Machine Learning-Based Longitudinal Phase Space Prediction of Particle Accelerators

NAPAC 2022

Claudio Emma / SLAC National Accelerator Laboratory

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FACET-II

LCLS Linac Coherent Light Source

Stanford University | U.S. DEPARTMENT OF ENERGY

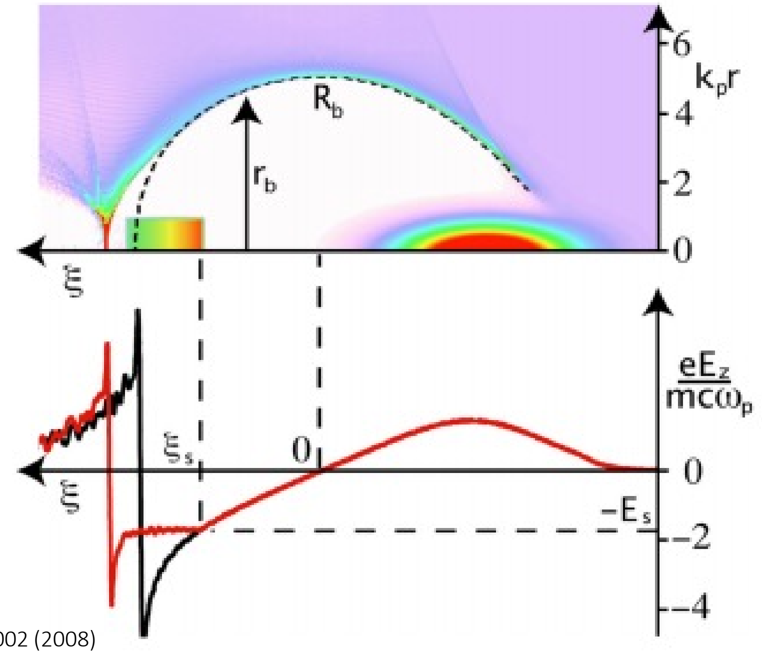
SLAC NATIONAL ACCELERATOR LABORATORY

Outline

- Context and Motivation
- Virtual LPS diagnostic examples:
  - Experimental Demo at LCLS
  - Simulations + early experiments at FACET-II
  - LPS predictions using spectral data
- Optimization using ML-based LPS predictions
- Conclusion

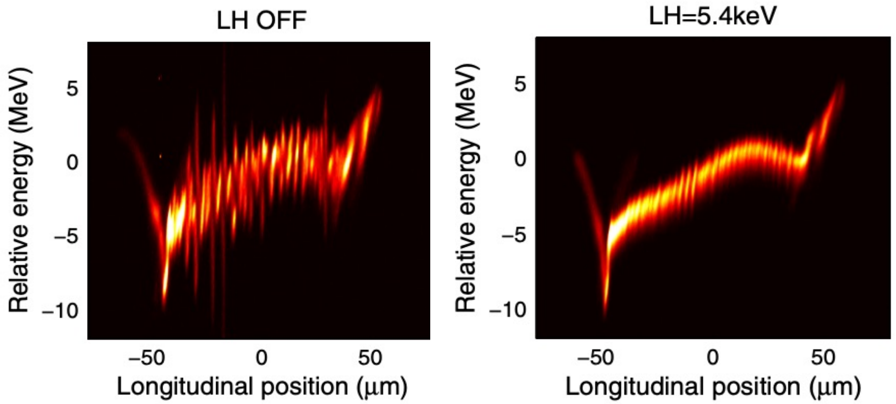
LPS diagnostics for linac-driven experiments

PWFA



Tzoufras et al., PRL **101,** 145002 (2008)

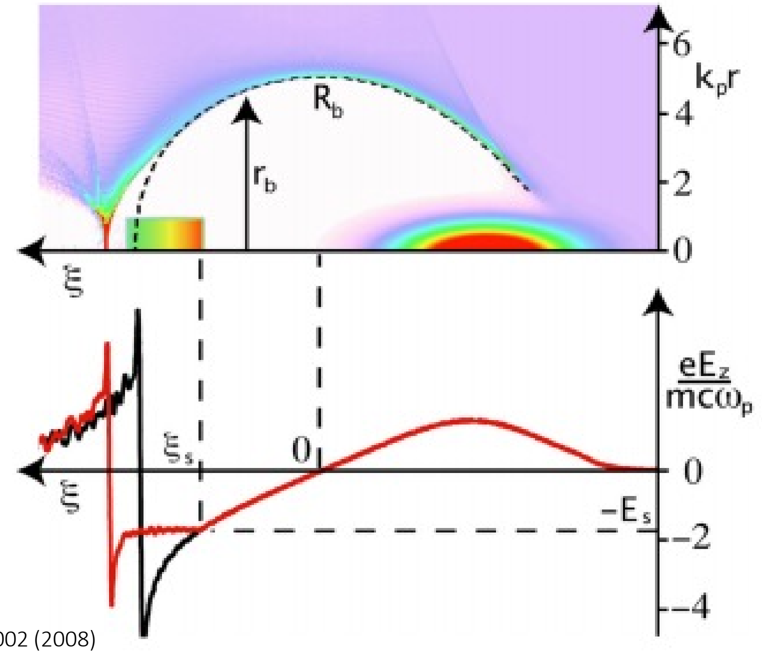
FEL



Ratner et al., PRSTAB **18,** 030704 (2015)

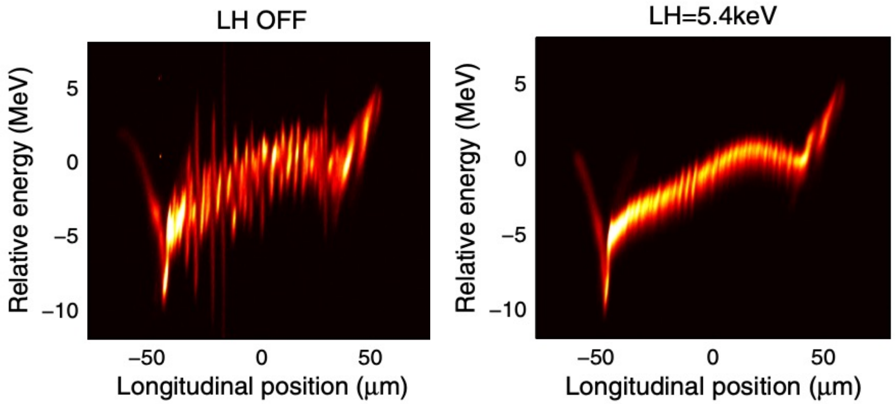
LPS diagnostics for linac-driven experiments

FACET-II (PWFA)



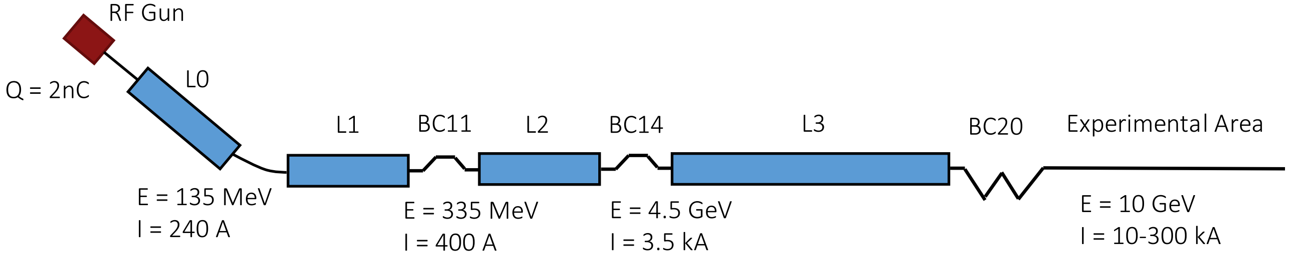
Tzoufras et al., PRL **101,** 145002 (2008)

