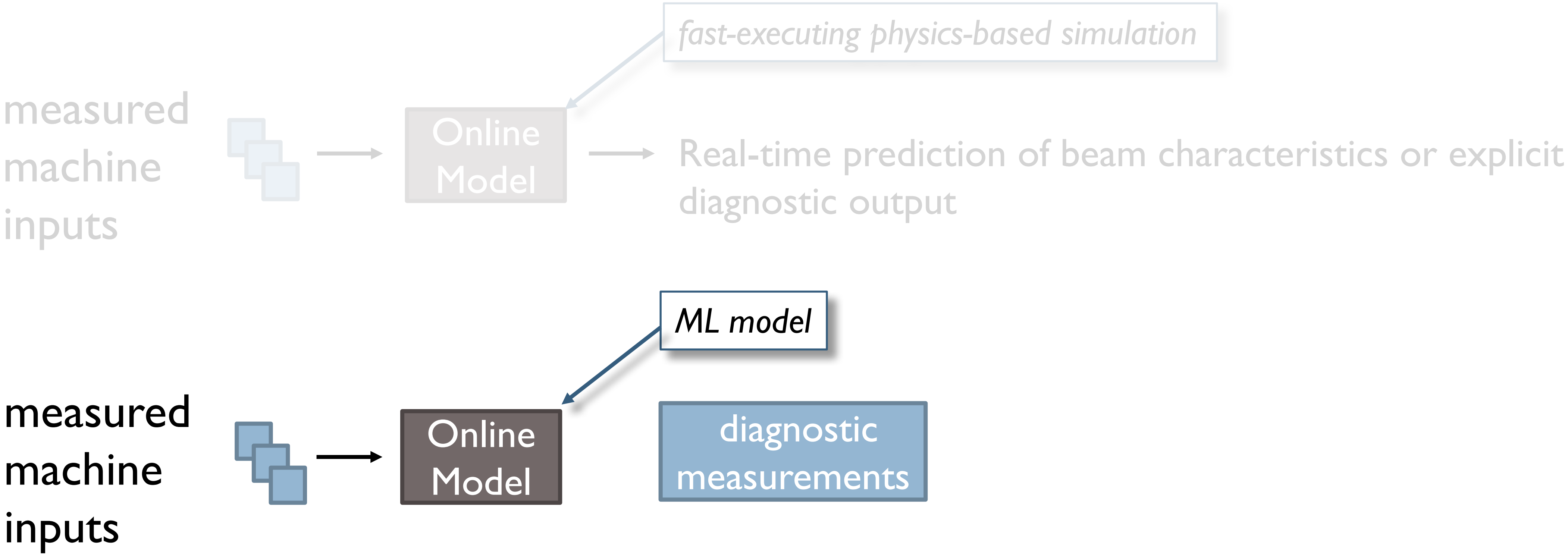
A. L. Edelen, et al. NAPAC16, TUPOA51

One PARMELA run with 2-D space charge: ~ 20 minutes

Neural network model: ~ a millisecond

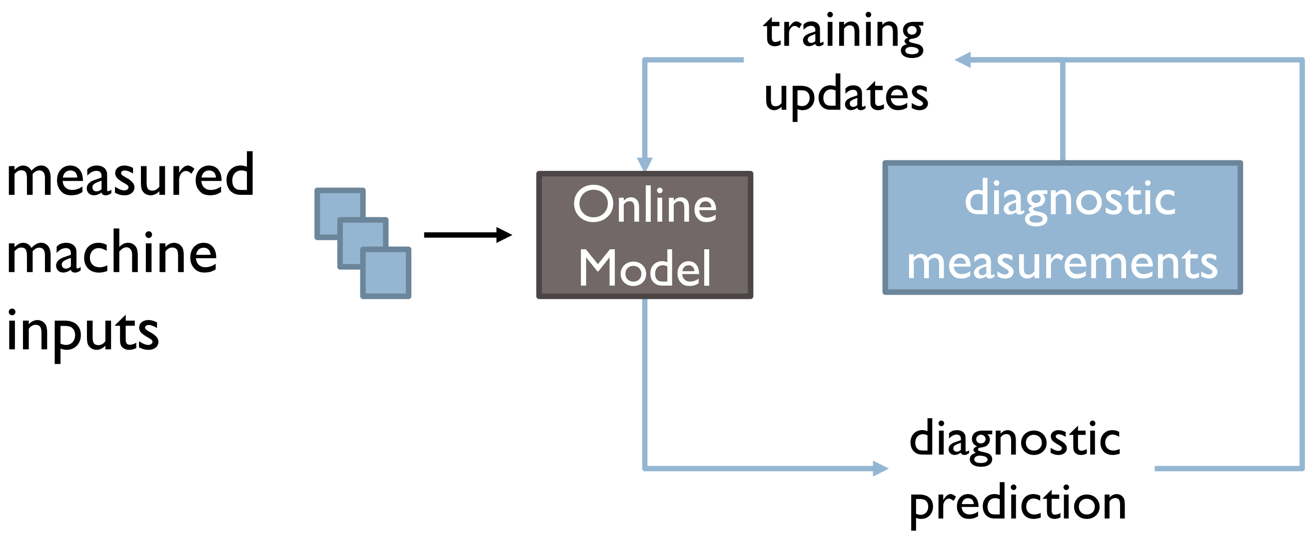
Virtual Diagnostics

Predict what the output of a diagnostic would look like when it is unavailable



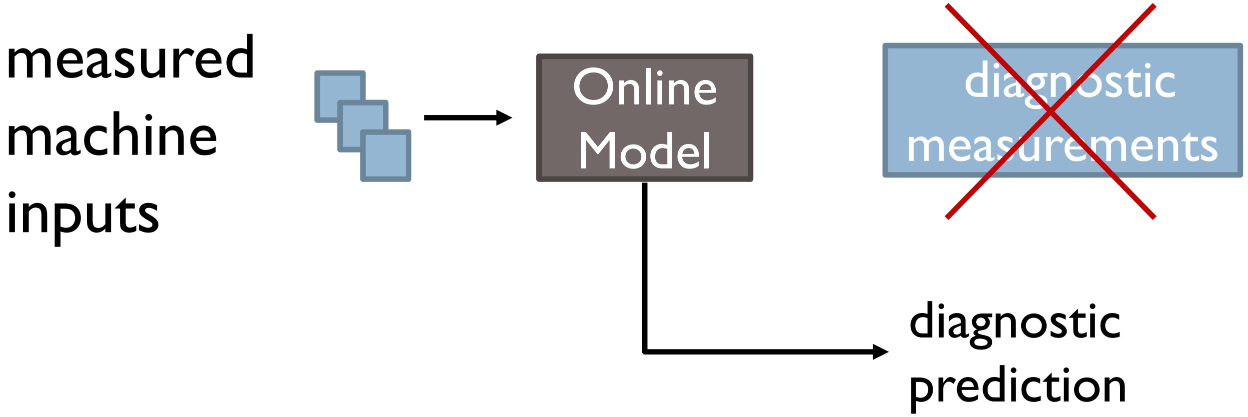
Virtual Diagnostics

Predict what the output of a diagnostic would look like when it is unavailable



Virtual Diagnostics

Predict what the output of a diagnostic would look like when it is unavailable



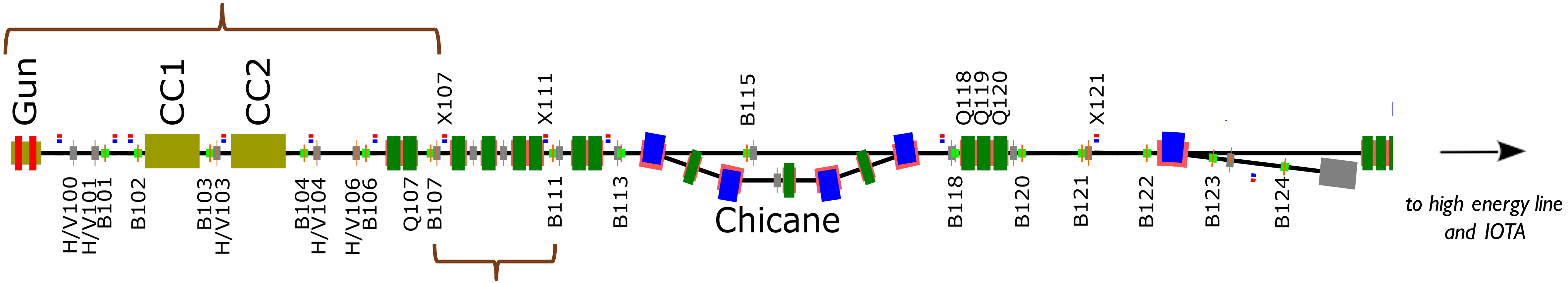
Real diagnostic no longer available:

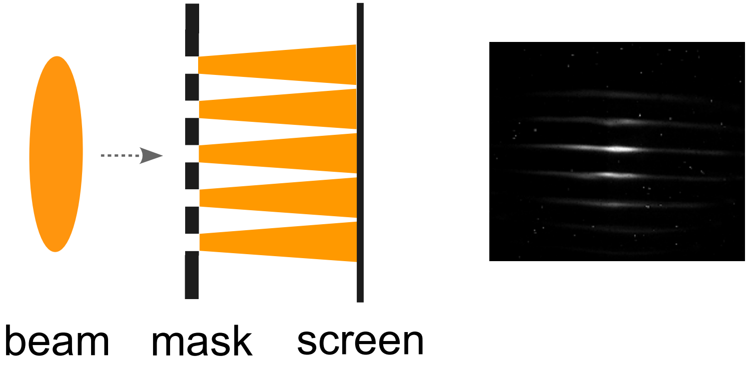
- *moved to another location (e.g. cost constraints)*
- *destructive, would interrupt normal ops*
- *blocked for update time*

