Machine Learning Experiments at FACET-II

C. Emma

FACET-II Science Workshop, October 2019, SLAC

FACET-II
Facility for Advanced Accelerator Experimental Tests

U.S. DEPARTMENT OF ENERGY | Stanford University

SLAC NATIONAL ACCELERATOR LABORATORY

Outline

1. ML-based diagnostics - background and motivation

2. ML diagnostic examples:
    1. Longitudinal Phase Space (LPS) prediction
    2. Single-shot emittance reconstruction

3. Timeline for first ML experiments at FACET-II

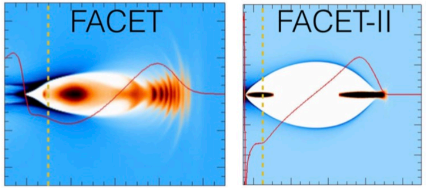
4. Conclusions

FACET-II goals - Motivation for ML diagnostics

Emittance Preservation with Efficient Acceleration

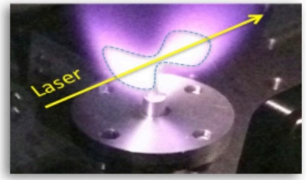
- High-gradient high-efficiency (instantaneous) acceleration has been demonstrated @ FACET

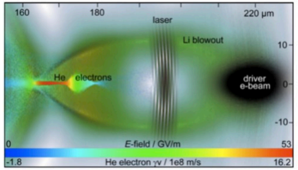
- Full pump depletion and preservation of emittance at μm level is planned as the first high impact experiment



High Brightness Beam Generation & Characterization

- 10's nm emittance preservation is necessary for collider applications
- Ultra-high brightness plasma injectors may lead to first applications of PWFA technology





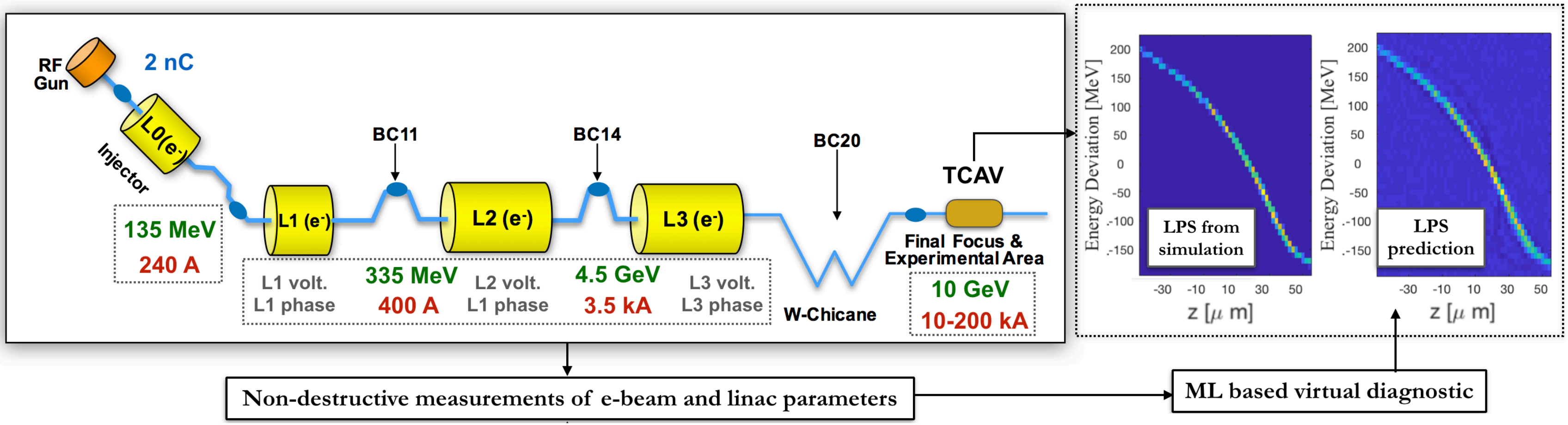
M.J. Hogan, FACET-II Science Workshop 2017

Research priorities at FACET-II require single-shot non-destructive measurement of beam characteristics

- FACET-II experimental program requires accurate characterization of beams to successfully meet its goals.
- Current diagnostic approaches for measuring LPS and emittance are destructive to the beam and cannot be made in conjunction with PWFA experiments
- We are developing novel diagnostics based on machine learning to non-destructively predict the beam properties, support the experimental program and improve interpretation of results.

ML-based LPS diagnostic for FACET-II

ML diagnostic learns the mapping between non-destructive measurements of beam/linac parameters and the LPS profile at the IP.



High level goals

- Implement a single-shot non-destructive ML diagnostic to predict the e-beam LPS.
- Use the ML-diagnostic with a conventional optimizer to customize/control the LPS at the IP for different experiments.

ML diagnostic trained on simulation data

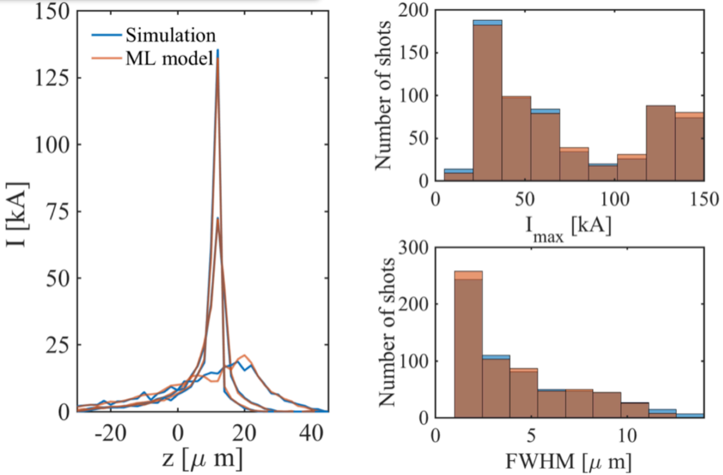
PHYSICAL REVIEW ACCELERATORS AND BEAMS **21,** 112802 (2018)

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)

Current Profile Prediction



Simulation parameter scanned	Range
L1 & L2 phase [deg]	±0.25
L1 & L2 voltage [%]	±0.1
Bunch charge [%]	±1
Input to ML model	**Accuracy**
L1 & L2 phase [deg]	±0.1
L1 & L2 voltage [%]	±0.05
I_{pk} at BC (11,14,20) [kA]	$\pm(0.25, 1, 5)$
ϵ_n at BC (11,14) [μm]	±1
Beam centroid BC (11,14) [m]	

ML can predict variations in LPS using typical jitter of linac parameters in simulation

Sensitivity to inputs shows importance of reliable diagnostics e.g. BC20 current monitor

ML diagnostic trained on simulation data

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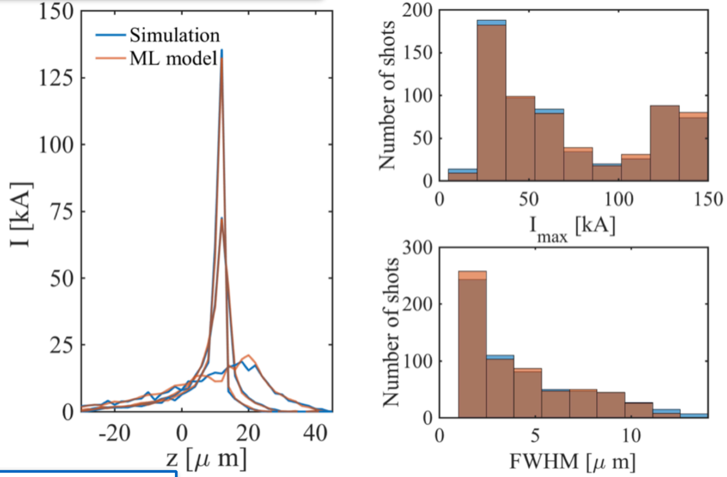

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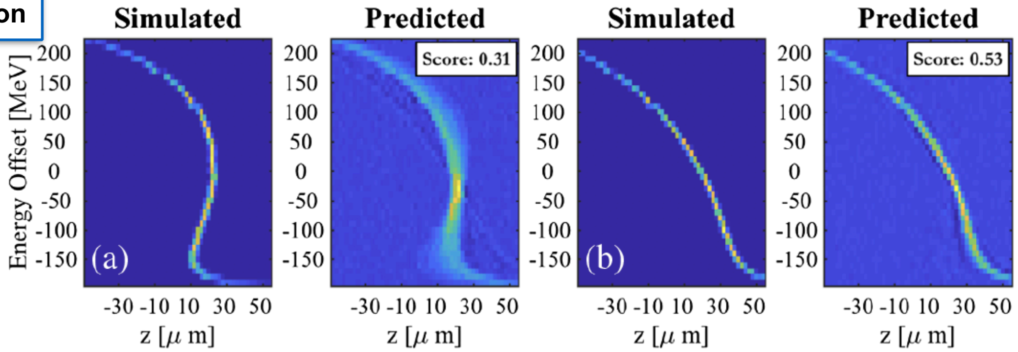
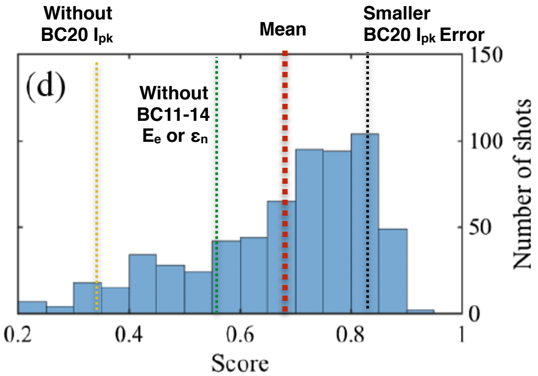
LPS Prediction