LCLS (FEL)

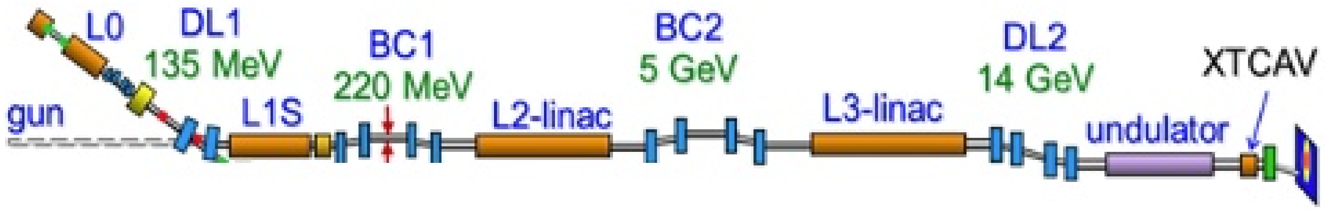


Ratner et al., PRSTAB **18,** 030704 (2015)

FACET-II schematic

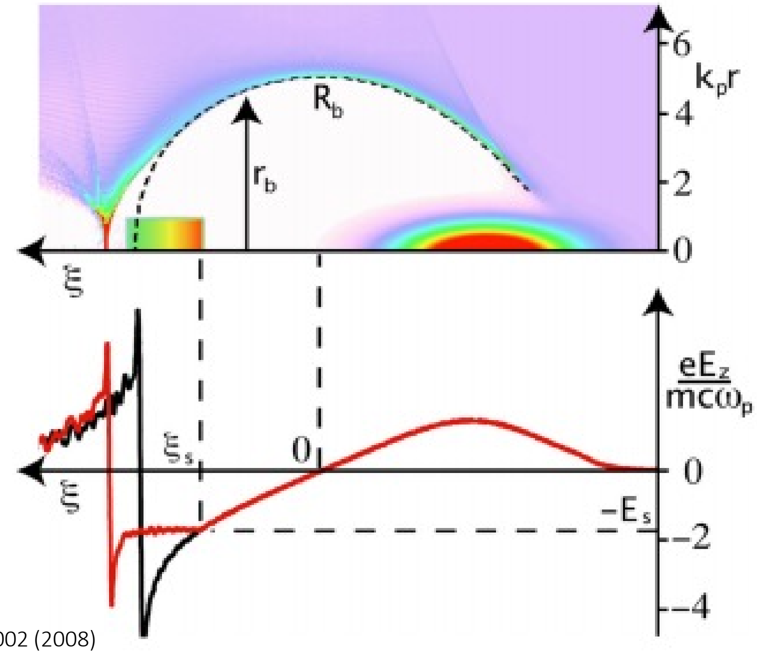


LCLS schematic



LPS diagnostics for linac-driven experiments

FACET-II (PWFA)



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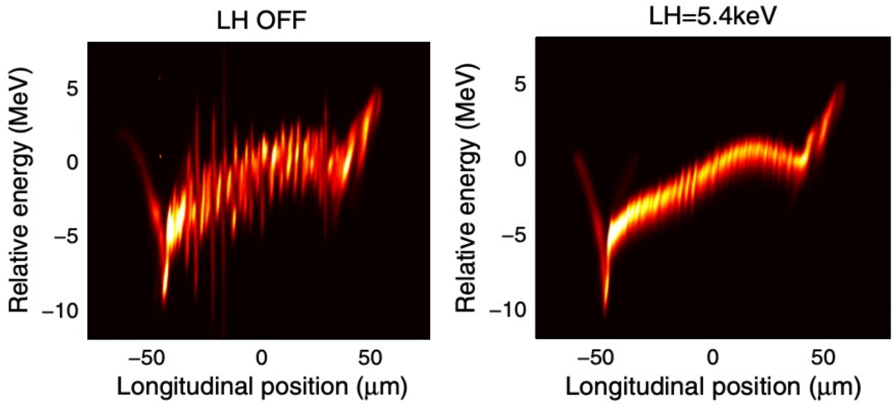
LCLS (FEL)



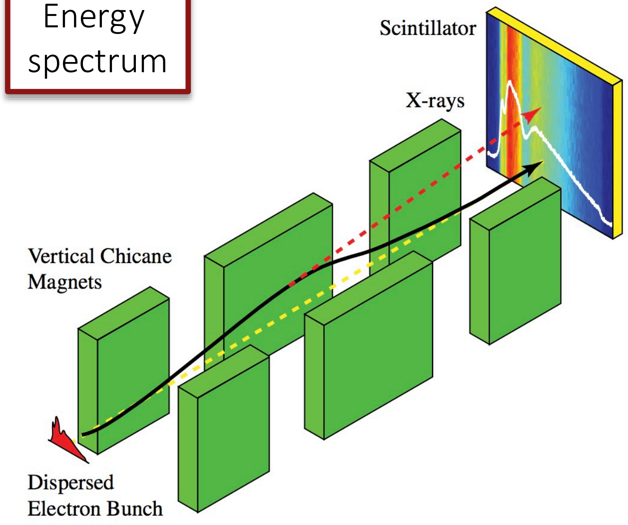
Ratner et al., PRSTAB **18,** 030704 (2015)

$\Delta E/E \sim \%level$

$\sigma_z \sim 0.1 - 10\mu m$

$\Delta z \sim 10 - 200\mu m$

Energy spectrum

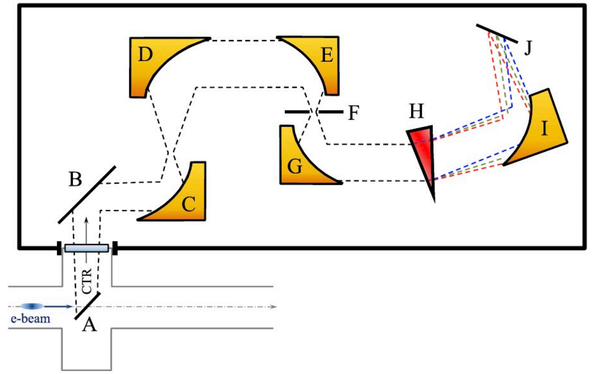


Scheinker, Gessner, PRSTAB **18** 102801 (2015)

Bunch Profile

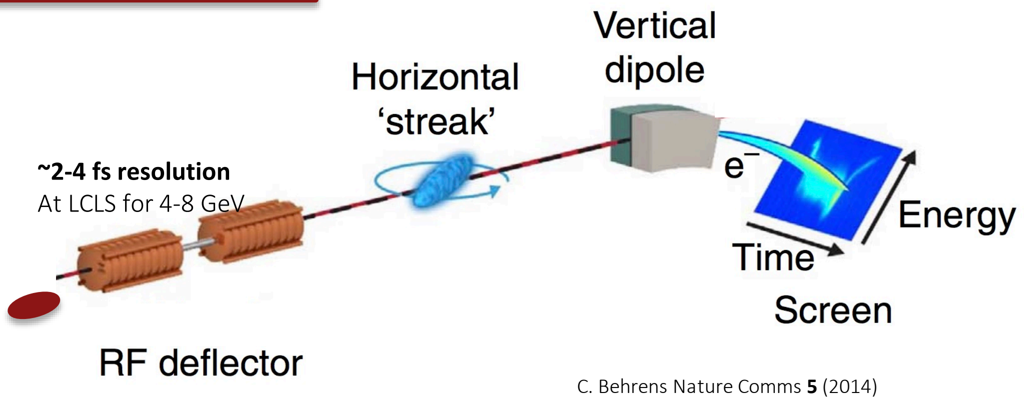
~0.7 fs resolution
at LCLS using OTR

Maxwell, PRL **111** 184801 (2013)