But still have diagnostic prediction

The Low Energy Beamline at FAST

Generally consistent machine configuration (changing settings only)





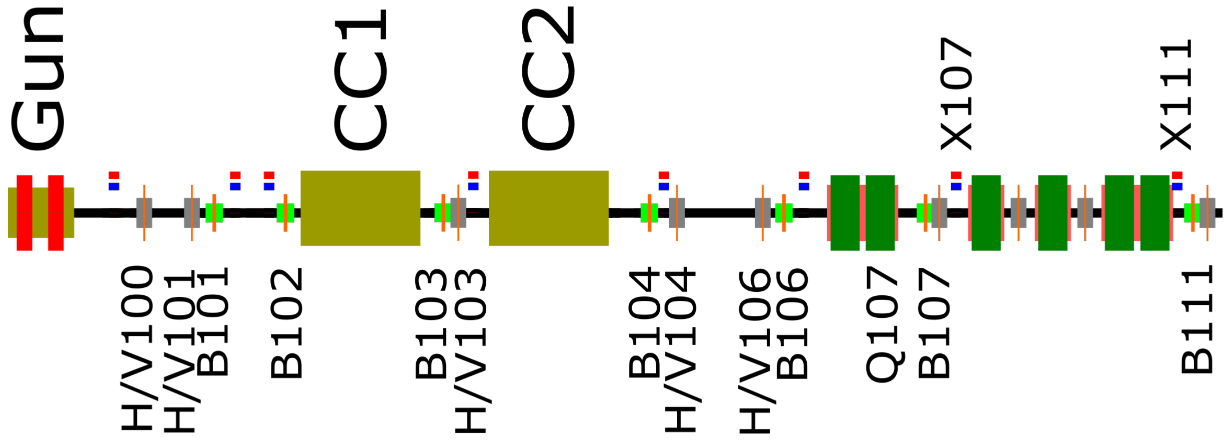
→

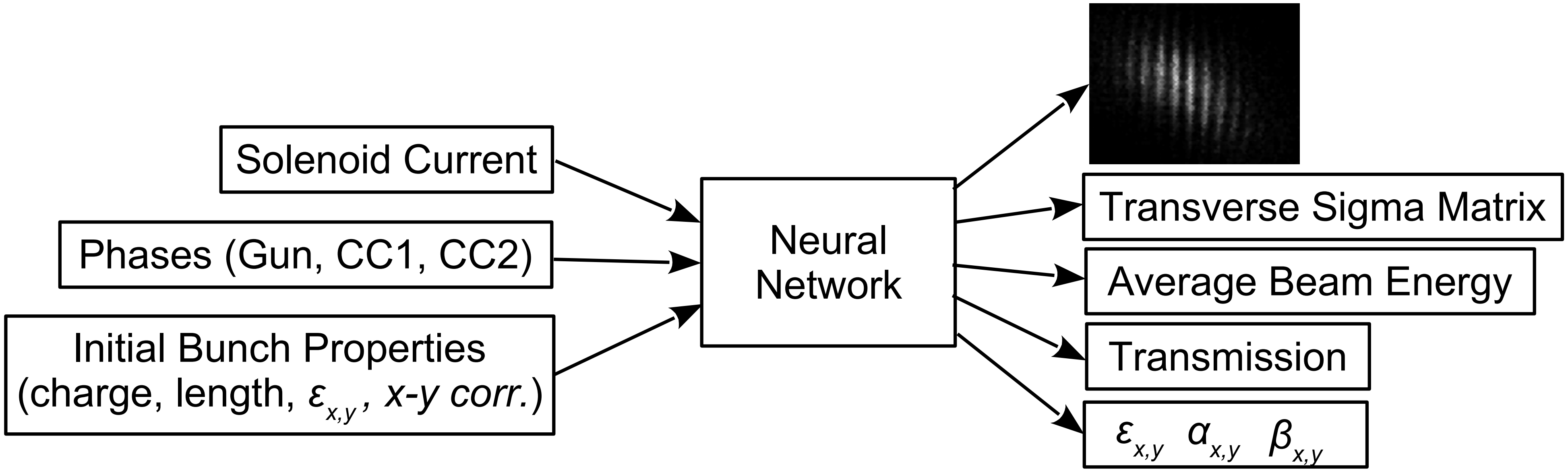
fit to obtain
subset of phase
space parameters

$\langle y^2 \rangle$
$\langle yy' \rangle$
$\langle y'^2 \rangle$

Multi-slit phase space measurement takes 10-15 seconds
For studies, often want both an upstream and downstream measurement
→ *can we get an online prediction of what the upstream intercepting diagnostic would show?*

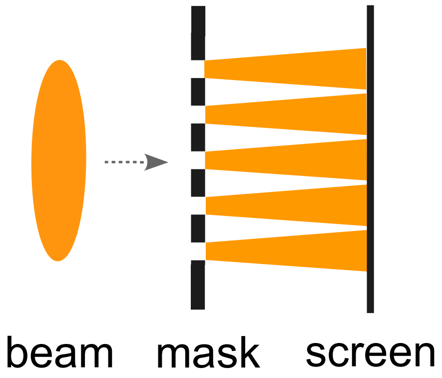
Neural Network Model

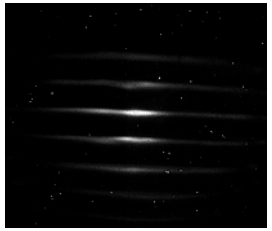




Scanned Parameters on Machine

gun phase scans
solenoid current scans
(with two different laser intensities)





fit to obtain
subset of phase
space parameters

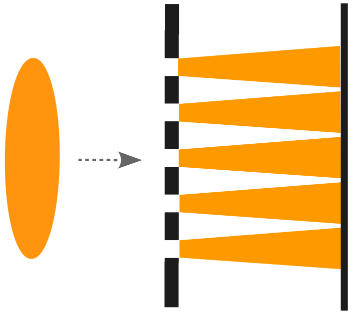
$\langle y^2 \rangle$
$\langle yy' \rangle$
$\langle y'^2 \rangle$

change slit mask and repeat for measurements in x

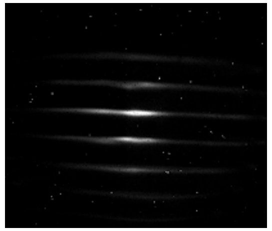
Could in principle use measured data alone, but want to be efficient with machine time

→ use simulation data to fill in wider range of settings

gun phase scans
solenoid current scans
(with two different laser intensities)



beam mask screen



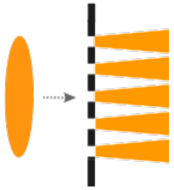
fit to obtain
subset of phase
space parameters

$\langle y^2 \rangle$
$\langle yy' \rangle$
$\langle y'^2 \rangle$

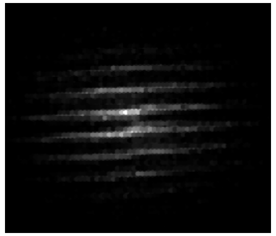
other setting
combinations

OPAL

cathode → CC2
with 3-D space charge routine



elegant

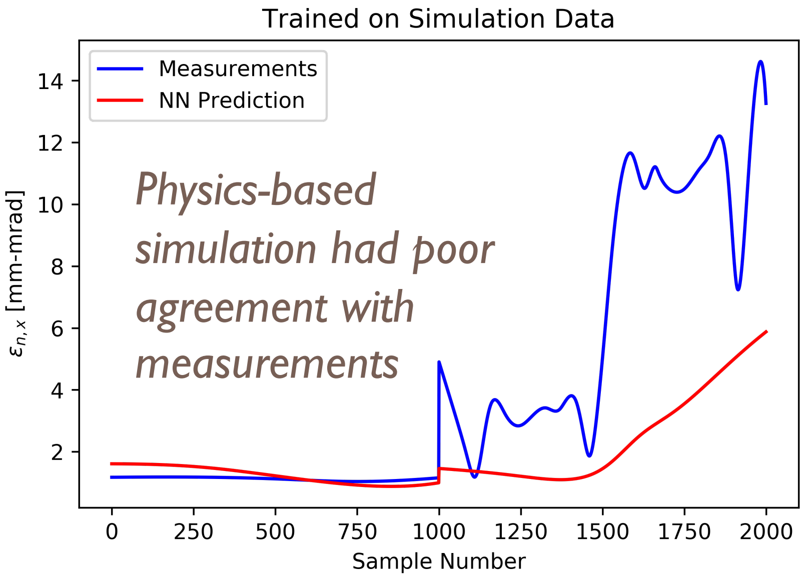


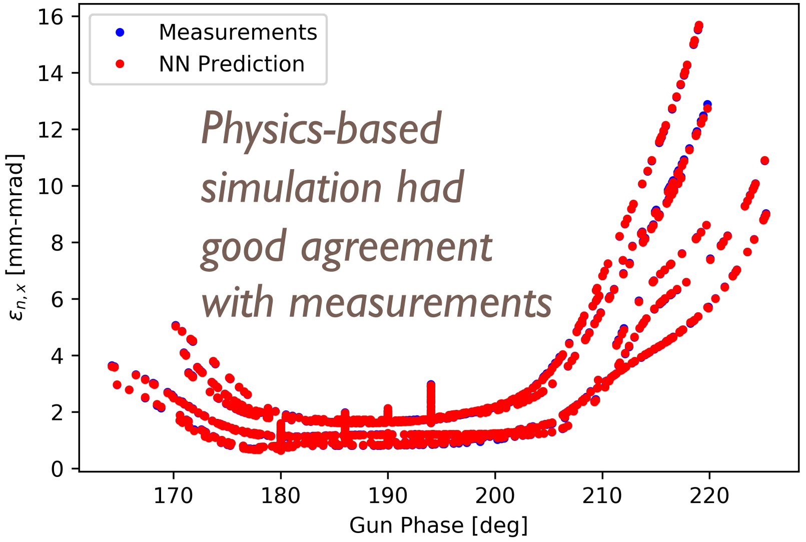
+ full sigma matrix

Training on physics model … NN will only be as accurate as the physics model

Poor agreement between simulation and measured data for some input/output relationships