Experimental proof-of-concept at LCLS

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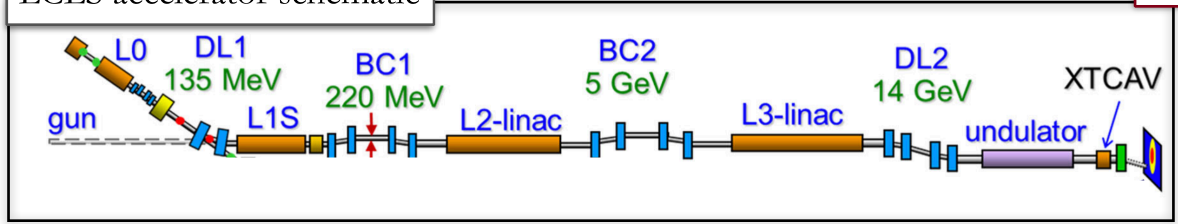
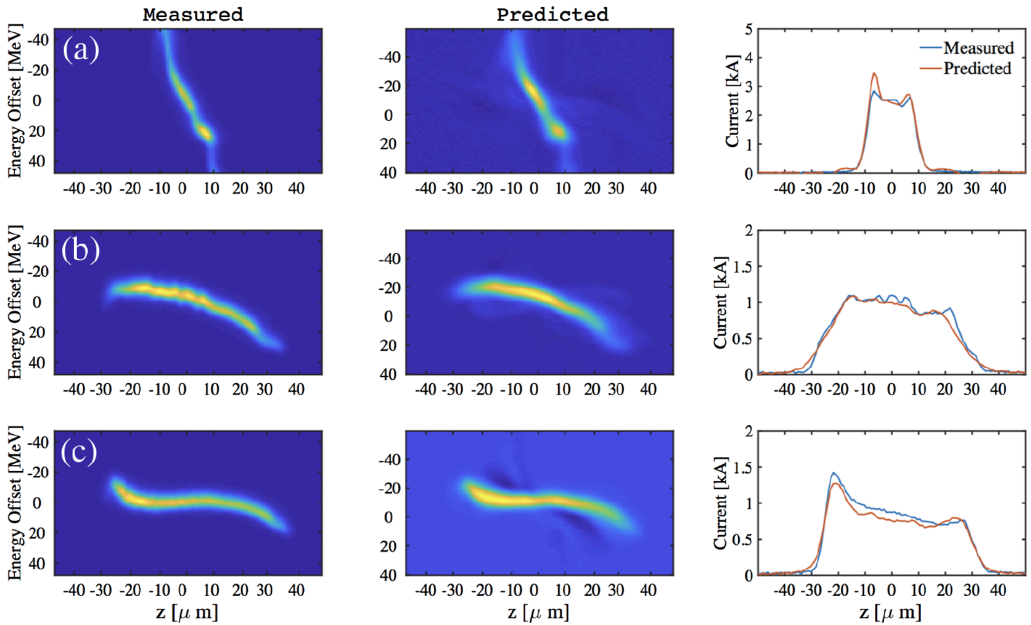
LCLS accelerator schematic





LCLS Experiment:

<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

Successful ML prediction of LPS from **five** scalar inputs

Experimental proof-of-concept at LCLS

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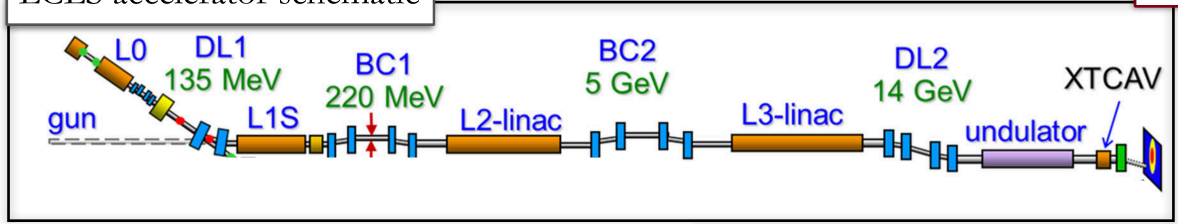

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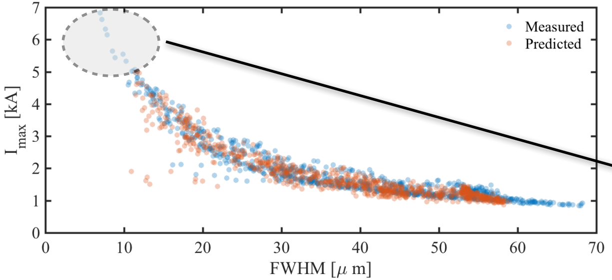
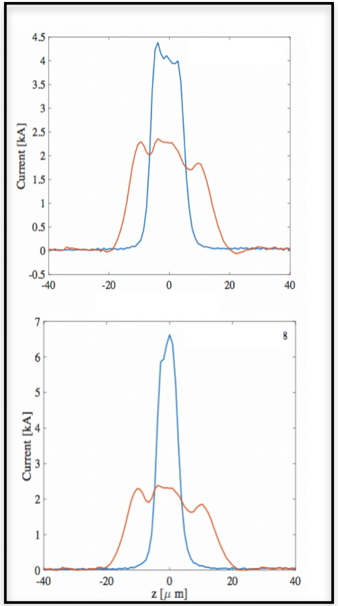
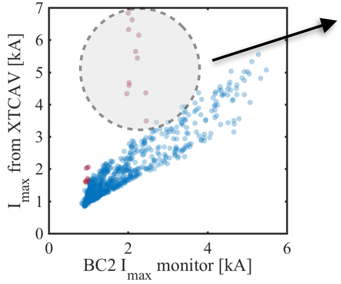




Successful ML prediction of LPS from **five** scalar inputs

'Bad' shots circled

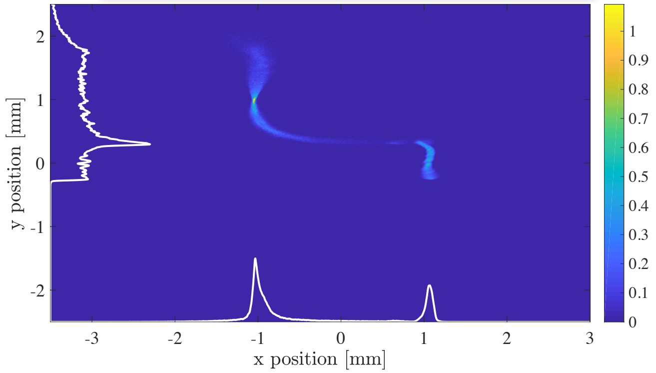


Discrepancy between diagnostic inputs/outputs can result in prediction errors.

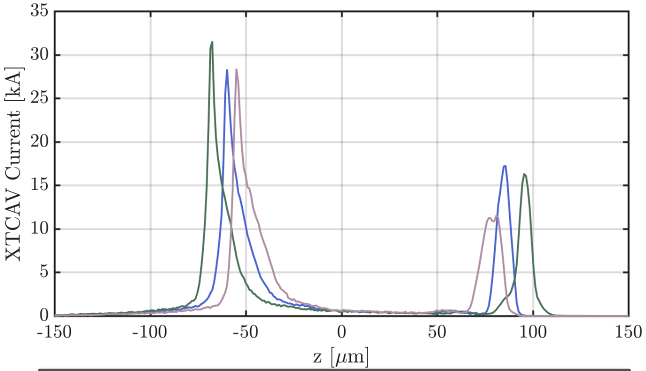
Tagging bad shots (e.g. with redundant diagnostic) is important for trusting ML diagnostic prediction.

Simulating the effect of the TCAV on the LPS measurement

Simulated OTR image downstream of TCAV



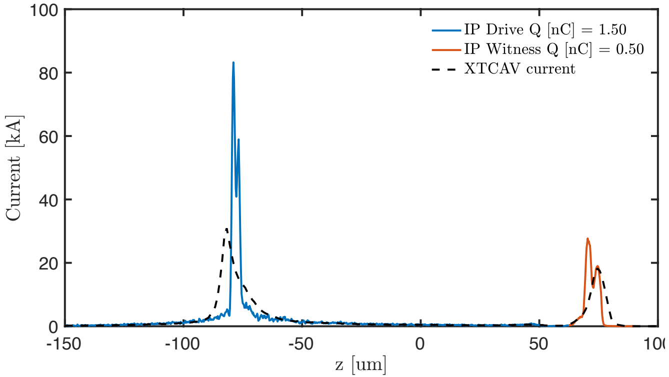
Current calculated from simulated TCAV image



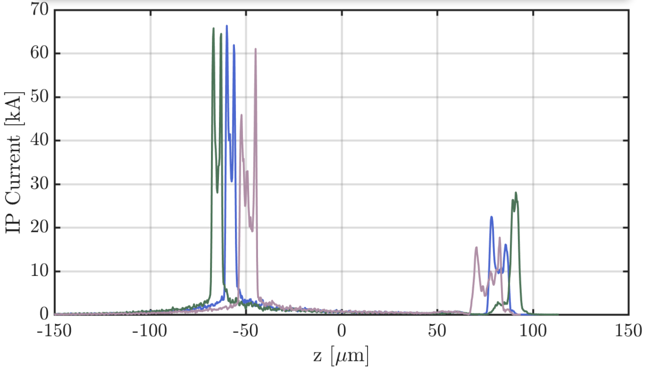
TCAV Resolution

$$\sigma_z = \frac{E_e}{eV_{rf}k_{rf}|\sin\Delta\psi|}\frac{\sqrt{\sigma_S^2 + \beta_S\epsilon}}{\sqrt{\beta_T\beta_S}}$$

$I_{pk,max} \approx 35kA$ (drive beam)