Longitudinal Phase Space

~2-4 fs resolution
At LCLS for 4-8 GeV



C. Behrens Nature Comms **5** (2014)

Virtual Diagnostics

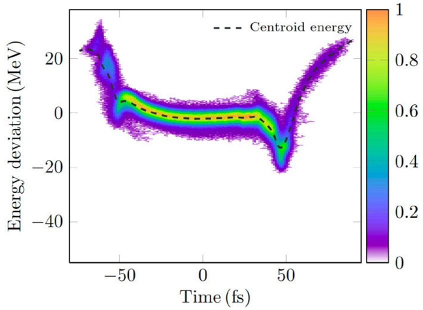
Predict what the output of a diagnostic would look like when it is unavailable

Fast physics-based simulation

ML model

Measured machine inputs (non-destructive)

Virtual diagnostic



"Real-time" prediction diagnostic output

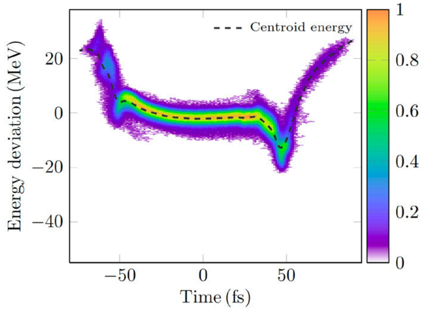
Virtual Diagnostics

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

Fast physics-based simulation

ML model

Measured machine inputs (non-destructive) → **Virtual diagnostic** →



"Real-time" prediction diagnostic output

Challenges with physics-based simulation approach:

Execution often still isn't so fast (sec-mins)

Can require HPC resources

Often takes much effort to replicate machine behavior!
(And even then, need to account for drifts)

Another approach:
Use a ML model

Once trained, neural networks can execute very quickly

Train on data from slow, high fidelity simulations
+
Train on measured data

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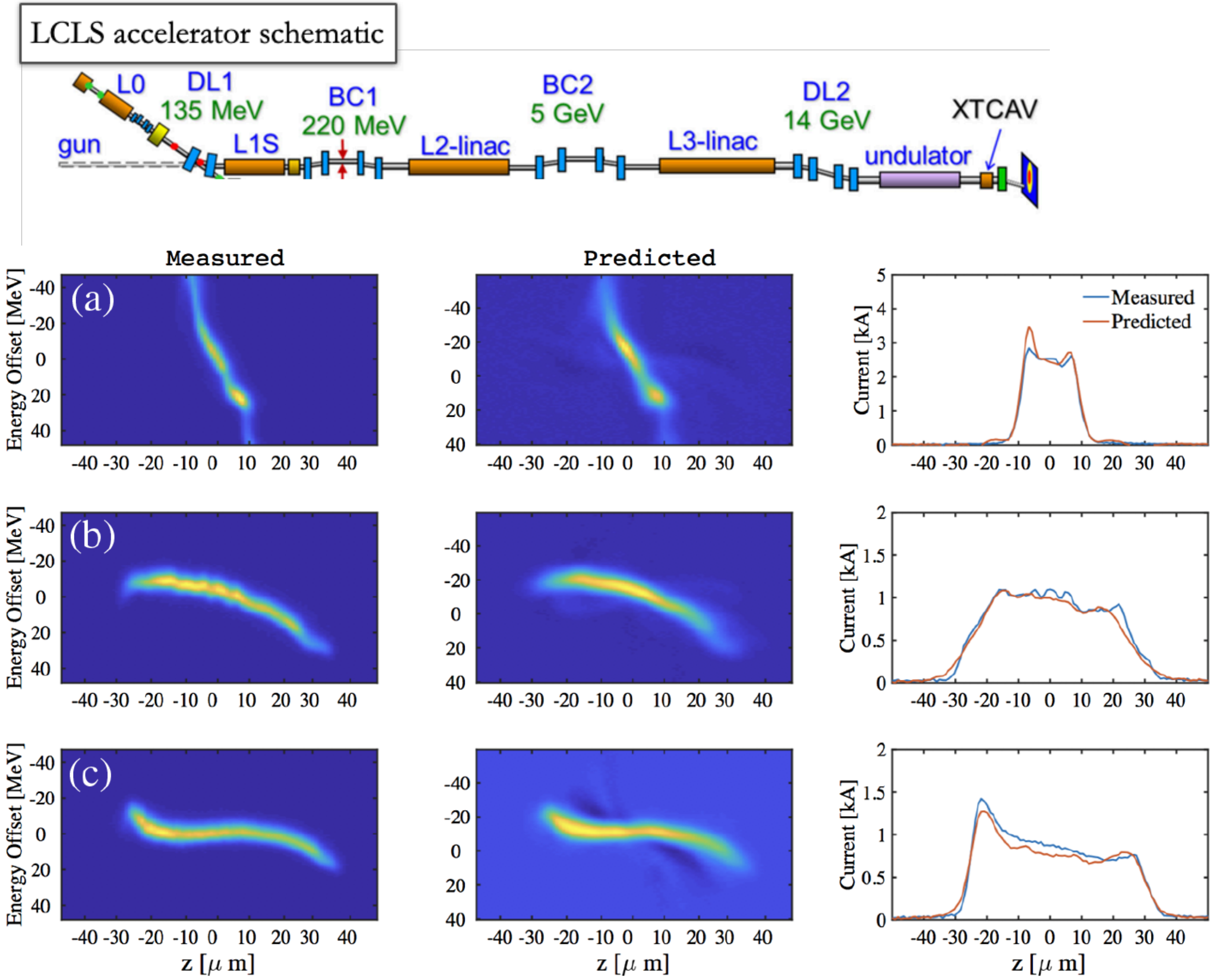
Experimental Demonstration at LCLS



Experimental Parameters:

<u>Machine parameters scanned</u>
L1s phase from -21 to -27.8 deg

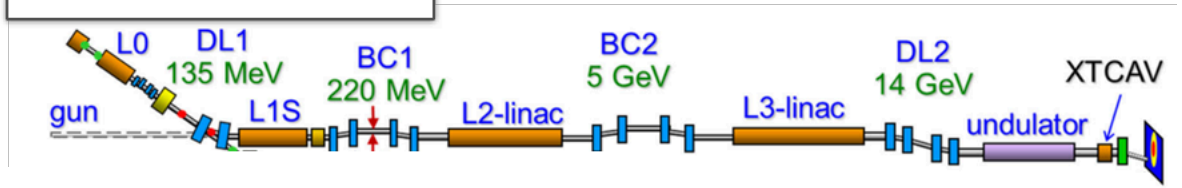
BC2 peak current from 1 to 7 kA

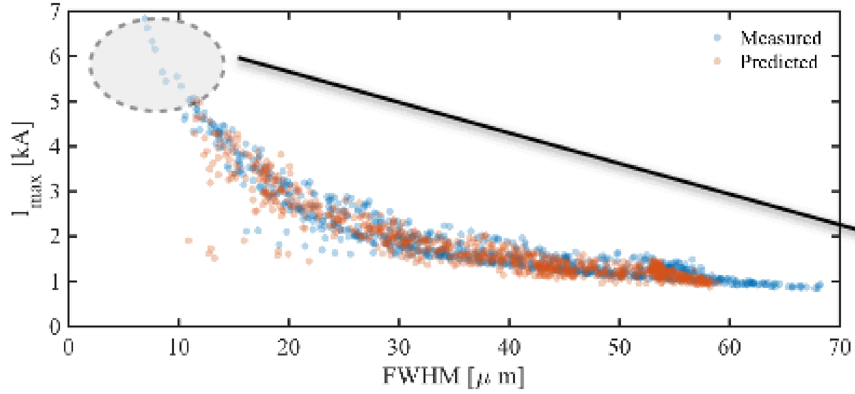
<u>Inputs to ML model</u>
L1s voltage & phase readbacks, L1x voltage, BC1 and BC2 current