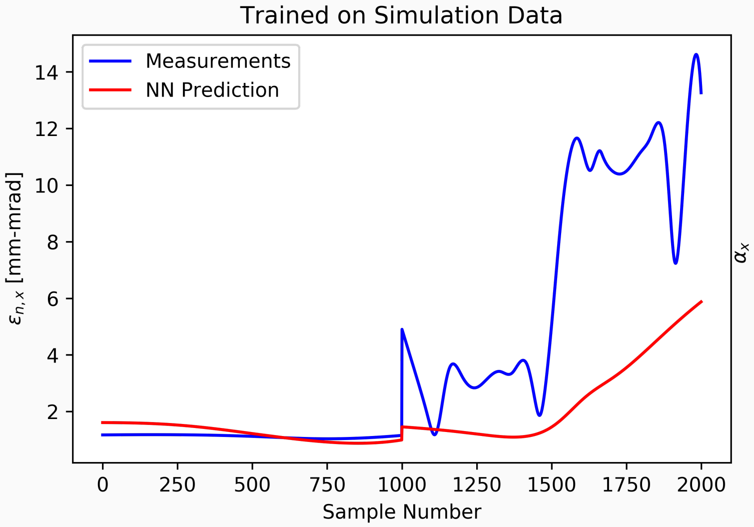
→ can we update the NN model with measured data without disrupting the other predictions?