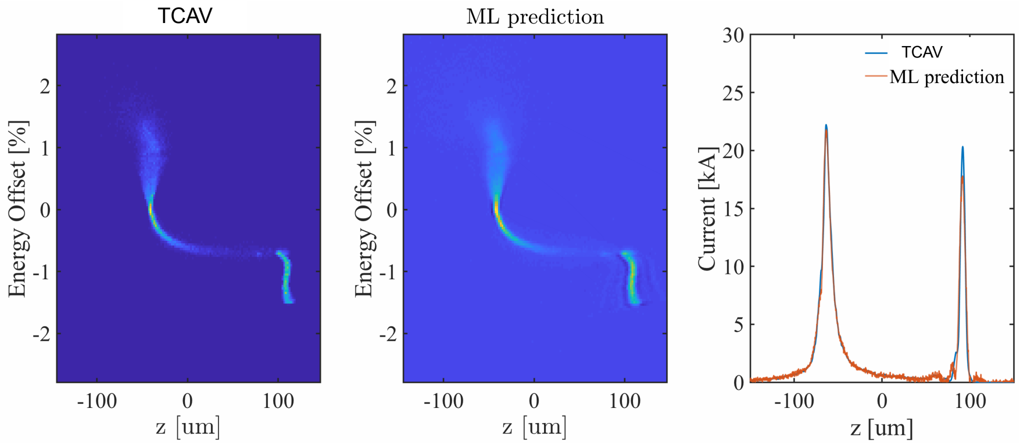
Current calculated from simulated particle distribution



ML-model will use TCAV measured LPS as input during training

This will give discrepancy between predicted I_{pk} from ML and *actual* I_{pk} at IP

Parameter scans with simulated TCAV

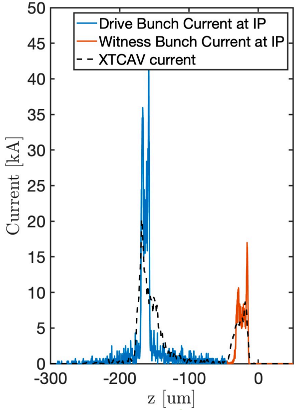


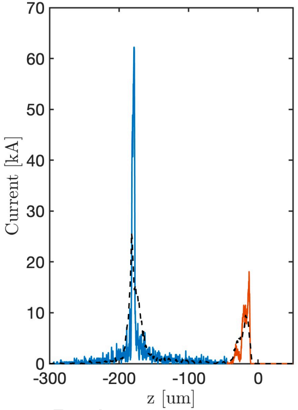
Good agreement in between ML prediction and simulated TCAV measurement

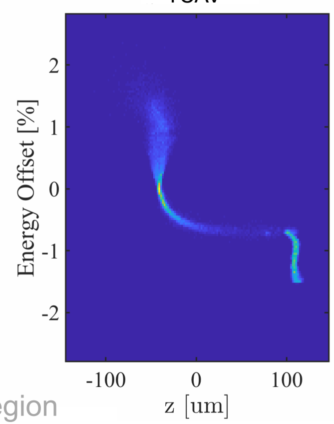
Parameter	L1 & L2 phase	L1 & L2 Volt.	Charge
Scan Range	± 0.25 deg	± 0.25 %	± 1 %
F2 Baseline	± 0.1, 0.2 deg	± 0.1,0.25 %	± 1 %

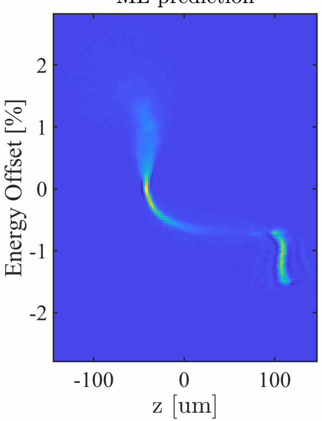
Parameter scans with simulated TCAV

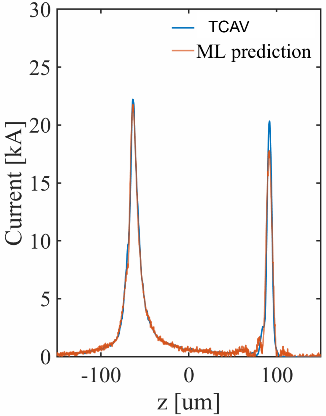
Single shots





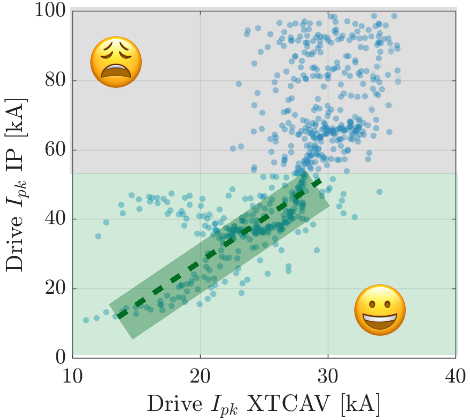




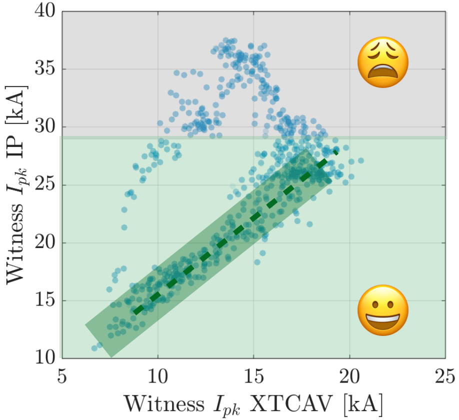


All shots

Good measurement region



Bad measurement region



Good agreement in between ML prediction and simulated TCAV measurement

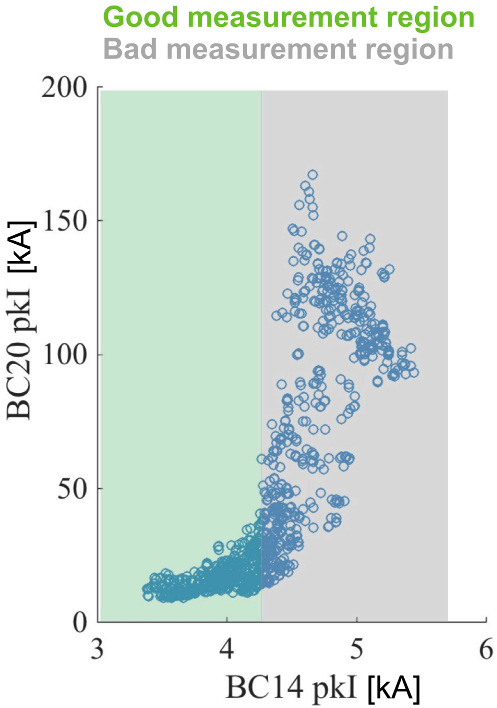
Using the ML prediction with additional input (e.g. correlations with other diagnostics) will add confidence in agreement between measured LPS and LPS at the IP

Tagging high I_{pk} shots by correlation with other measurements

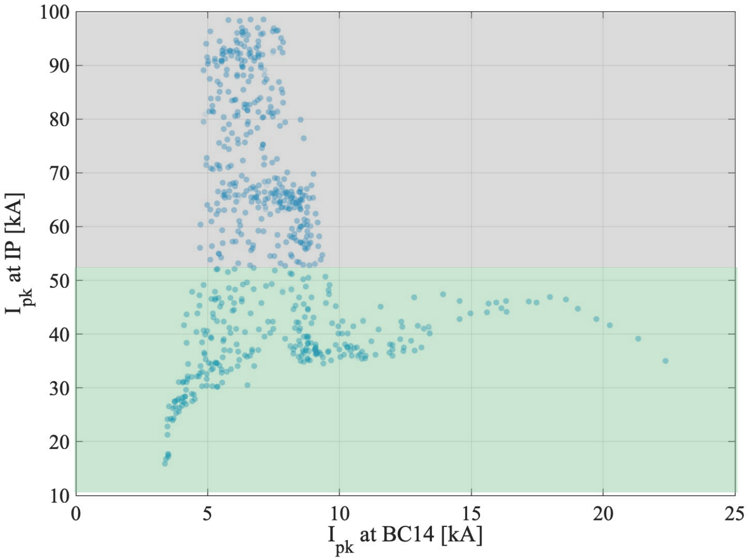
Single Bunch Mode

- Two 'populations' of shots:
    - I_{BC14} <4.5 kA
    - 4.5< I_{BC14} < 5.5 kA.

Correlation between BC20 & BC14 current can be used to bracket high current shots



Two Bunch Mode

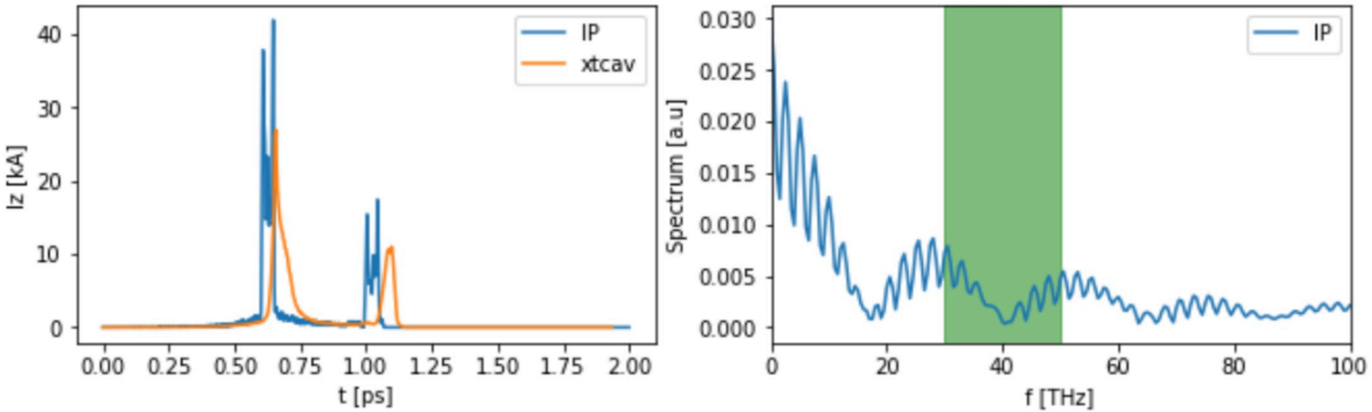


No simple correlation in two-bunch mode

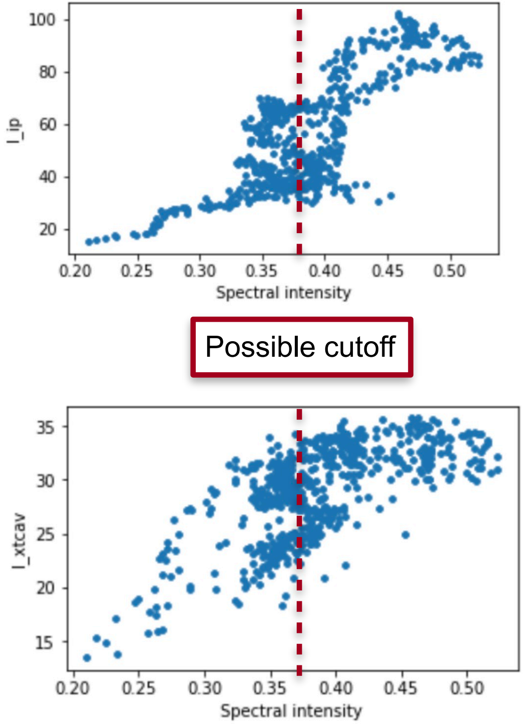
Spectral data may be used to bracket high I_{pk} shots