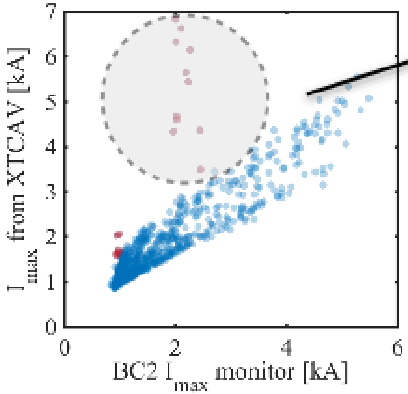
- ML prediction of LPS/current profile from five scalar inputs agrees well with measurements.

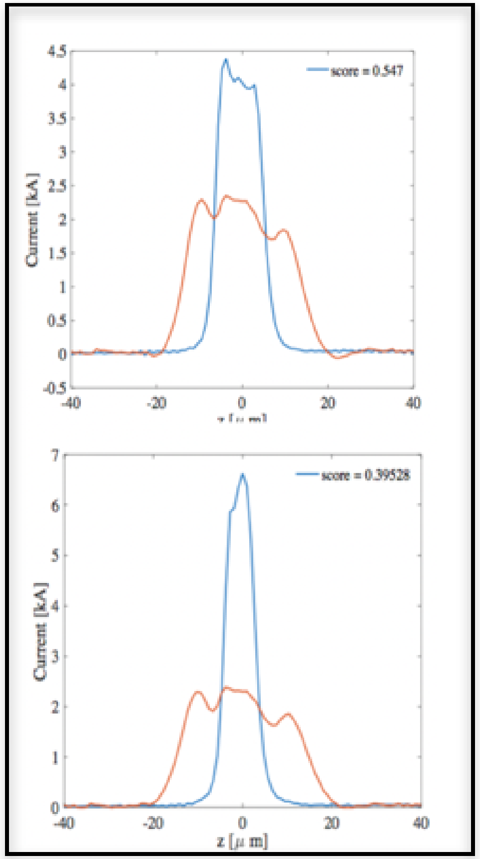
Experimental Demonstration at LCLS

LCLS accelerator schematic









Shots with bad predictions circled

Experimental Parameters:

Machine parameters scanned

L1s phase from -21 to -27.8 deg

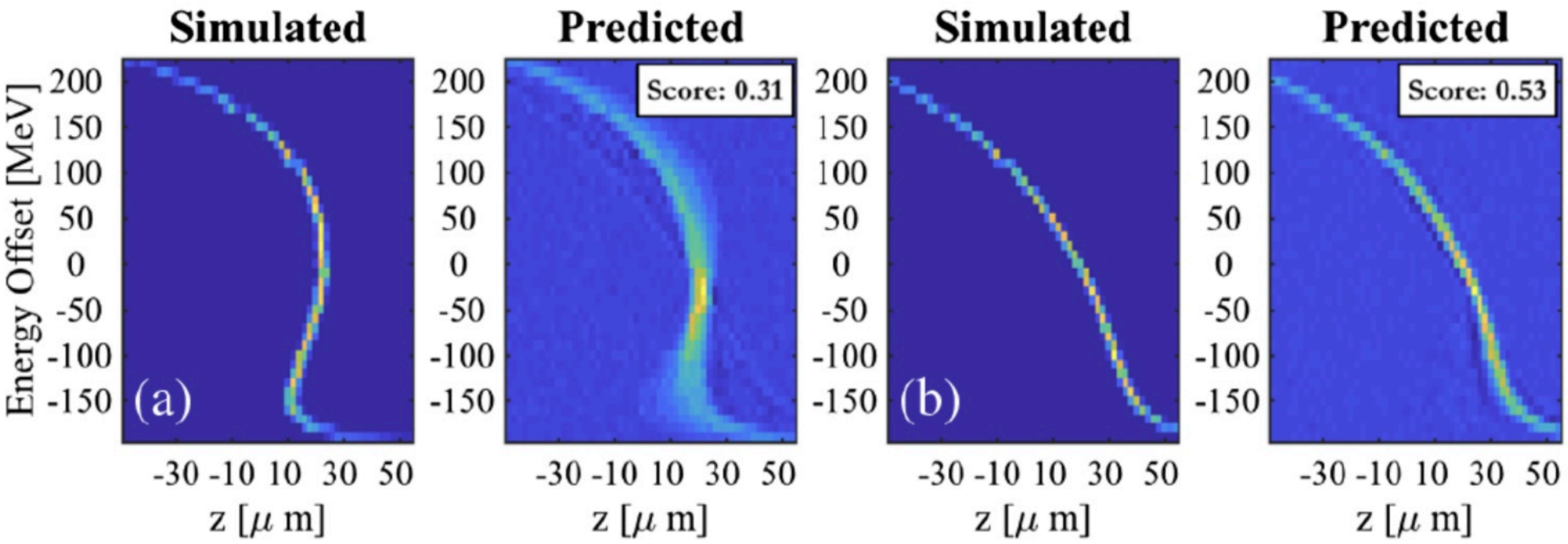
BC2 peak current from 1 to 7 kA

Inputs to ML model

L1s voltage & phase readbacks, L1x voltage, BC1 and BC2 current

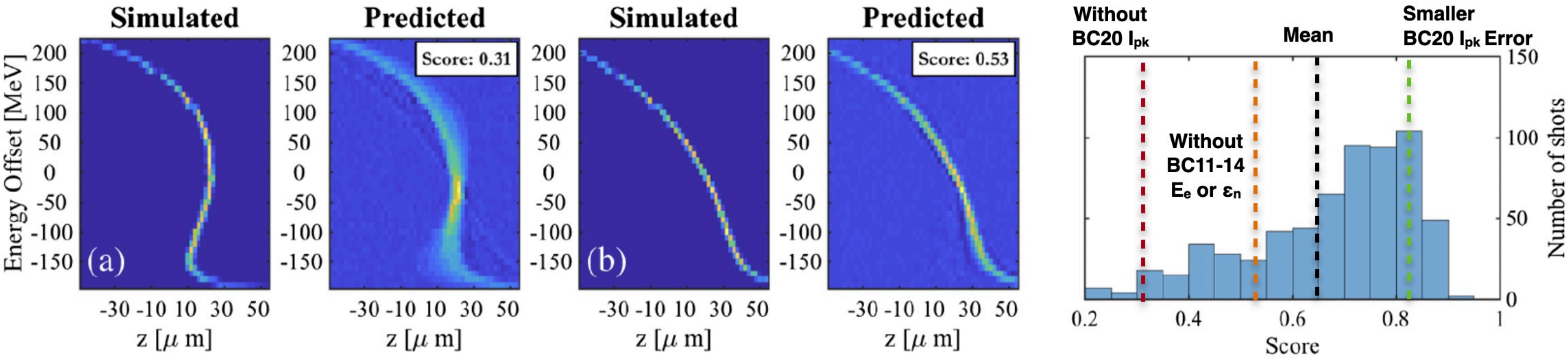
- ML prediction of LPS/current profile from five scalar inputs agrees well with measurements.
- Bad predictions can result from large discrepancy between diagnostic input (e.g. BC2 current) and XTCAV current (see bad shots).
- Flagging bad shots is important for trusting virtual diagnostic prediction.