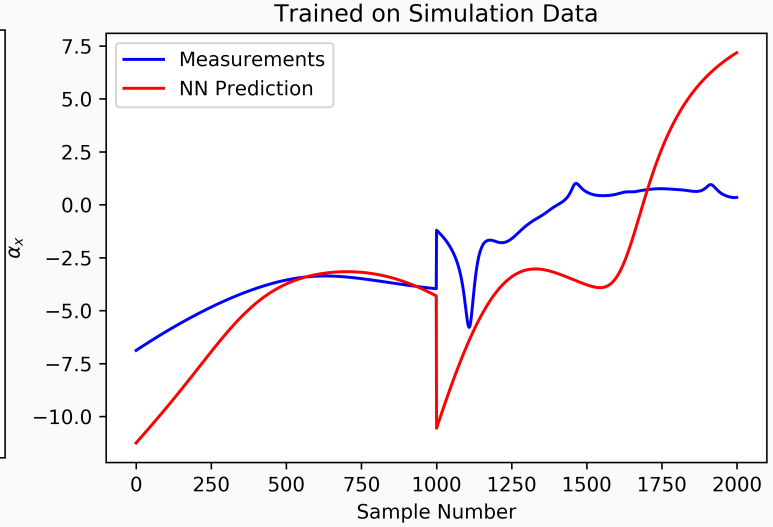




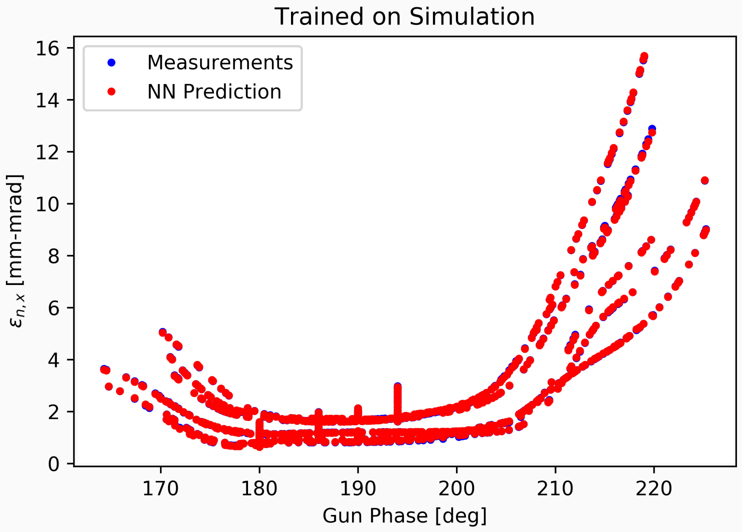
Trained on Simulation Only

Solenoid Scan

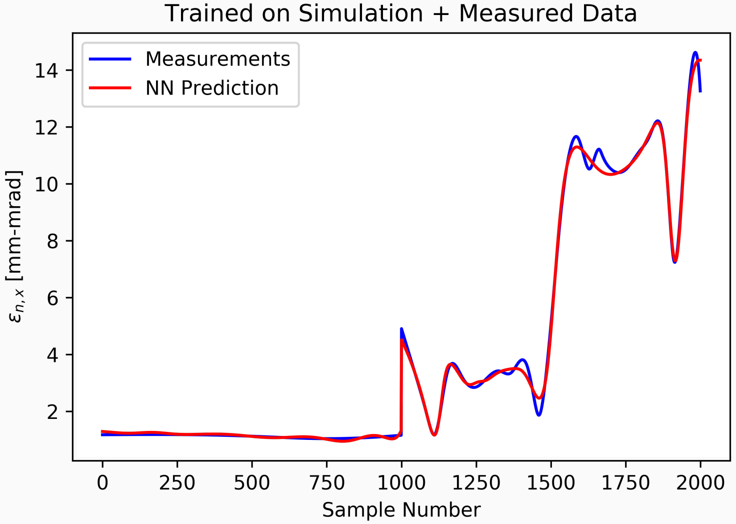


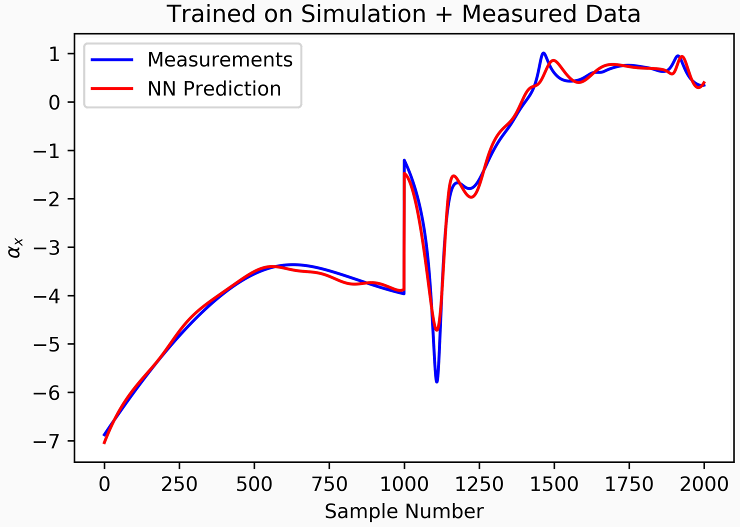


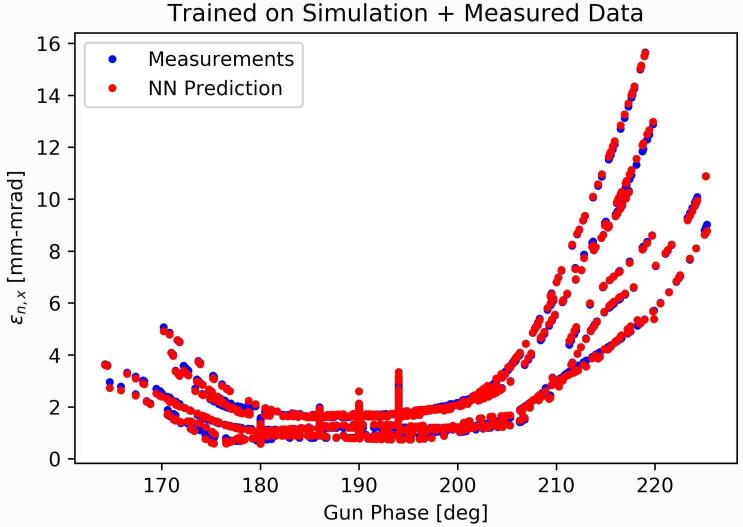
Phase Scan



Updated with Measured Data



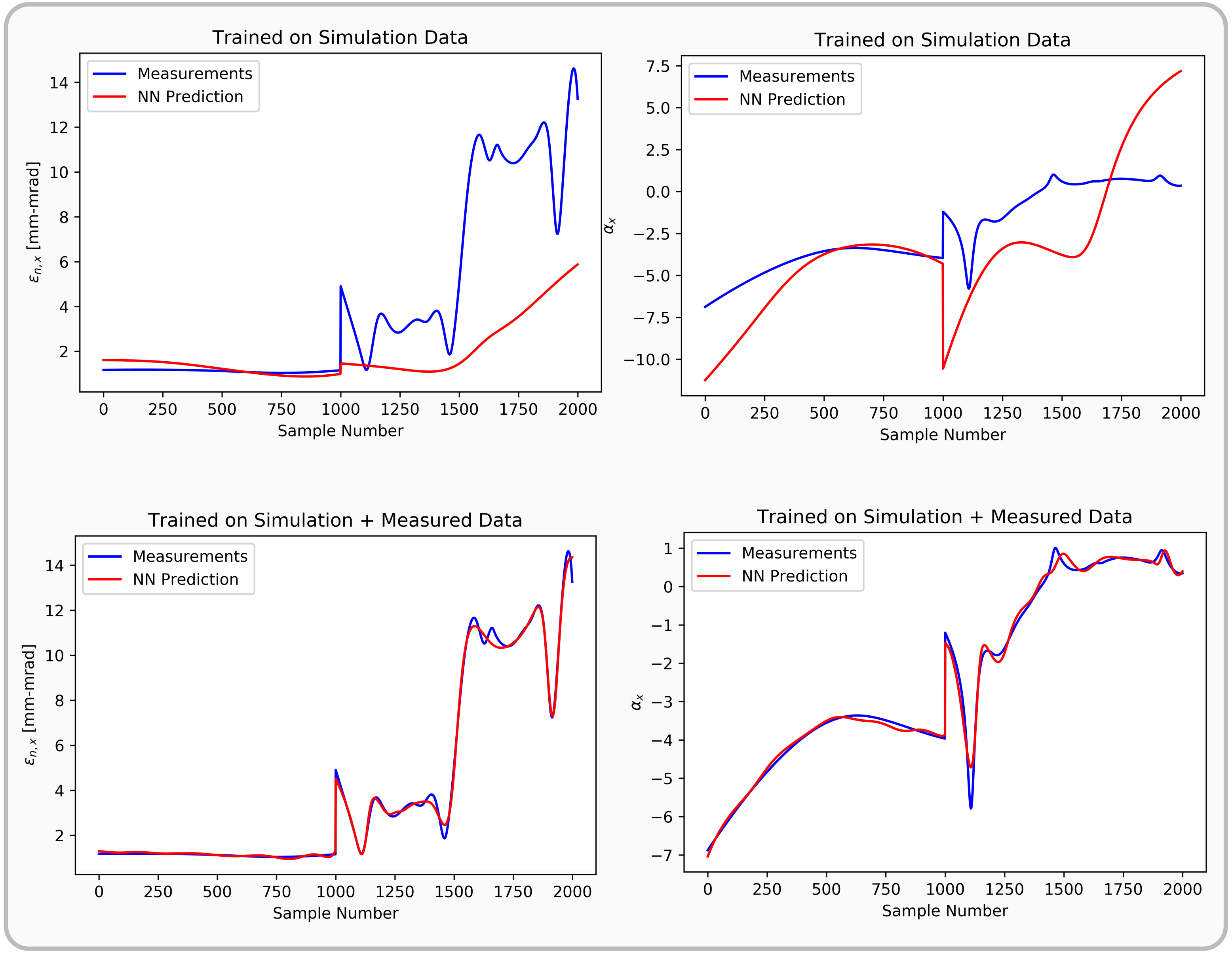




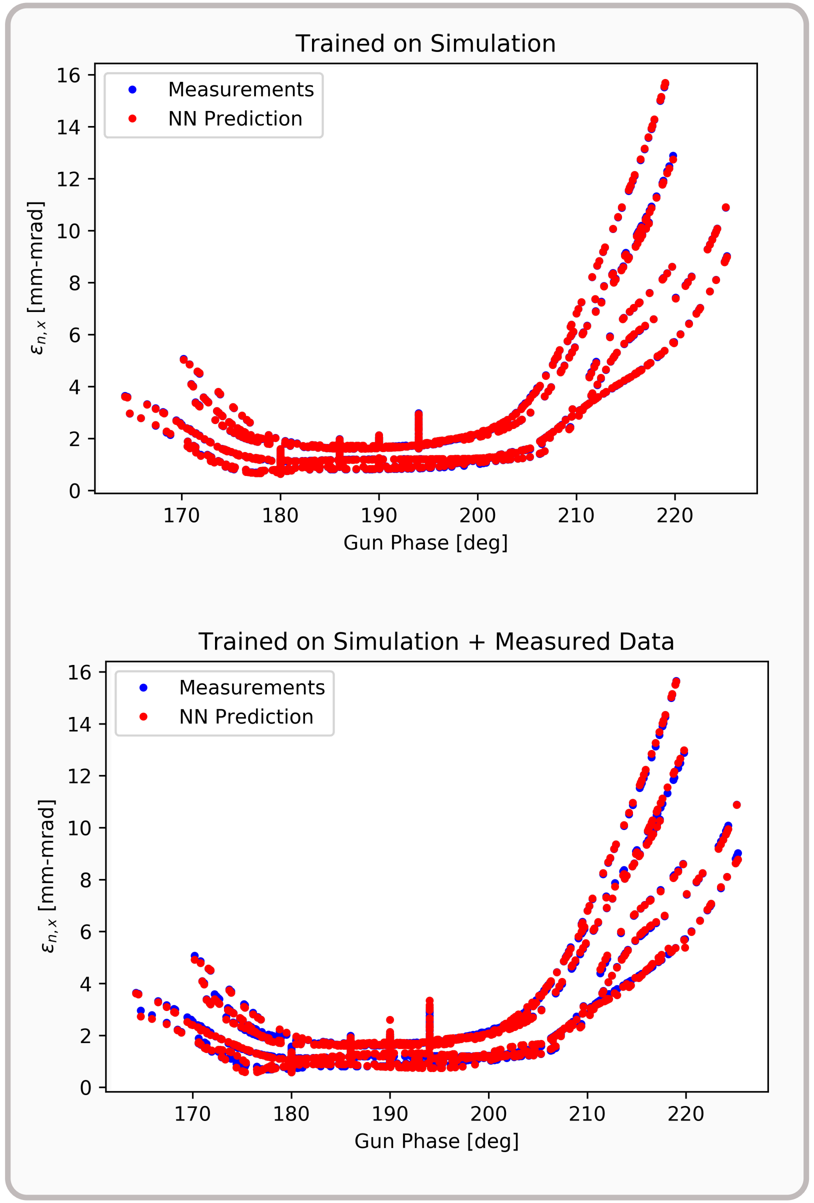
Trained on Simulation Only

Updated with Measured Data

Solenoid Scan



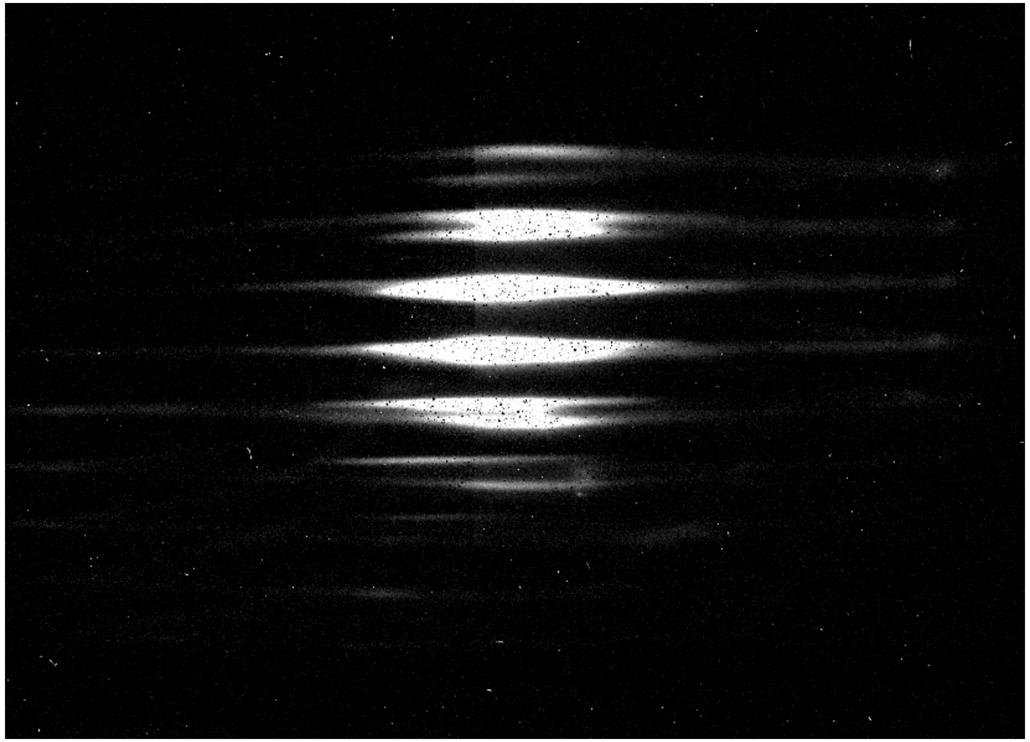
Phase Scan



Why bother with simulation? → Rough initial solution facilitates training with small amount of measured data