Tagging high I_{pk} shots using spectral measurements

Single Shot



All Shots

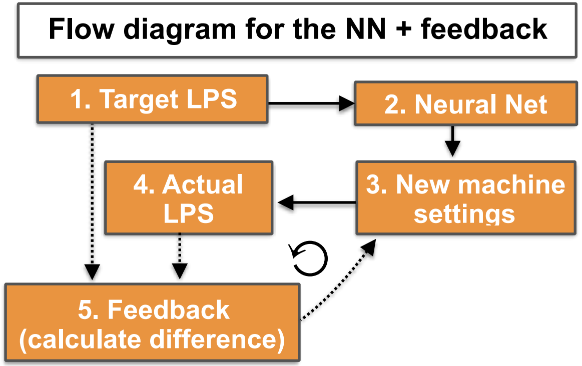


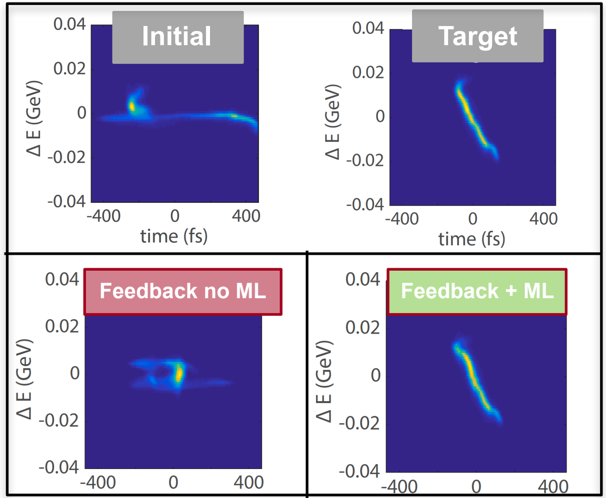
- Short bunches will radiate coherently at high frequency in BC20.
- Using spectral filters and integrating high-f content we can 'cut off' shots with large spectral intensity corresponding to I_{pk} above the TCAV resolution.

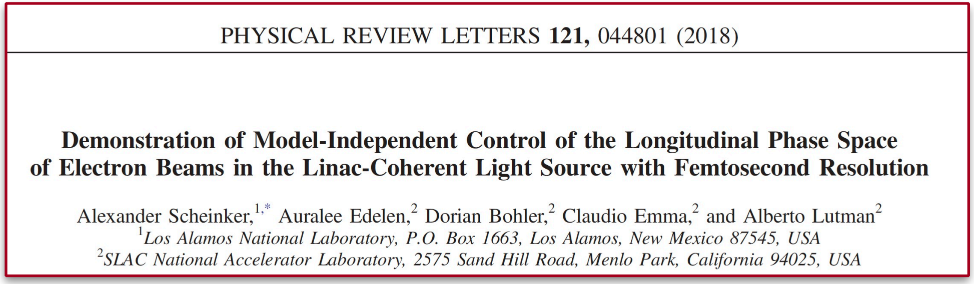
ML-based LPS optimization experiment at LCLS

NN provides "smart" initial guess for optimizer - avoids getting stuck in local minima to converge to correct solution

- Goal is decrease tuning time and improve beam quality for target beam parameters
- NN and an optimizer used to automatically change machine parameters to obtain a desired LPS
- By making an initial guess using the NN, the optimizer feedback is able to achieve the desired LPS



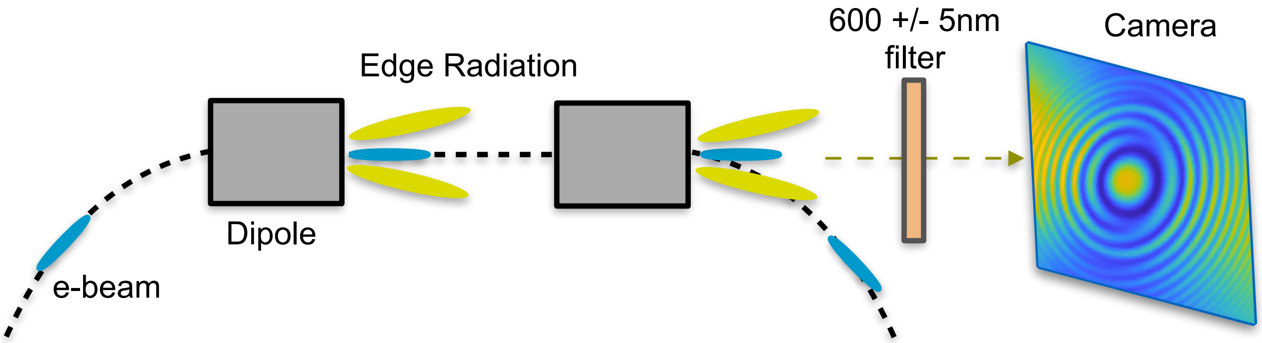


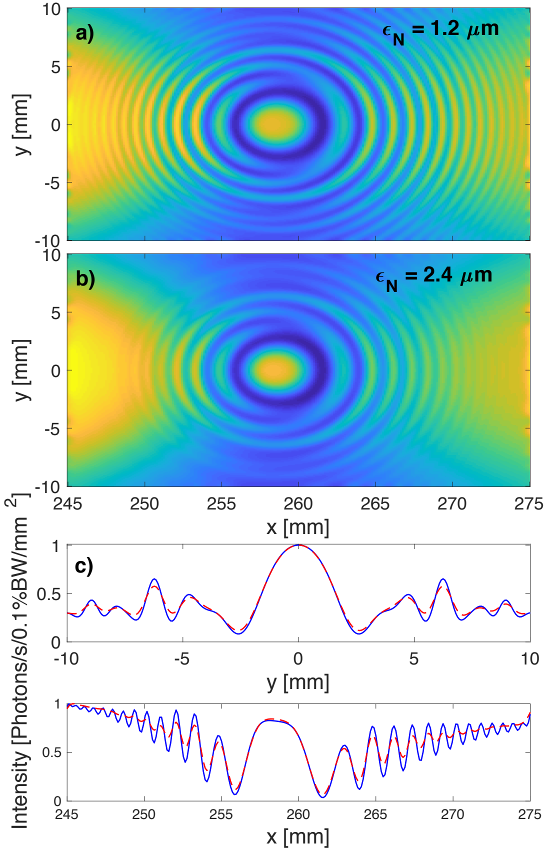

PHYSICAL REVIEW LETTERS **121**, 044801 (2018)

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*

ML-based edge radiation diagnostic for FACET-II





High level goals

- Implement a single-shot non-destructive ML diagnostic to measure the emittance at multiple locations along linac.
- To be fast, diagnostic requires implementing advanced image analysis using convolutional neural networks.

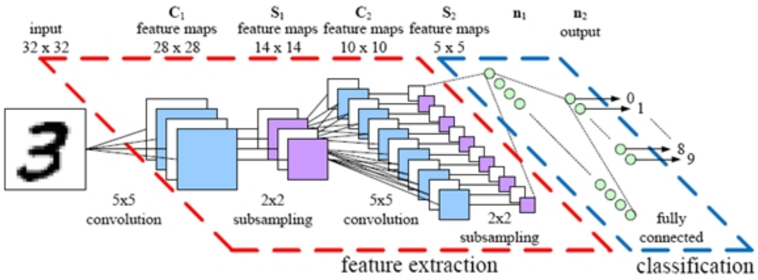
ML diagnostics will allow improve single-shot characterization of beam quality and enhance set-up/interpretation of experimental results

CNN for real-time image analysis of edge radiation

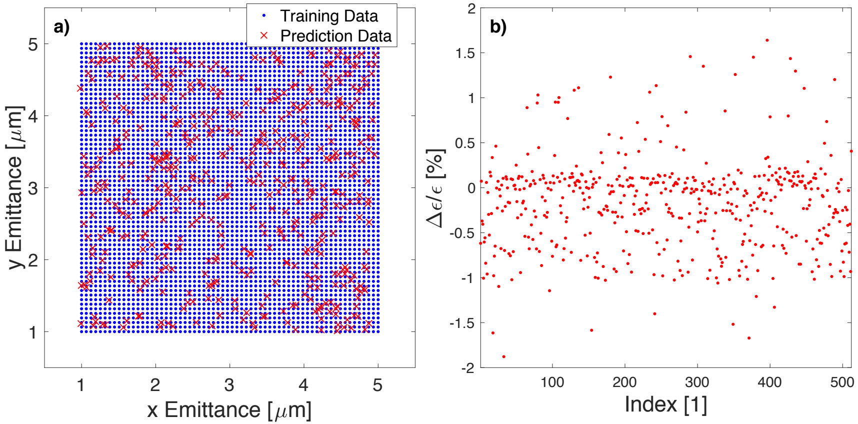
- Fitting on the fly with numerical integration/ simulation is "slow", $\mathcal{O}$(mins)
- CNN excel at rapid image analysis
- Examines entire image instead of lineouts - no data is lost for speed
- Trained on simulation data that is generated offline - no sacrifice of fidelity or accuracy for speed
- Similar work performed at SLAC by Hezaveh *et al* to parameterize gravitational lens galaxies
  - Image analysis rate of 10 Hz