Simulations for FACET-II single bunch mode



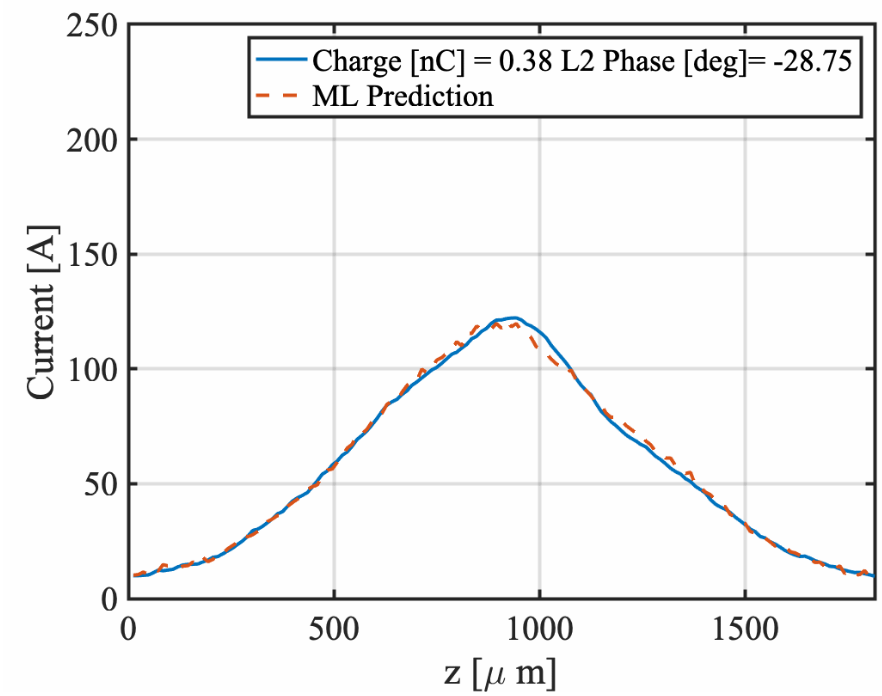
- Single bunch simulation studies show feasibility of using ML LPS diagnostic with high accuracy

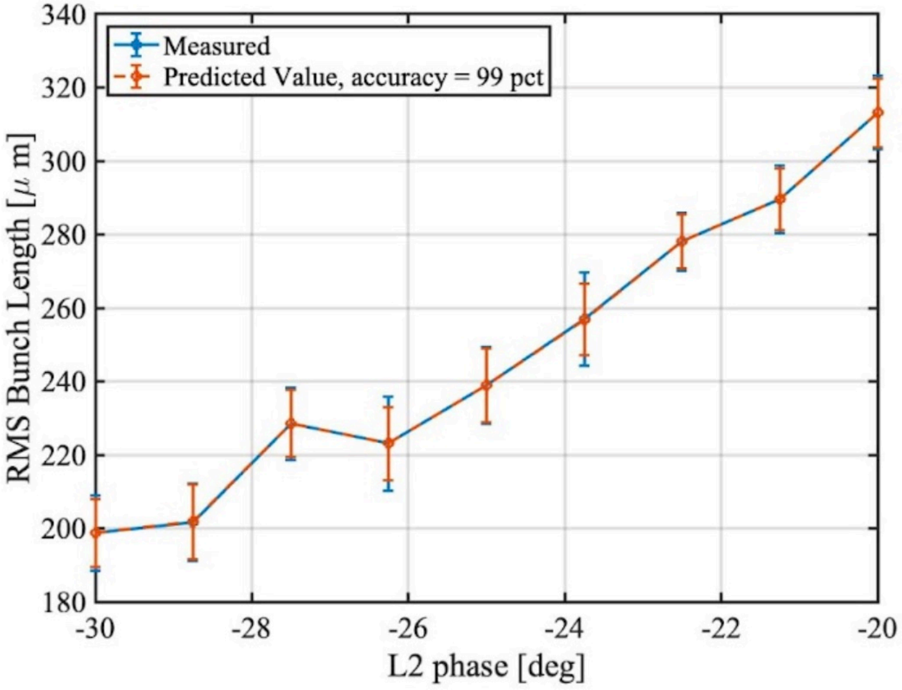
Simulations for FACET-II single bunch mode



- Single bunch simulation studies show feasibility of using ML LPS diagnostic with high accuracy
- Sensitivity studies reveal most critical input diagnostic is the peak current measurement after BC20, especially at full compression

FACET LPS Virtual diagnostic – first experiments

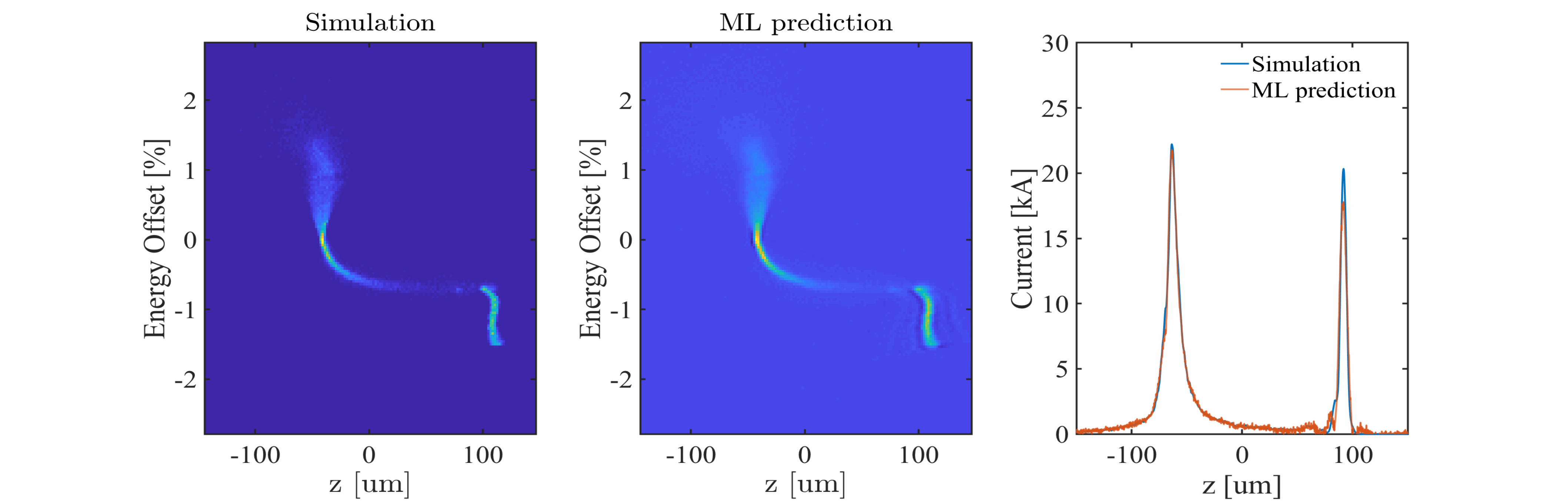




- First experimental data taken at FACET-II on 12/2021 in low charge mode with TCAV measuring current profile
- Results confirm feasibility of ML approach to reconstruct current profile from upstream scalars