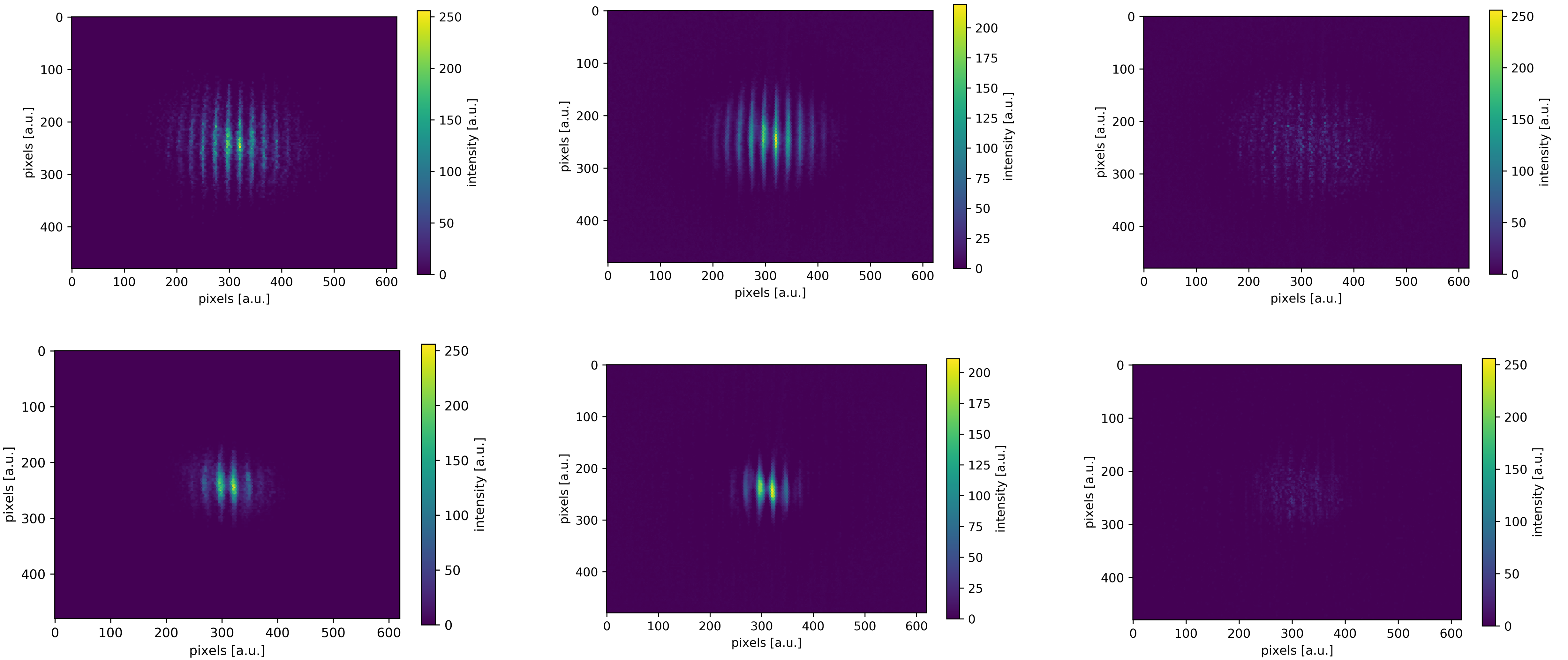
But that still relies on the slit fits…

- Fitting procedure changes (e.g. how image is processed, alignment) → *need to re-train*
- Non-ideal beam → *poor slit fits*



Predicting Image Output Directly

A. L. Edelen, et al. IPAC18, WEPAF040



Simulated NN Predictions Difference

Bigger Picture for FAST

Fast-executing, accurate machine model

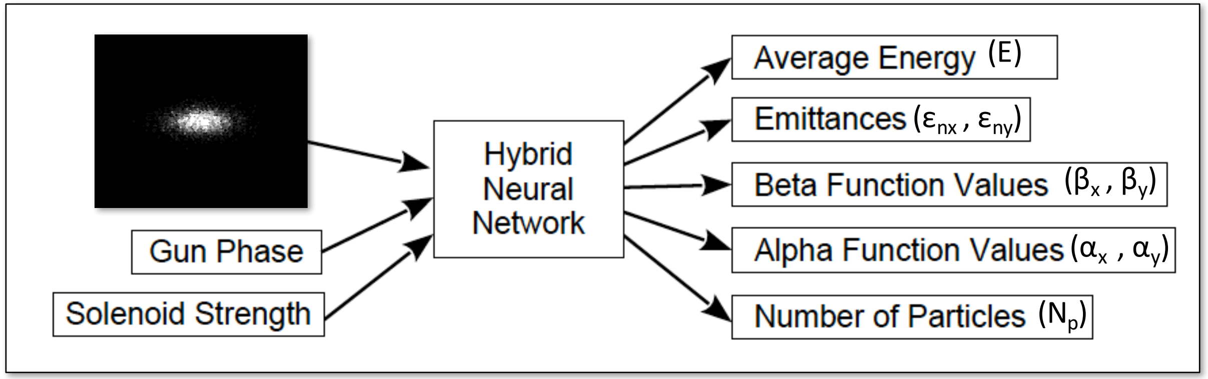
Online: *faster machine studies + online optimization*

Offline: *study planning*
downstream component design
controller training

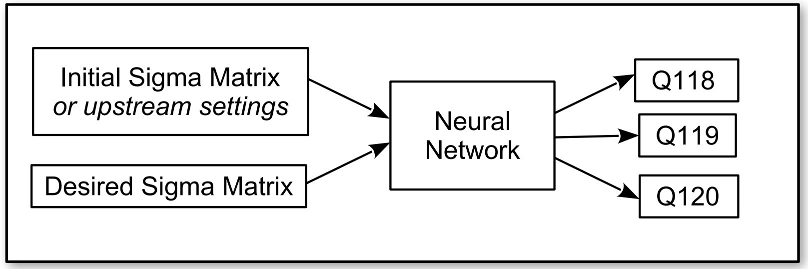
One piece of a larger set of studies:

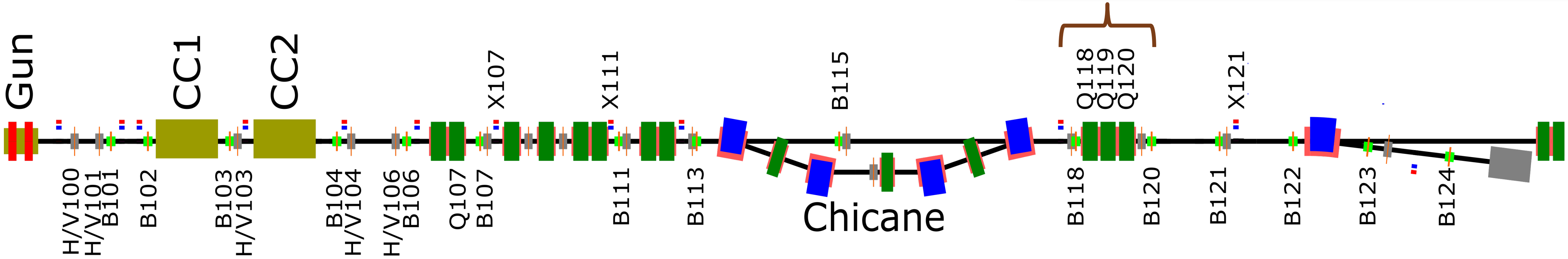
- *Accounting for laser spot changes*
- *NN controller (e.g. round-to-flat beam transform)*
- *Final aim would be to combine these*

Earlier work: account for changes in laser spot
A. L. Edelen, et al. NAPAC16, TUPOA51



NN-based round-to-flat beam transform





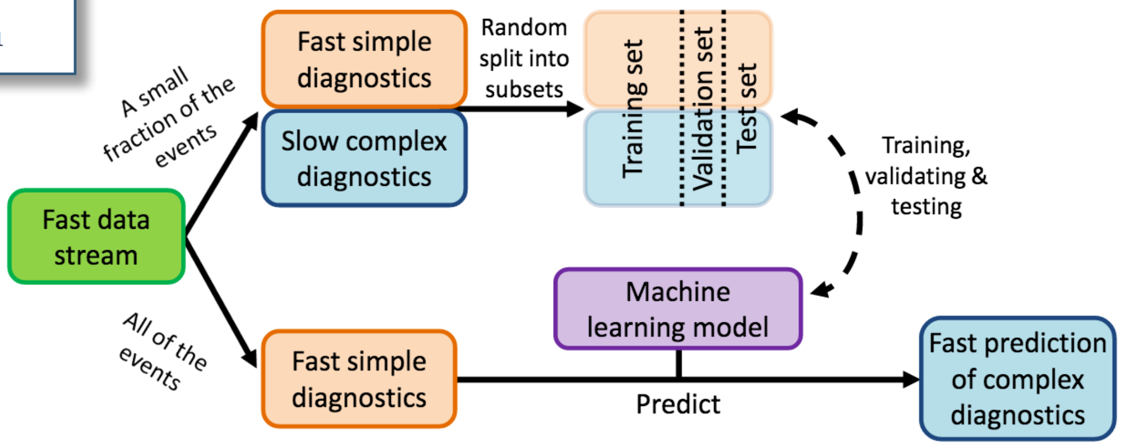
Lots of interesting work now at SLAC along these lines …