Hezaveh *et al*, *Nature* **548,** 555-557 (2017)

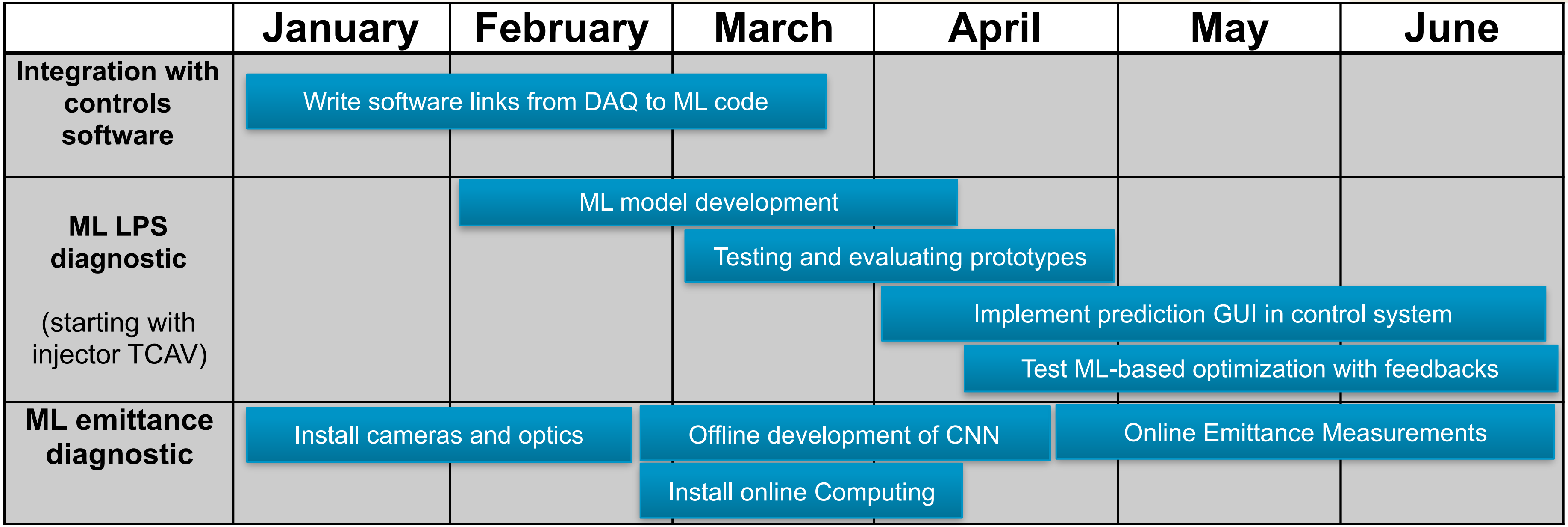
Image from PARsE http://parse.ele.tue.nl/education/cluster2



Simple CNN Predicting Emittance from SRW Simulations



Timeline for first ML experiments at FACET-II



- ML experiments at FACET-II will start using injector data and continue along beam line as commissioning progresses.
- Useful information (sensitivity to input, long term robustness of models, performance of different model architectures) will be gathered using TCAVs in injector and Sector 15 and applied to predicting LPS using TCAV IP

ML at FACET-II in broader SLAC collaboration

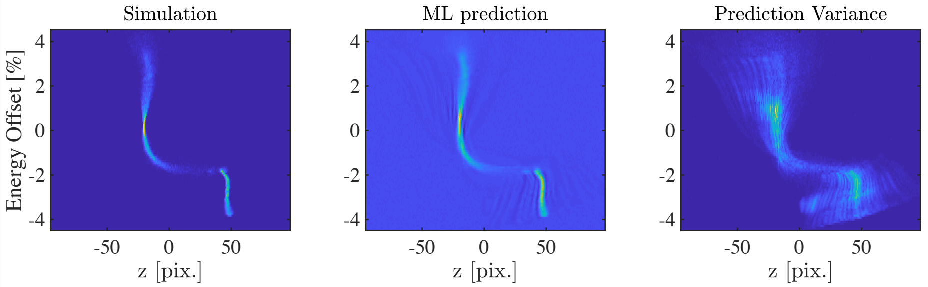
Shared motivation

- Facility users will be limited in what they can do by existing diagnostics.
- ML diagnostics will boost scientific discovery by improving data analysis/ understanding of experimental results.
- Important to test novel ML diagnostic systems early (commissioning phase) to enable more science/new operating modes.
- FACET-II work supports lab-wide efforts in utilizing ML to realize the maximum machine performance and maintaining high availability

Overlap in ongoing/future projects

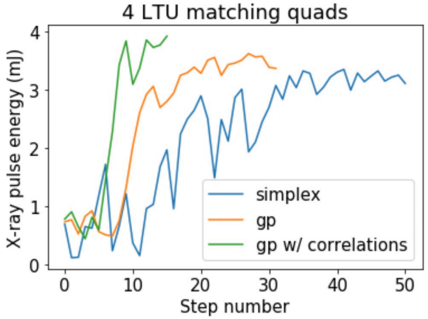
- ML based prediction of electron beam distribution/evolution on single shot basis.
- ML-based accelerator tuning with built-in safety constraints.
- Uncertainty quantification and evaluation of model robustness.
- ‘Beyond the resolution’ virtual measurements combining simulation and experimental data.

Collaboration between FACET-II/LCLS/SLAC CS



J. Duris, *et al.*, arXiv:1909.05963 (2019)

J. Kirchner *et al.*, ICFA ML workshop 2019



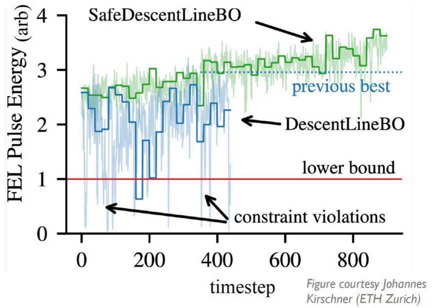
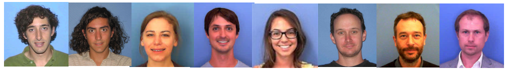


Figure courtesy Johannes Kirschner (ETH Zurich)

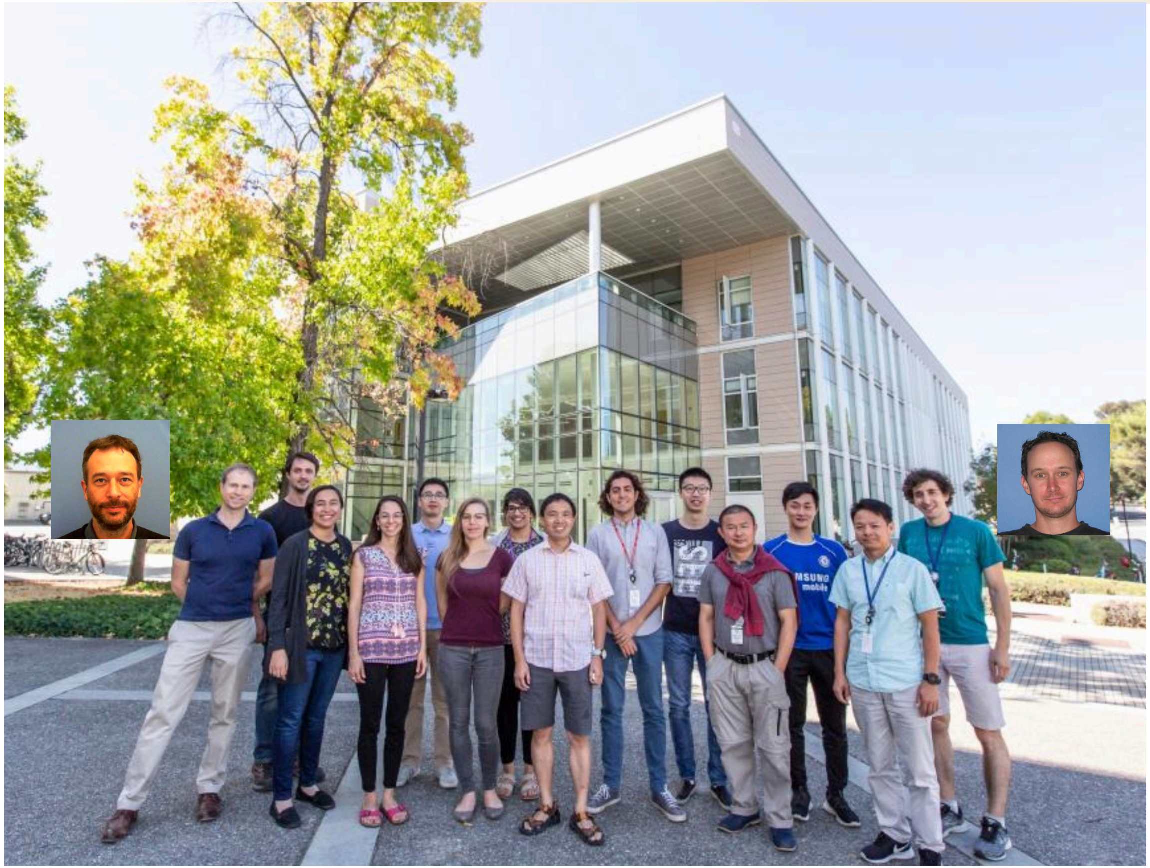
Growing group of students, postdocs and staff