First experimental results demonstrate ML-based current profile + bunch length prediction

Simulations for FACET-II two bunch mode with TCAV resolution

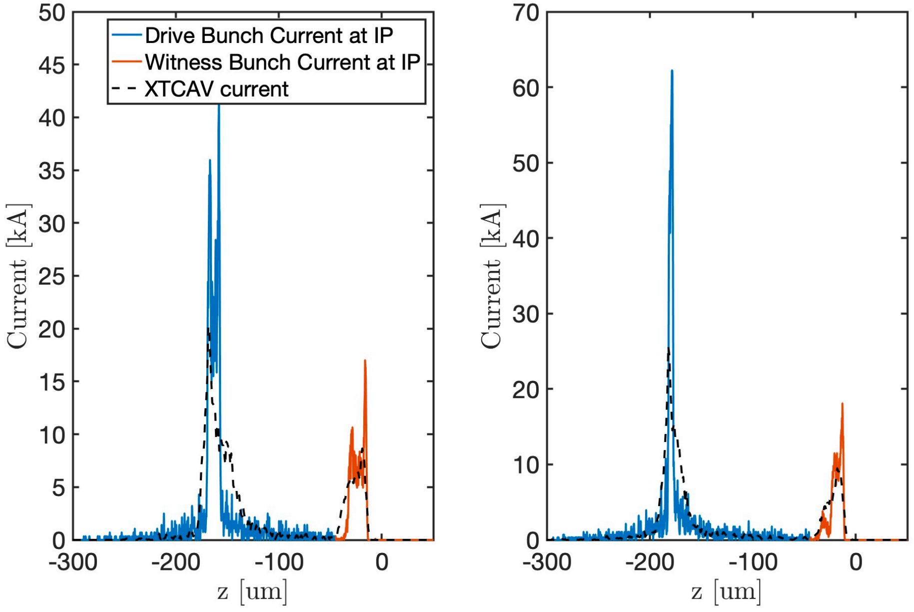


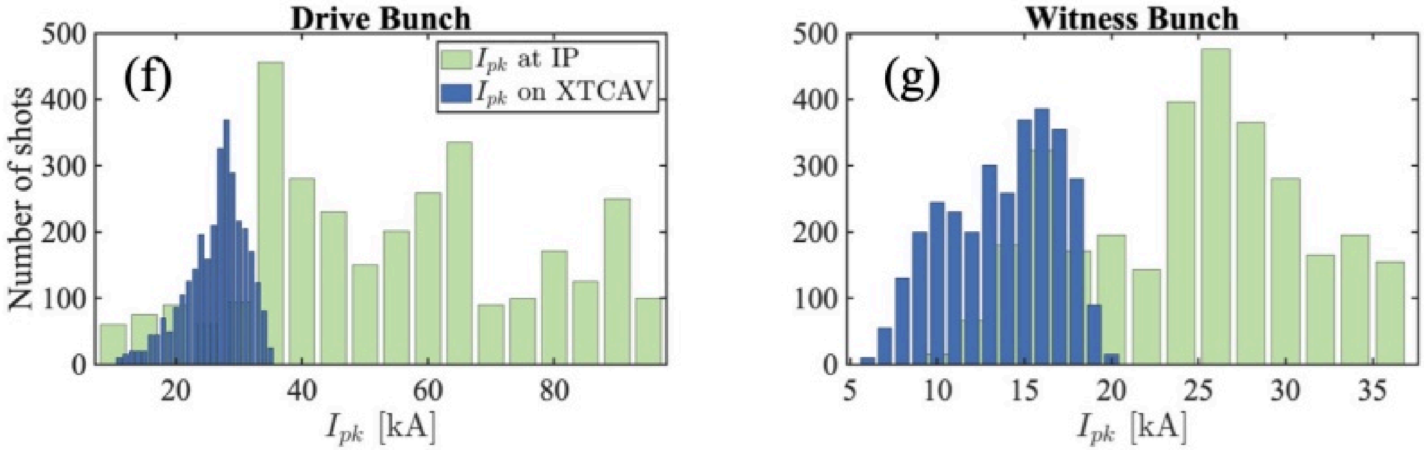
- Good agreement between ML prediction and simulated TCAV measurement