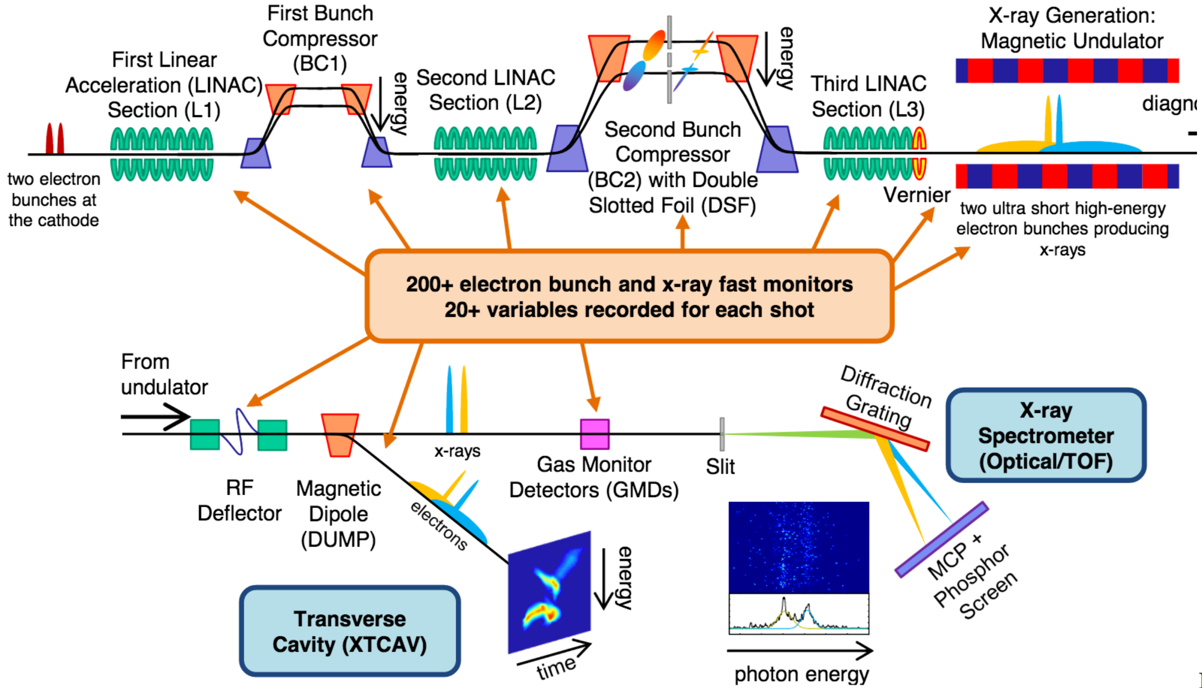
Machine learning applied to single-shot x-ray diagnostics in an XFEL

A. Sanchez-Gonzalez,[1] P. Micaelli,[1] C. Olivier,[1] T. R. Barillot,[1] M. Ilchen,[2,3] A. A. Lutman,[4] A. Marinelli,[4] T. Maxwell,[4] A. Achner,[3] M. Agåker,[5] N. Berrah,[6] C. Bostedt,[4,7] J. Buck,[8] P. H. Bucksbaum,[2,9] S. Carron Montero,[4,10] B. Cooper,[1] J. P. Cryan,[2] M. Dong,[5] R. Feifel,[11] L. J. Frasinski,[1] H. Fukuzawa,[12] A. Galler,[3] G. Hartmann,[8,13] N. Hartmann,[4] W. Helml,[4,14] A. S. Johnson,[1] A. Knie,[13] A. O. Lindahl,[2,11] J. Liu,[3] K. Motomura,[12] M. Mucke,[5] C. O'Grady,[4] J-E. Rubensson,[5] E. R. Simpson,[1] R. J. Squibb,[11] C. Såthe,[15] K. Ueda,[12] M. Vacher,[16,17] D. J. Walke,[1] V. Zhaunerchyk,[11] R. N. Coffee,[4] and J. P. Marangos[1]

A. Sanchez-Gonzalez, et al. https://arxiv.org/pdf/1610.03378.pdf

- Used archived data to learn correlation between fast and slow diagnostics
- Looked at a variety of ML methods and different diagnostics





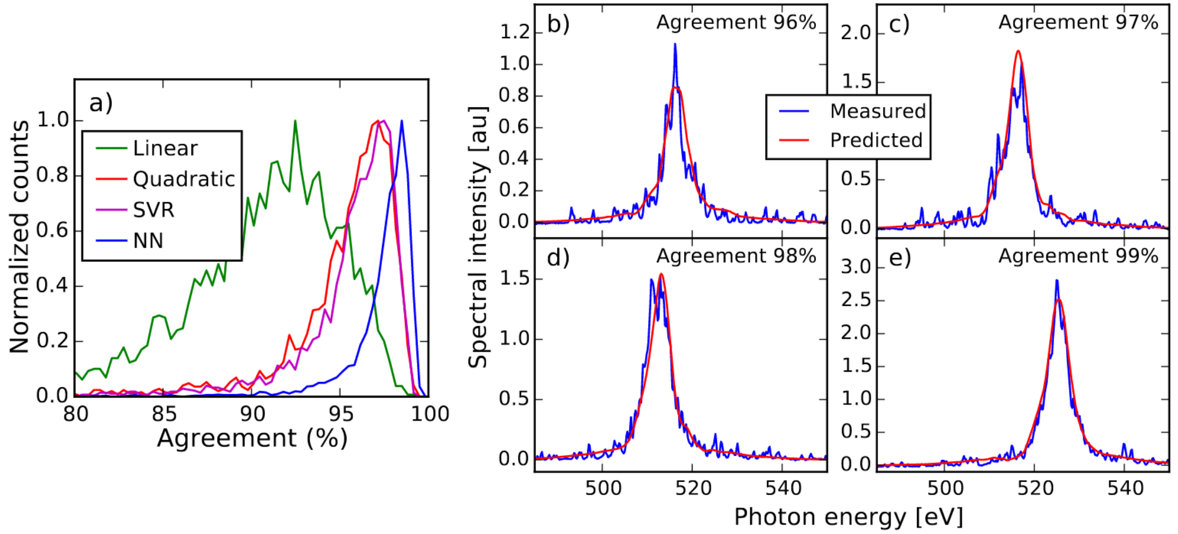
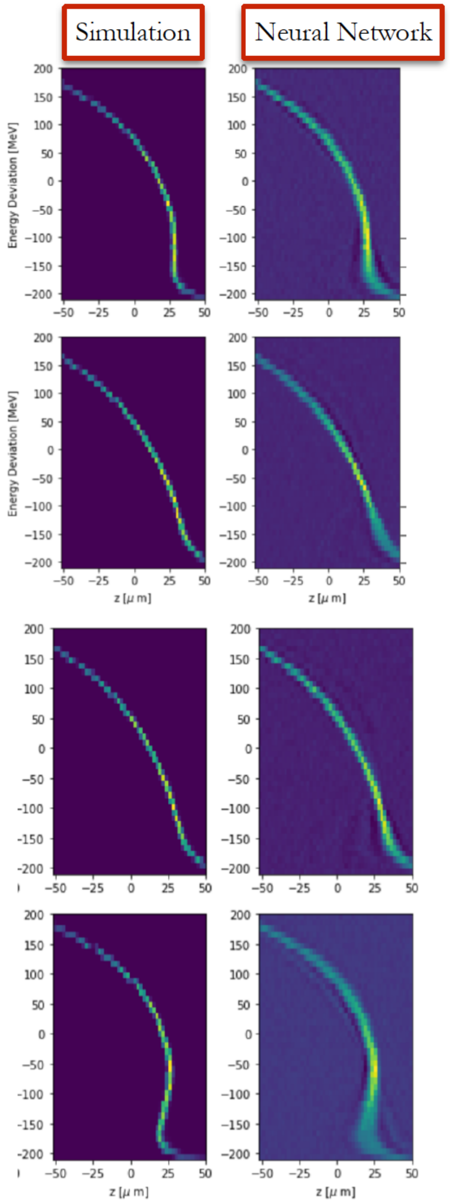
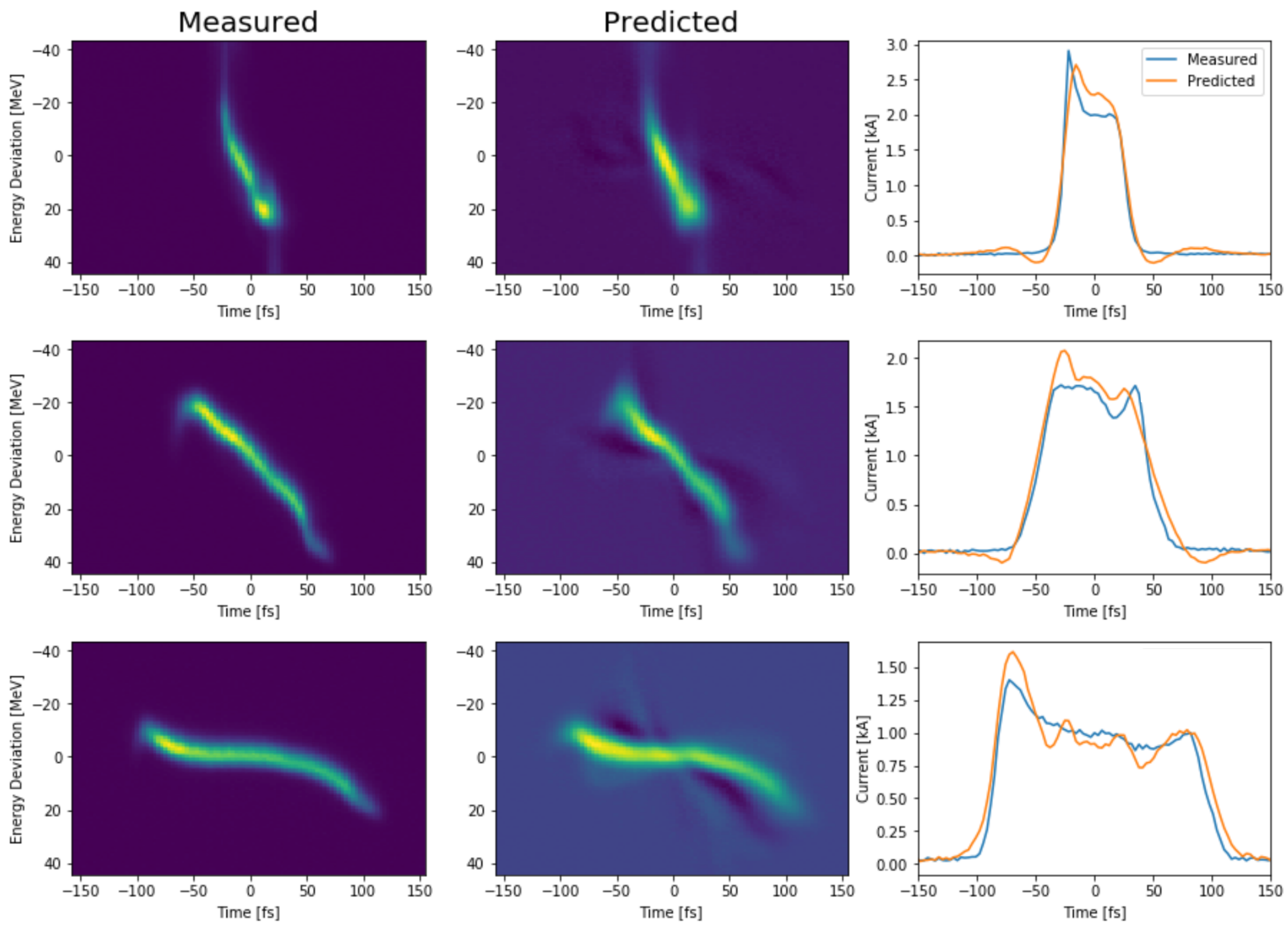


FIG. 4. Spectral shape prediction for a single pulse. (a) Histogram of agreements between the predicted and the measured spectra for the test set using the 4 different models. (b-e) Examples of the measured and the predicted spectra using a neural network to illustrate the accuracy for different agreement values.