Conclusion and future work

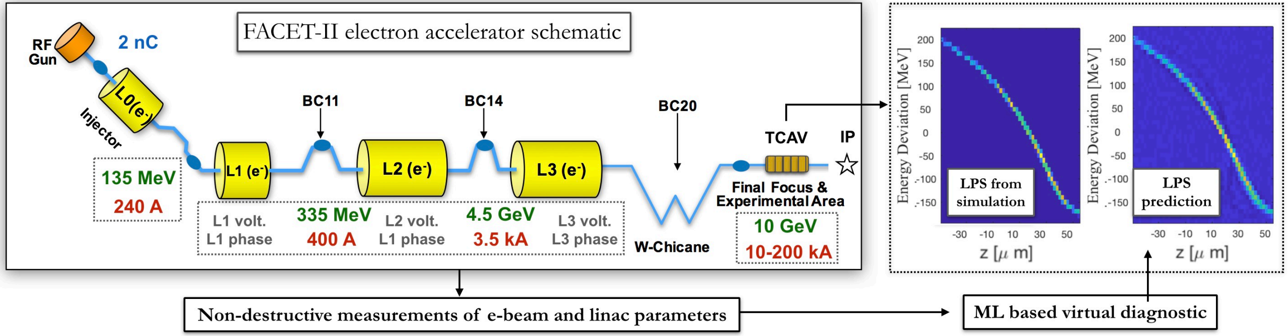
- We are developing ML-based diagnostics for shot-to-shot prediction of the e-beam properties at FACET-II.
- ML-based shot-to-shot emittance measurements using edge radiation are enabled by real-time images analysis.
- We have shown that ML based diagnostics are capable in simulation (FACET-II) and experiment (LCLS) of predicting the LPS given few non-destructive diagnostic inputs and LPS images from TCAVs.
- Multiple TCAVs at FACET-II (injector, S15, IP area) may provide single shot prediction and optimization of LPS at different points along linac.
- TCAV resolution limits will result in discrepancies between predicted current and *actual* current at IP - reinforces the importance of redundant diagnostics.
- Accurate quantification of the prediction uncertainty, and model robustness over time are under study and will be investigated during initial commissioning.

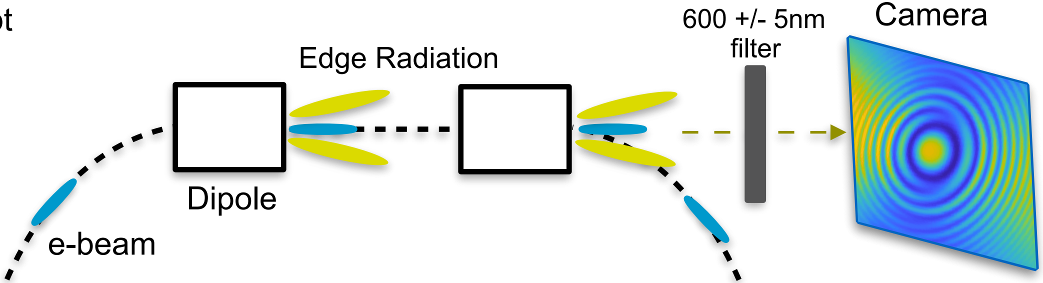
THANK YOU!

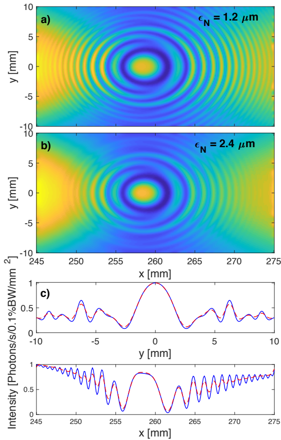


Summary slide

- Non-invasive diagnostics are critical for monitoring and controlling the performance of PWFAs
- Additional information from ML diagnostics will help demonstrate *high efficiency* as well as *high quality* acceleration of e-/e+ beams in PWFA
- ML diagnostic for measurement and control of LPS is planned for FACET-II with simulations and proof-of-concept studies showing promising results.
- Non-invasive emittance measurements will incorporate ML-based analysis for shot-to-shot beam characterization.







Extra slides

E-beam profile prediction at FACET

PHYSICAL REVIEW SPECIAL TOPICS—ACCELERATORS AND BEAMS 18, 102801 (2015)

Adaptive method for electron bunch profile prediction

Alexander Scheinker*
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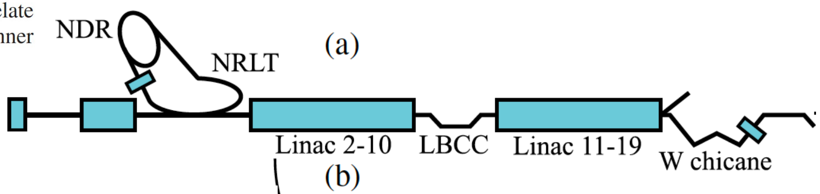
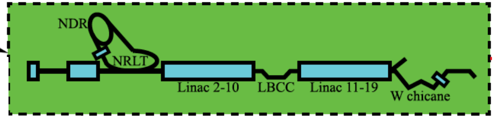
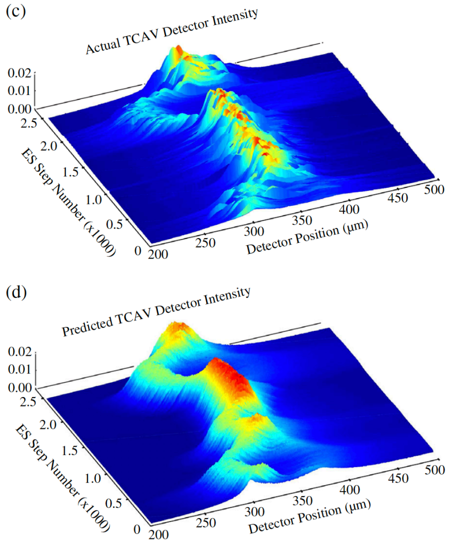
(Received 16 June 2015; published 15 October 2015)

The measured energy spectrum is observed to correlate with the longitudinal bunch profile in a one-to-one manner

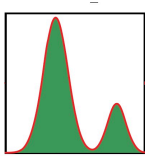




LiTrack Simulation

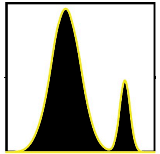


Guess machine parameters and simulate with LiTrack

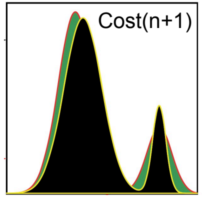


Simulated Spectrum

Measure energy spectrum on SYAG



Detected Spectrum



Compare LiTrack spectrum with SYAG

Adapt machine parameters to minimize difference

With "correct" machine parameters estimate longitudinal bunch profile based on LiTrack output LPS

E-beam profile prediction at FACET

PHYSICAL REVIEW SPECIAL TOPICS—ACCELERATORS AND BEAMS 18, 102801 (2015)

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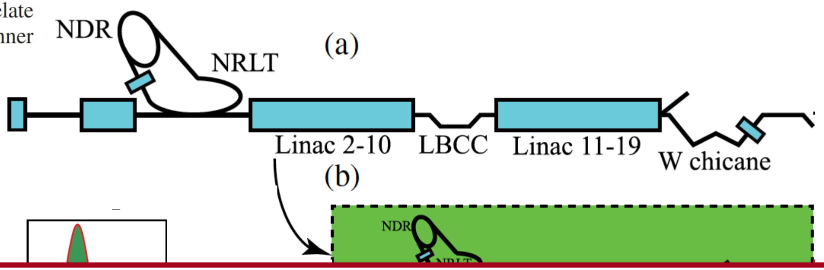
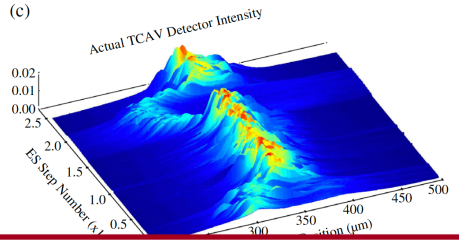
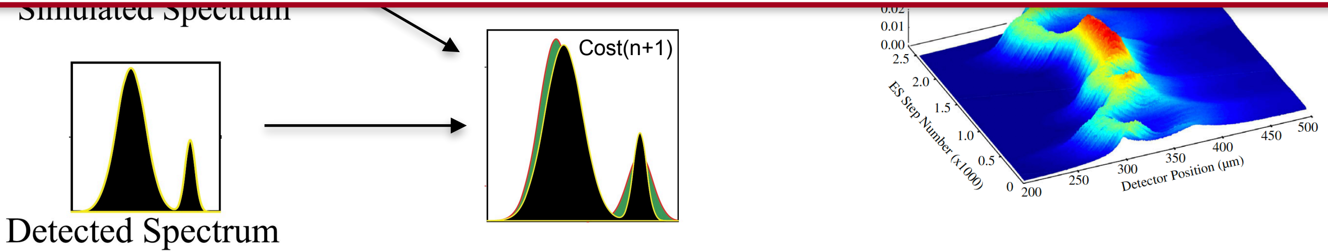
Convergence Rate/ Accuracy sensitive to initial parameter guess





Challenge - Wakefields, microbunching, longitudinal space charge, CSR affect distribution: **Computationally expensive to model online**