Simulations for FACET-II two bunch mode with TCAV resolution

Single shots

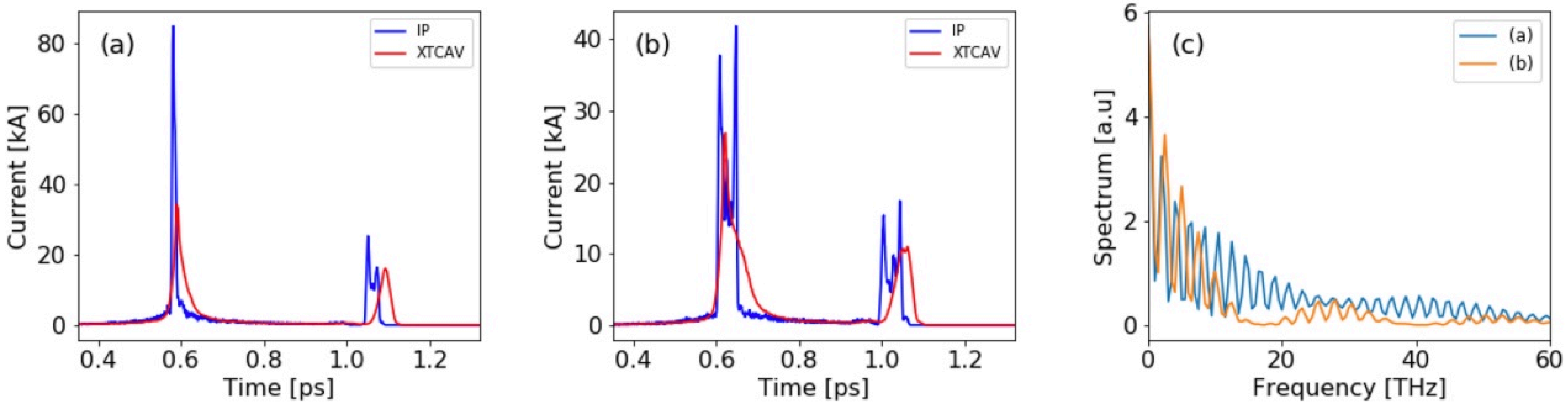
All shots





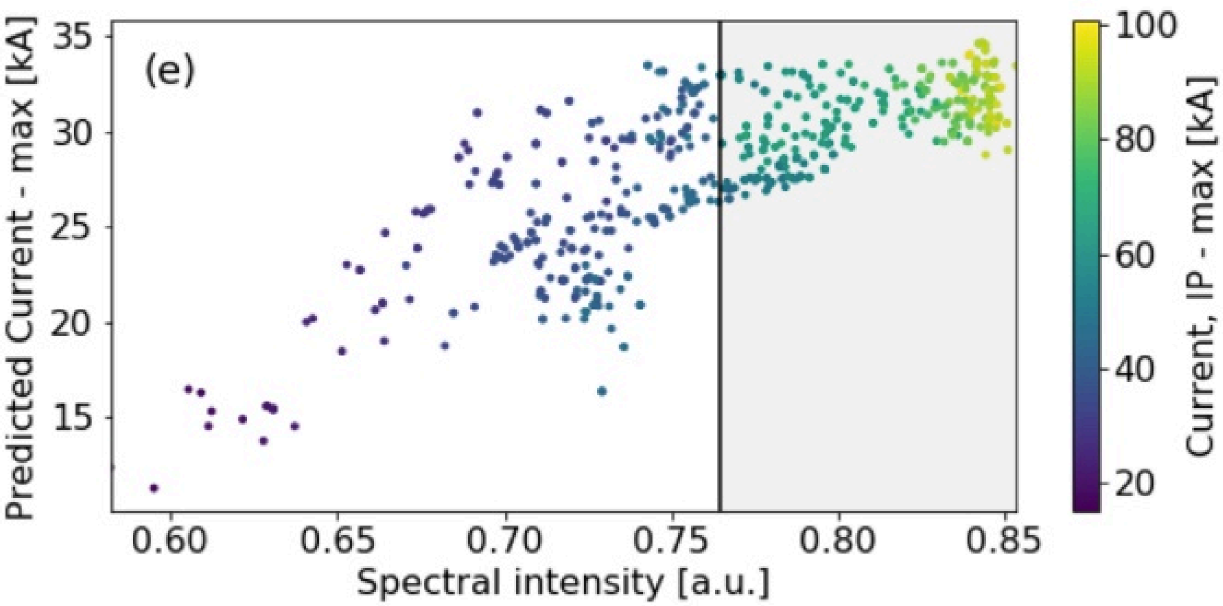
- Good agreement between ML prediction and simulated TCAV measurement
- TCAV smears out current profile => need a way of identifying when the ML diagnostic prediction is beyond TCAV resolution

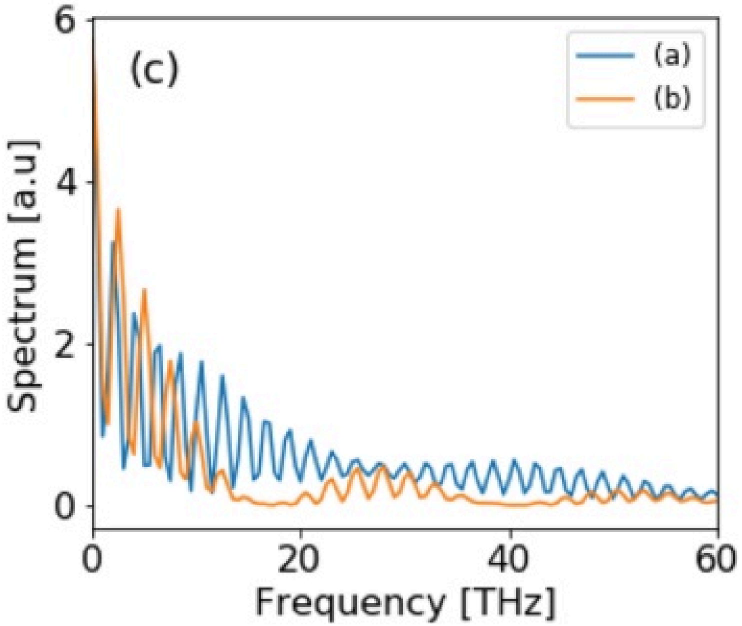
Spectral diagnostics for increased ML prediction confidence



- Radiated spectrum for low/high current shots which appear as equal on TCAV measurement has distinct features

Spectral diagnostics for increased ML prediction confidence





- Radiated spectrum for low/high current shots which appear as equal on TCAV measurement has distinct features
- Integrated spectral intensity serves as a proxy for peak current => allows single shot rejection of 'bad prediction' outside TCAV resolution

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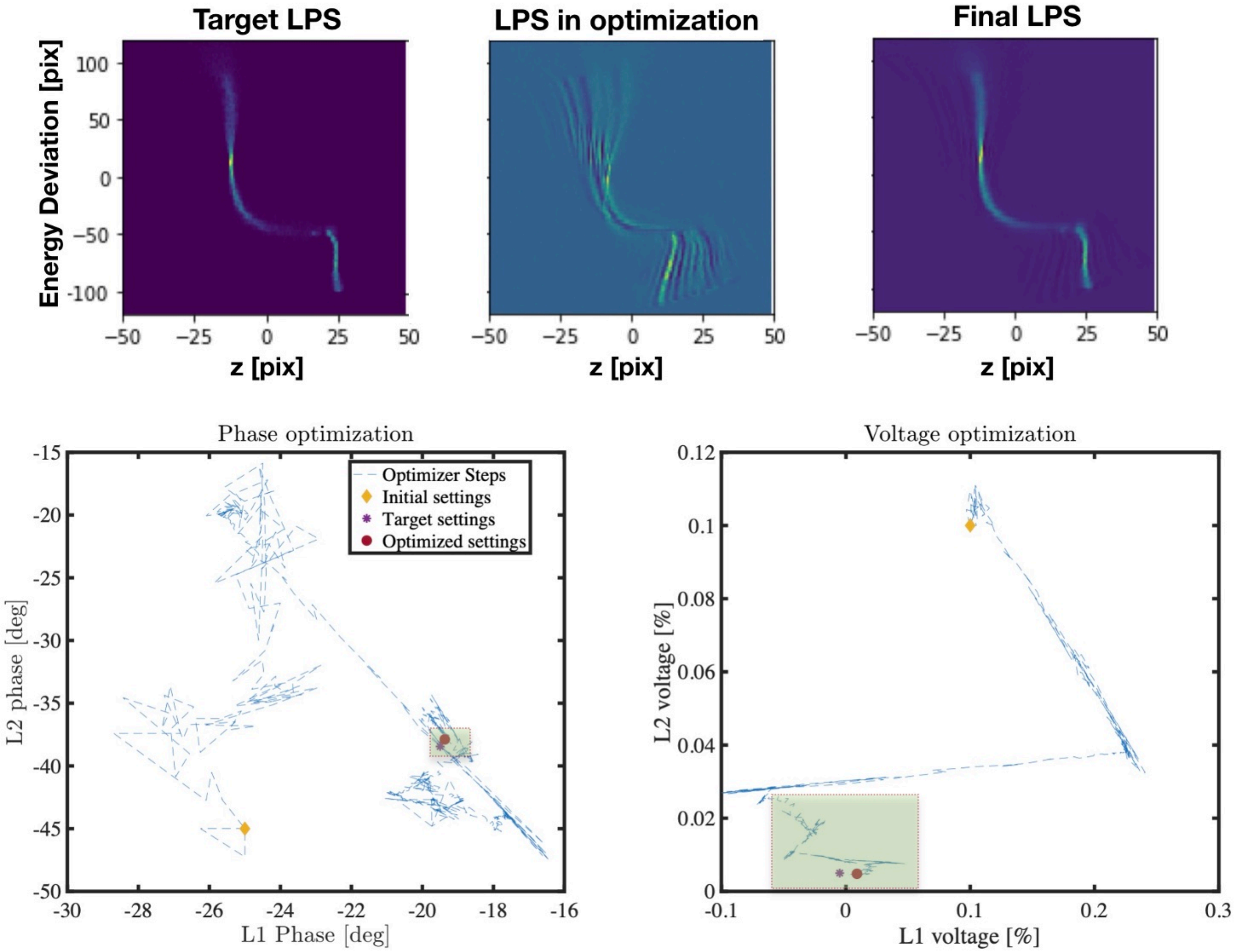
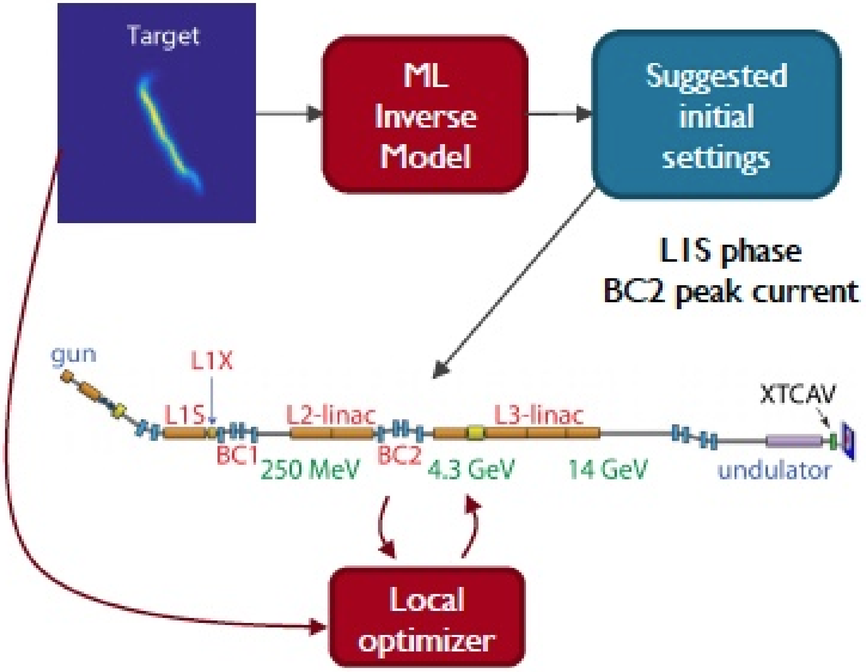
LPS optimization for two-bunch at FACET-II