Longitudinal Phase Space Prediction for FACET-II and LCLS



- Simulation + NN results match well for FACET-II *(see left)*
- Small proof-of-principle study with LCLS machine data and XTCAV images *(see below)*

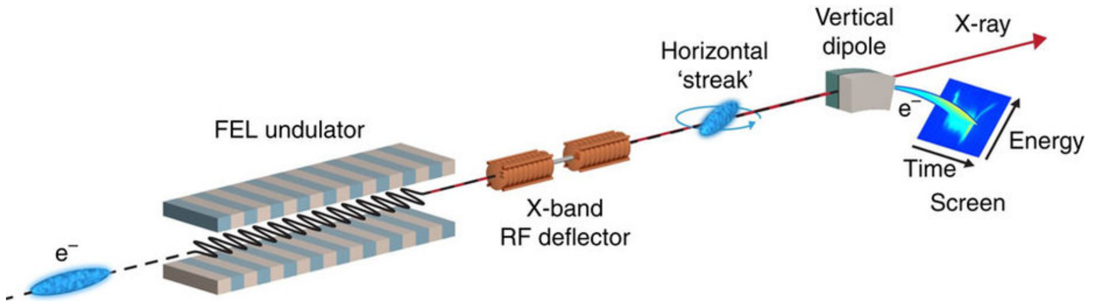


Figures courtesy C. Emma

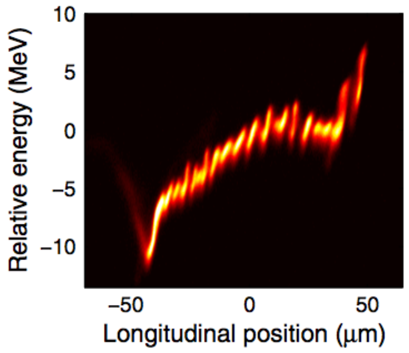
Emma, Edelen, et al. in preparation

Computer Vision + Neural Network-based Control Policies

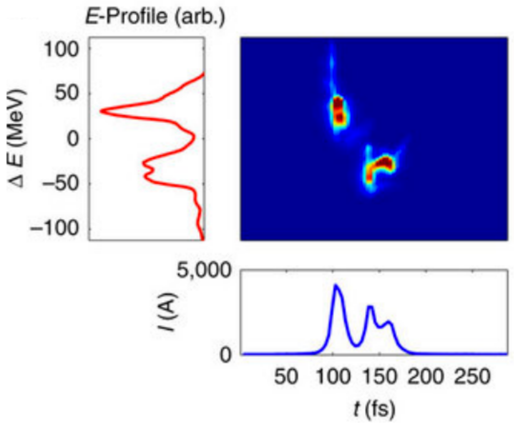
- **Image diagnostics** → nice to use directly, and some yield relatively complicated information



C. Behrens, et al., Nat. Commun. **5**, 3762 (2014)



D. Ratner, et al., PRSTAB18, 030704 (2015)



A. Marinelli, et al., Nat. Commun. **6**, 6369 (2015)

- **Neural Networks** → very good for image processing + can learn control policies from data

Could use image-based diagnostics directly in learned control policies to switch quickly between requested operating conditions, including to different target phase space images from the XTCAV

Use neural network as a warm start for a standard optimizer

- The Extremum Seeking (ES) algorithm has been used successfully for particle accelerator tuning

- ES can get stuck in local minima and takes awhile to converge

- Given some desired beam characteristics, a NN can provide initial settings

  → *fewer iterations of ES then needed to converge*

  (see A.L. Edelen et al., FEL '17 for a simple NN control policy example)

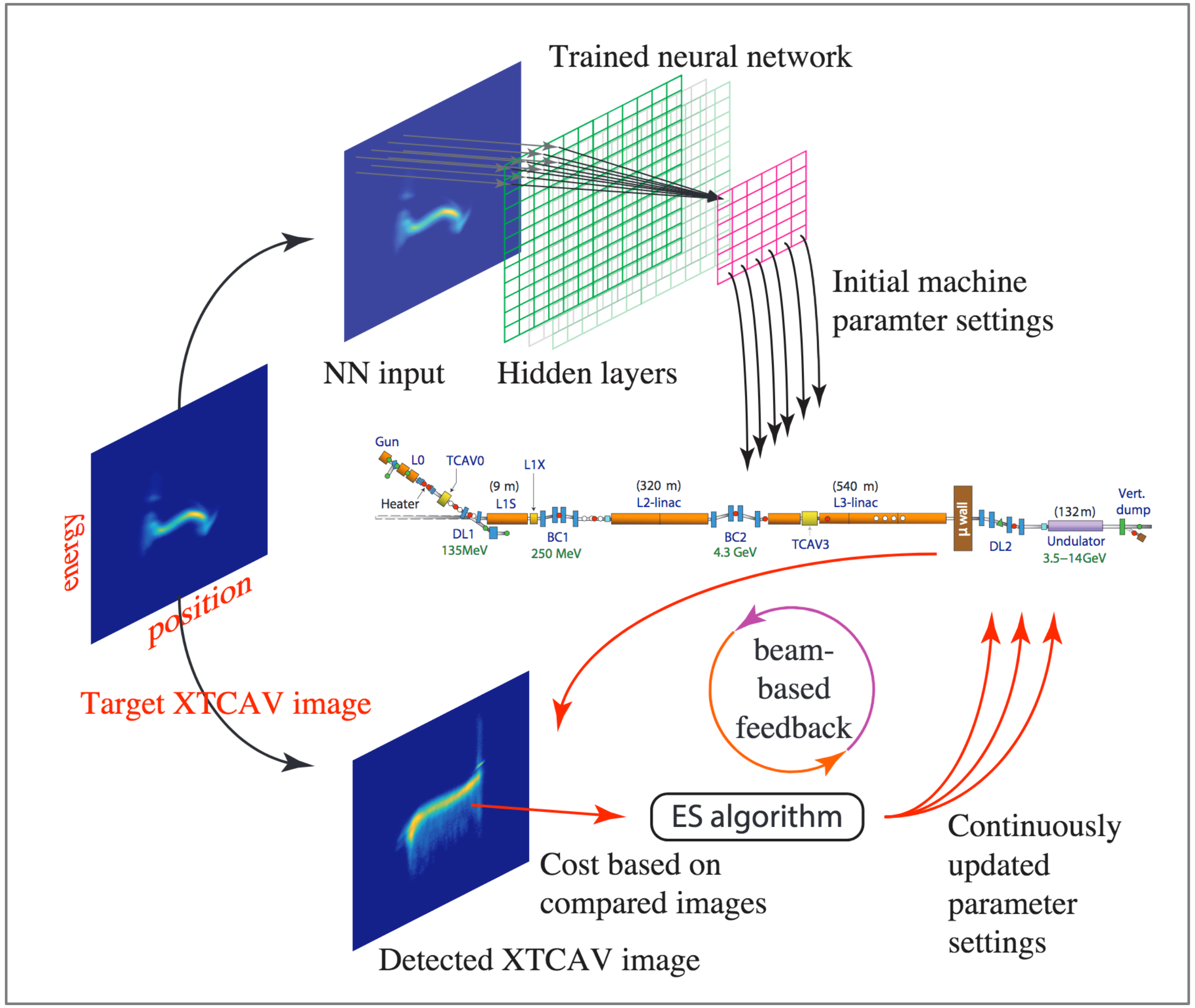
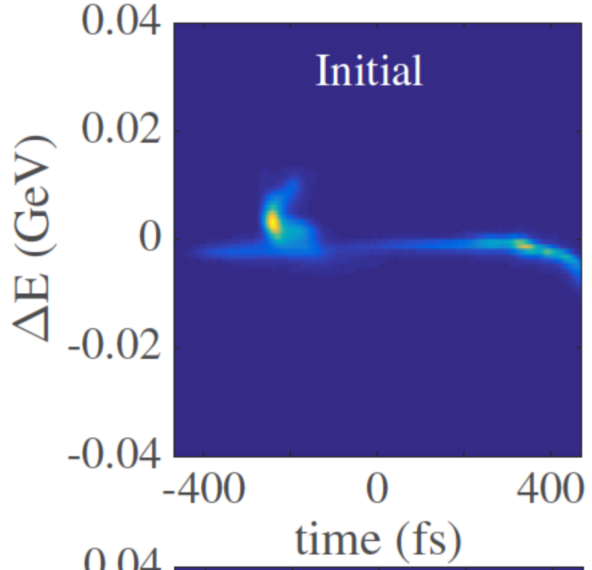
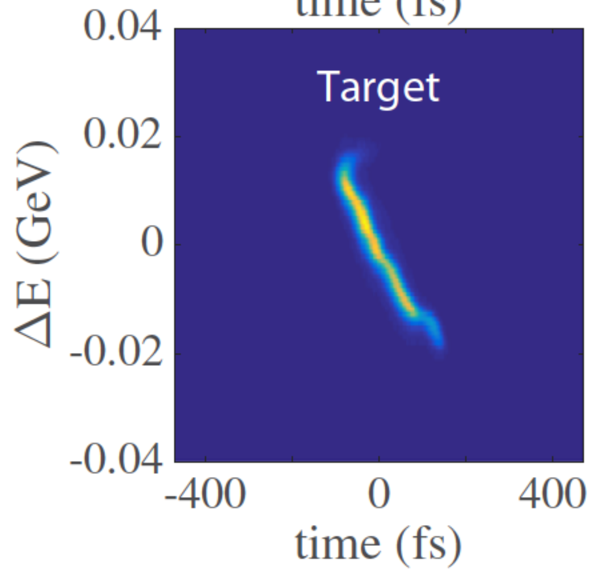