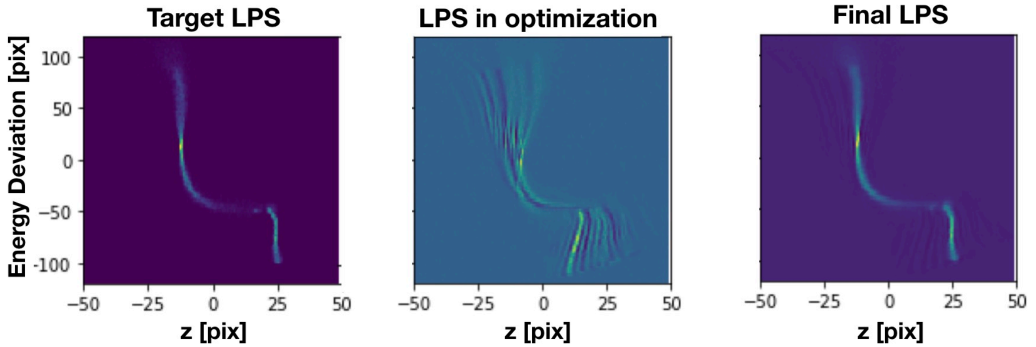
Measure energy spectrum on SYAG

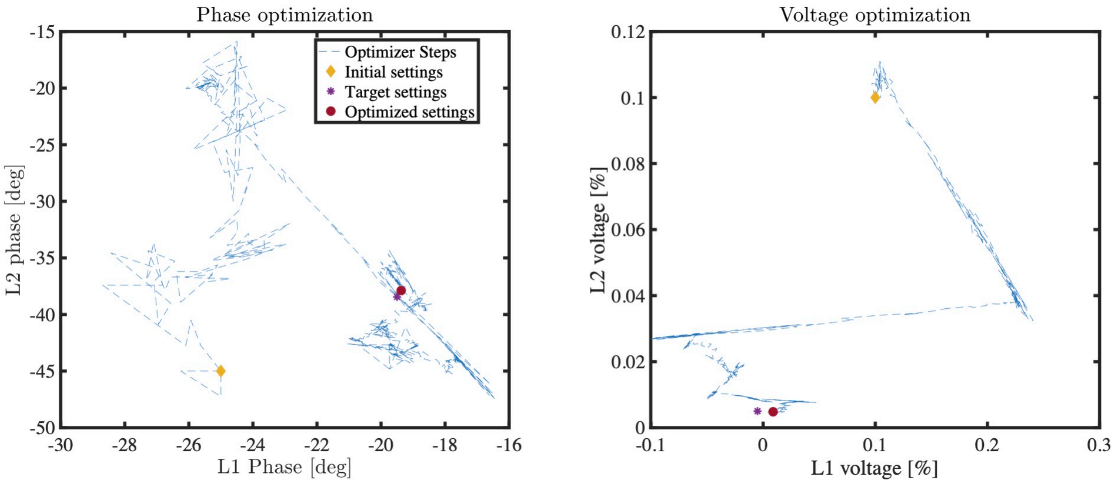
“Furthermore we hope to one day utilize LiTrackES as an actual feedback to the machine setpoints in order to tune desired e-beam properties”

ML-based LPS optimization at FACET-II

ML prediction of LPS can be used for accelerator tuning (e.g. set linac phases)

- Rapid prediction of ML model (~ms) makes it a good fit for pairing with iterative optimizer.
- Tested this concept in simulation, starting from an unwanted LPS using ML model to find the L1 & L2 phase setting to achieve the desired LPS.
- **Note:** Initial settings outside training set of ML model. Model shows ability to interpolate within training data.





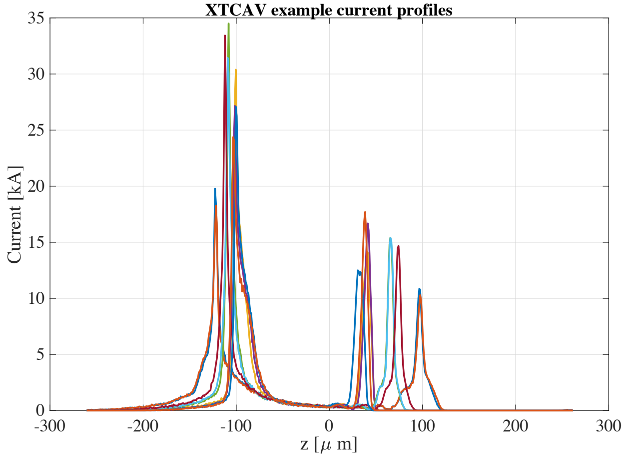
Parameter scans with simulated TCAV

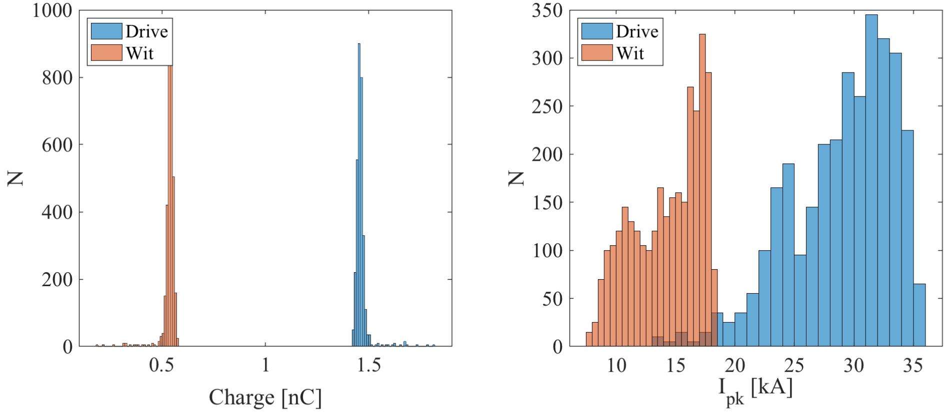
Parameter	L1 & L2 phase	L1 & L2 Volt.	Charge
Scan Range	± 0.25 deg	± 0.25 %	± 1 %
F2 Baseline	± 0.1, 0.2 deg	± 0.1,0.25 %	± 1 %

Expected *measured* jitter of beam parameters

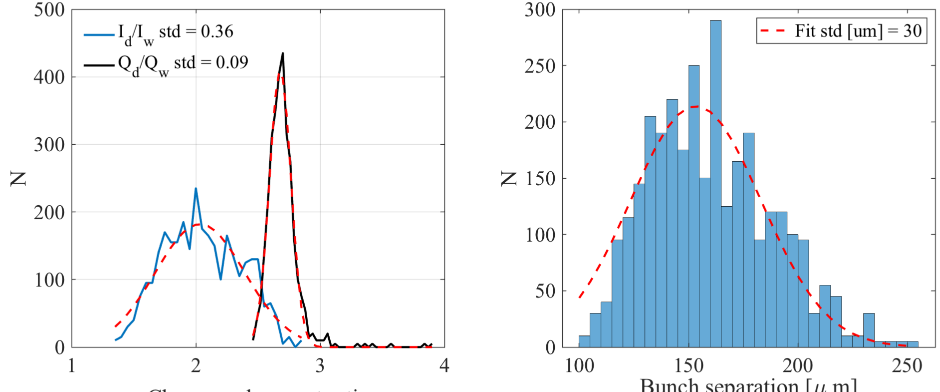
- Bunch separation jitter = **30 um** rms
- Peak current ratio jitter = **36 %** rms (TCAV) (~ 90% at IP)

- 3125 simulations of linac, Includes wakes 1d CSR, LSC, ISR. Same input distribution from the injector.





Data from XTCAV images

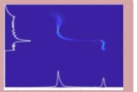
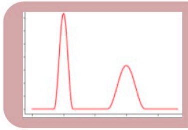


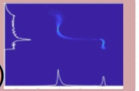
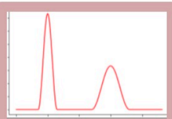
A. Hanuka

Spectrometer input for improved confidence in LPS prediction

Spectral measurements

$$\left.\frac{dU}{d\Omega d\omega}\right|_N = \begin{cases} N_e \left.\frac{dU}{d\Omega d\omega}\right|_1 & \omega > 1/\sigma_t \\ \boxed{N_e^2 f(\omega) \left.\frac{dU}{d\Omega d\omega}\right|_1 \qquad \omega < 1/\sigma_t} \end{cases}$$

VD: Input scalers → NN (Ground Truth:TCAV)  → 

S - VD: Spectrum → NN (Ground Truth: TCAV)  → 

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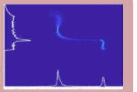
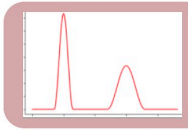
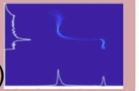
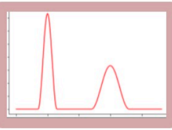
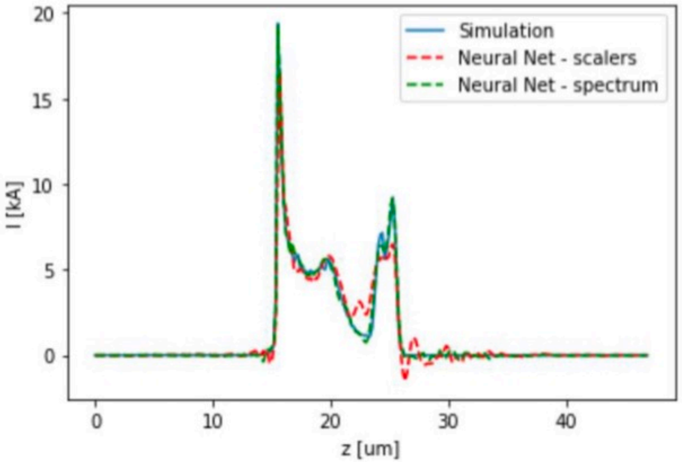
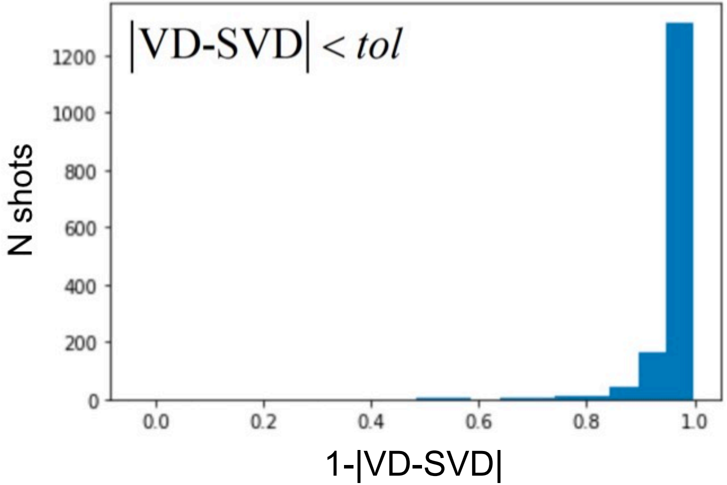
VD: Input scalers → NN (Ground Truth:TCAV)  → 