- ML prediction of LPS used with conventional optimizer to tune L1-2 phases/voltages for desired LPS.
- Initial settings outside training set of ML model.
- Model shows ability to interpolate within training data.

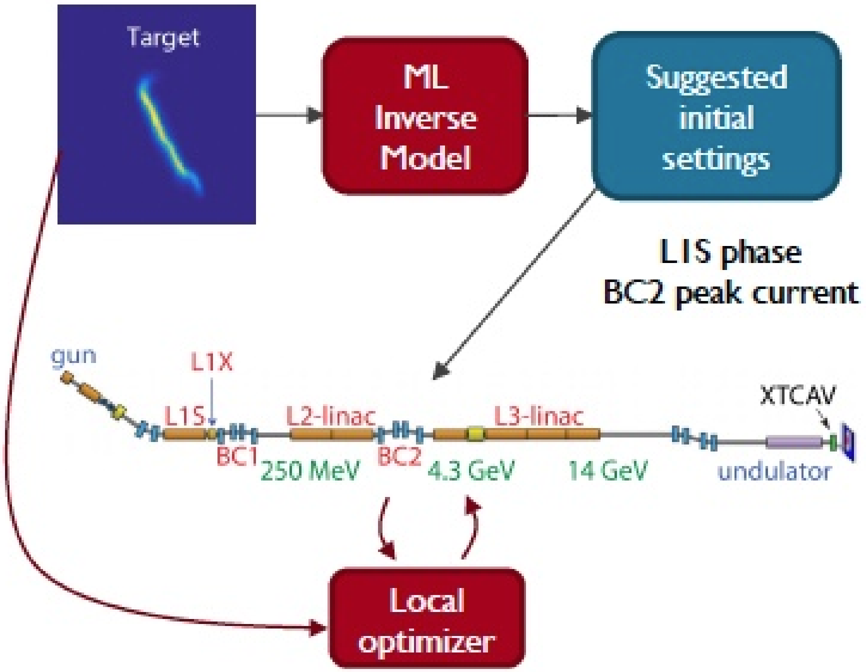


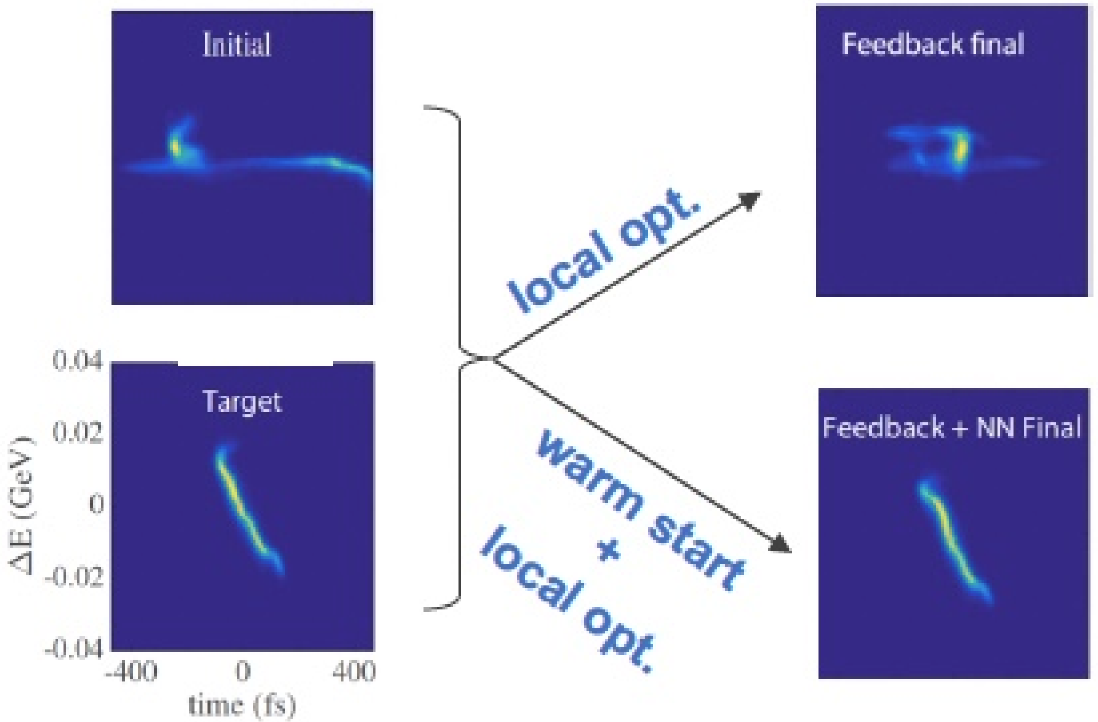
Optimization using ML inverse model



- Use global inverse model to give rough suggested settings then fine-tune with local optimizer
- Preliminary study at LCLS: Two settings scanned (L1S phase, BC2 peak current)
- - Compared optimization algorithm with/without warm start

Optimization using ML inverse model





- Use global inverse model to give rough suggested settings then fine-tune with local optimizer
- Preliminary study at LCLS: Two settings scanned (L1S phase, BC2 peak current)
- - Compared optimization algorithm with/without warm start

Local optimizer alone was unable to converge. **Able to converge after initial settings from NN**

Conclusions

- ML based LPS diagnostics are promising tools that can be used to aid machine setup, optimize beam delivery for experiments, on-the-fly data analysis to rapidly extract beam parameters, and offline data analysis/interpretation of experimental results.
- Recent work has shown the feasibility of the ML diagnostic for predicting longitudinal beam properties given only non-destructive inputs both in simulation and experiment.

- **Major challenges to address:**
  - Accurate quantification of robustness/model uncertainty,
  - Retraining strategies, how best to combine machine + simulation data, scale to complex operation modes.

Thank you!

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