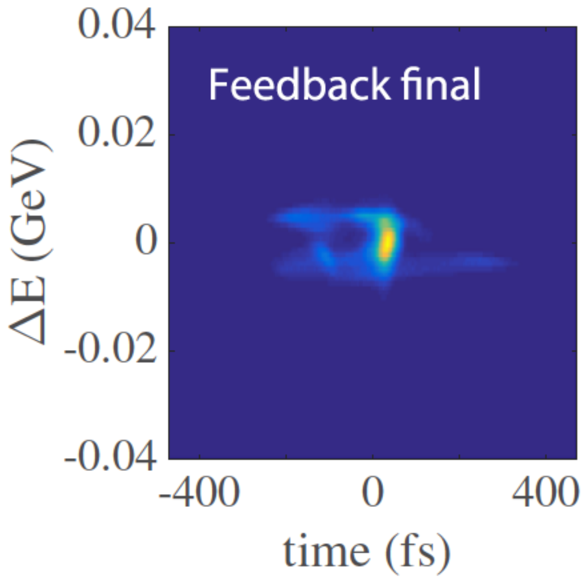
Figure: Alex Scheinker

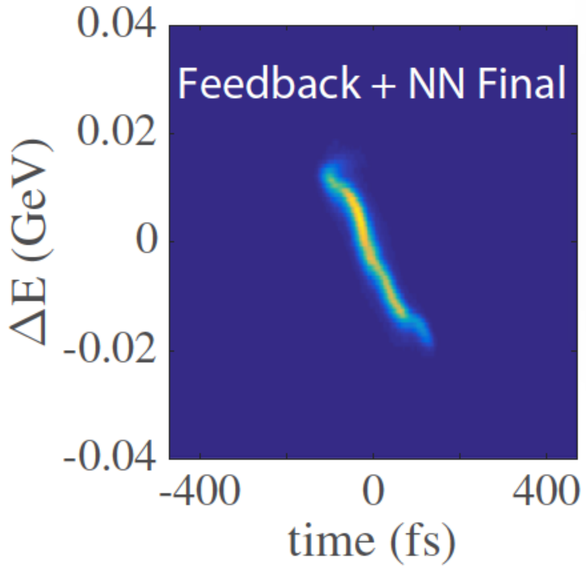
Preliminary Results



- Conducted scan of L1S phase and BC2 peak current → trained NN
- Used NN to give suggested settings based on a new target XTCAV image, starting from far away
- *ES alone unable to converge in this case, but able to converge with suggested settings from NN*

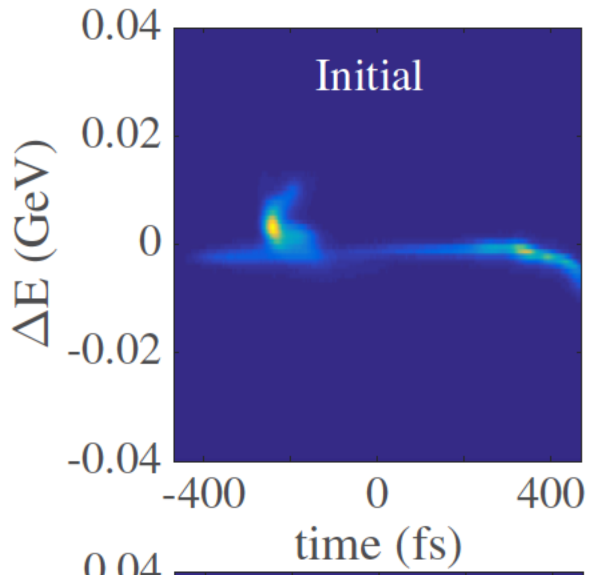






Figures: Alex Scheinker

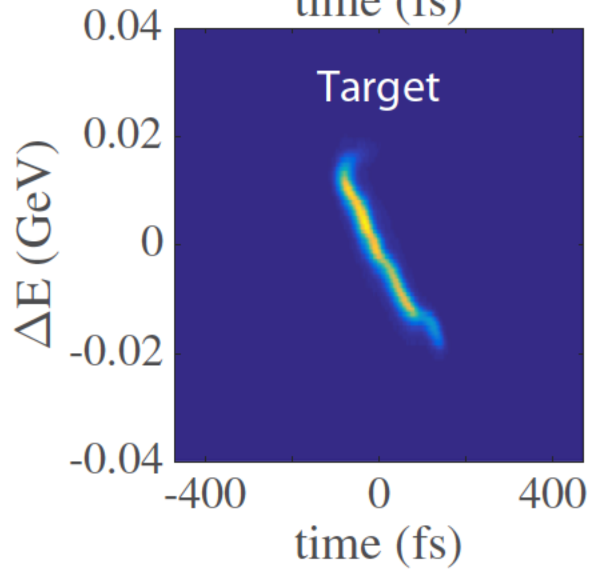
Preliminary Results

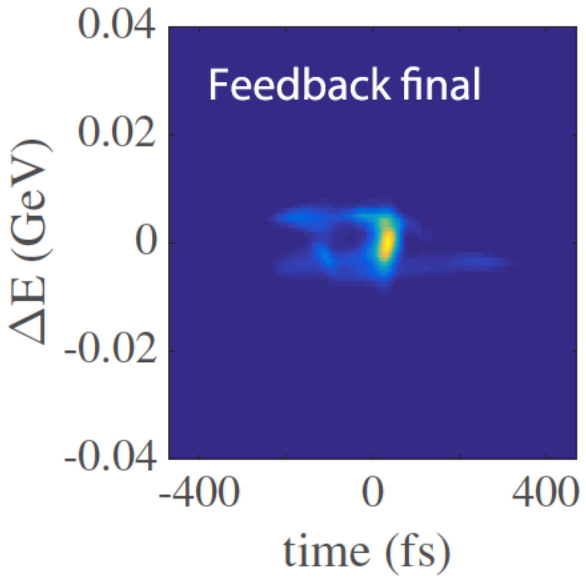


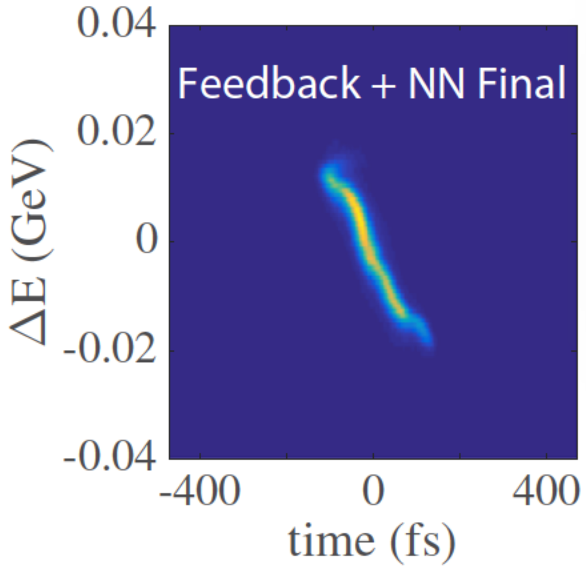
PHYSICAL REVIEW LETTERS **121,** 044801 (2018)

Demonstration of Model-Independent Control of the Longitudinal Phase Space of Electron Beams in the Linac-Coherent Light Source with Femtosecond Resolution

Alexander Scheinker,[1,*] Auralee Edelen,[2] Dorian Bohler,[2] Claudio Emma,[2] and Alberto Lutman[2]
[1]*Los Alamos National Laboratory, P.O. Box 1663, Los Alamos, New Mexico 87545, USA*
[2]*SLAC National Accelerator Laboratory, 2575 Sand Hill Road, Menlo Park, California 94025, USA*







Figures: Alex Scheinker

Conclusions + Outlook

- Virtual diagnostics using ML

  → *potentially useful both for prediction and control when physical diagnostics have some limitations to their use (e.g. destructive measurement, too slow to update)*

  → *limitations need to be more fully explored (e.g. sensitivity to machine drift, upstream errors)*

- Good preliminary results + experience from transverse phase space diagnostic at FAST

- Previous demonstration at SLAC using quickly-updating diagnostics to predict measurements derived from slow diagnostics

- Ongoing work at SLAC (FACET-II and LCLS) to rigorously demonstrate in operation for longitudinal phase space prediction, as well as to facilitate control