S - VD: Spectrum → NN (Ground Truth: TCAV)  → 

Example:





A. Edelen
THXBA1
NAPAC 2019

J. Kirschner, et al., ICML, 2019, https://tinyurl.com/y59sy6cs
J. Kirschner, et al., ICFA ML Workshop, 2019

Control / Tuning: Safety Constraints

SLAC

Don't just want to maximize FEL energy → we have other requirements

- pulse energy briefly drops below certain level → *angry users!*
- beam losses go above a certain threshold → *damage machine!*

Add these requirements as safety constraints

Has been developed by ETH Zurich and tested experimentally at SwissFEL

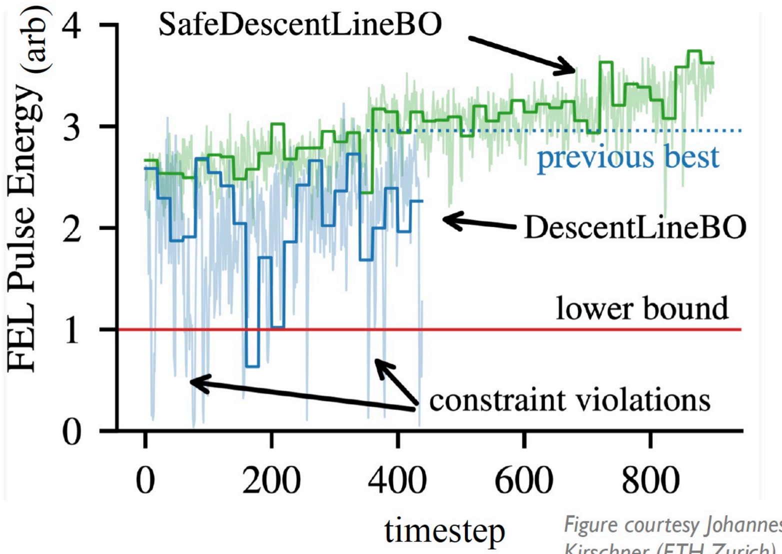
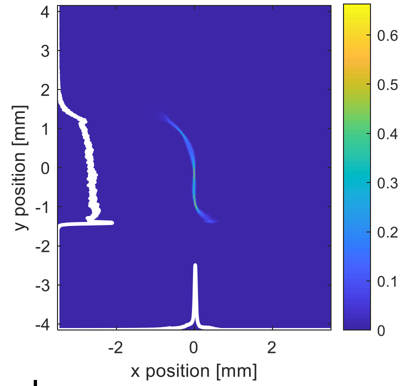


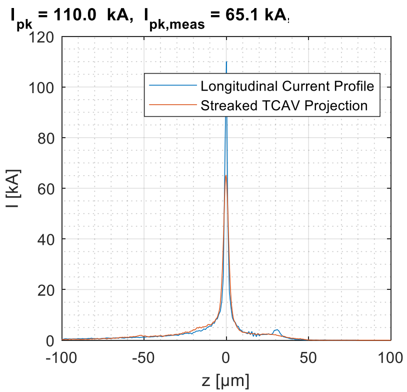
Figure courtesy Johannes Kirschner (ETH Zurich)

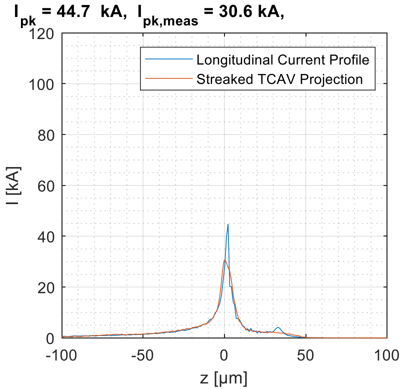
D. Storey

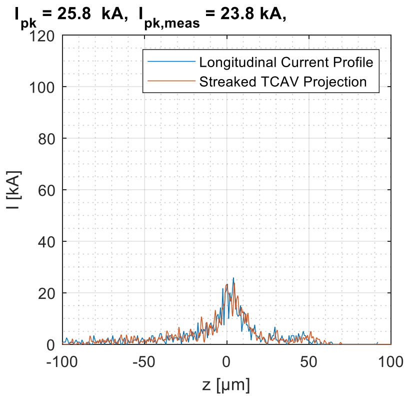
FACET-II Two-bunch simulations with TCAV

Single:

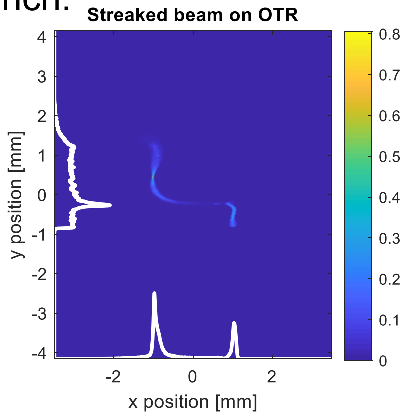


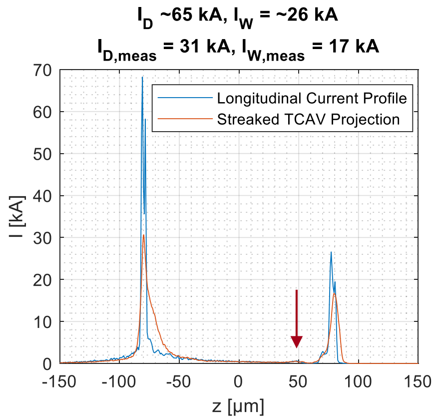






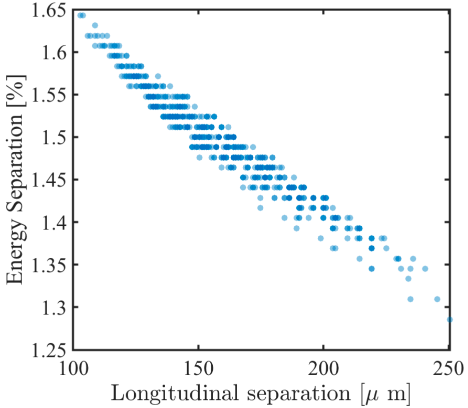
2 Bunch:



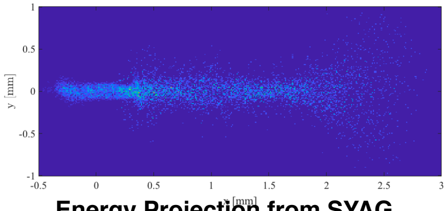


	Real	**Focus at 10 GeV**
Single Bunch:		
I_{pk}	110 kA	65 kA
2 Bunch:		
Drive I_{pk}	65 kA	31 kA
Witness I_{pk}	26 kA	17 kA
Charge ratio	1.5/0.5 nC	1.503/0.497

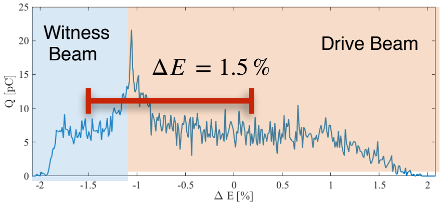
Correlations in two-bunch simulations

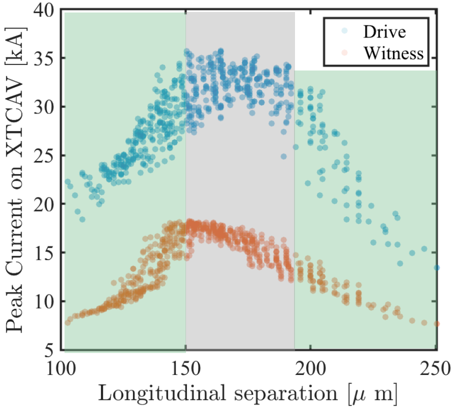


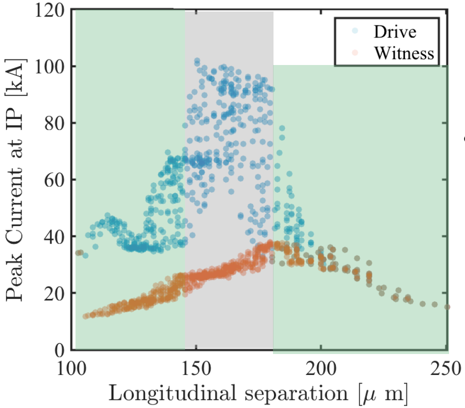
Transverse Profile at SYAG

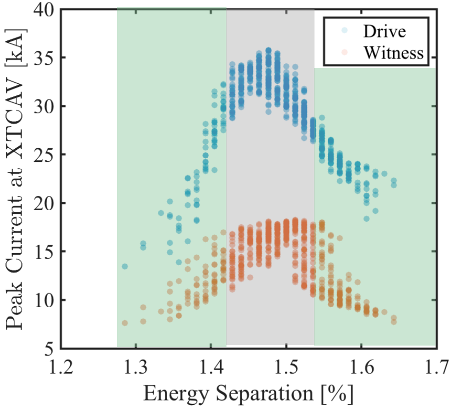


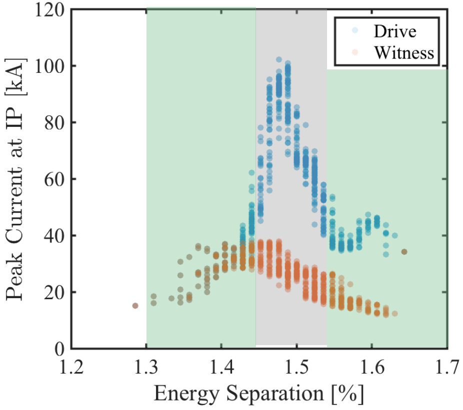
Energy Projection from SYAG







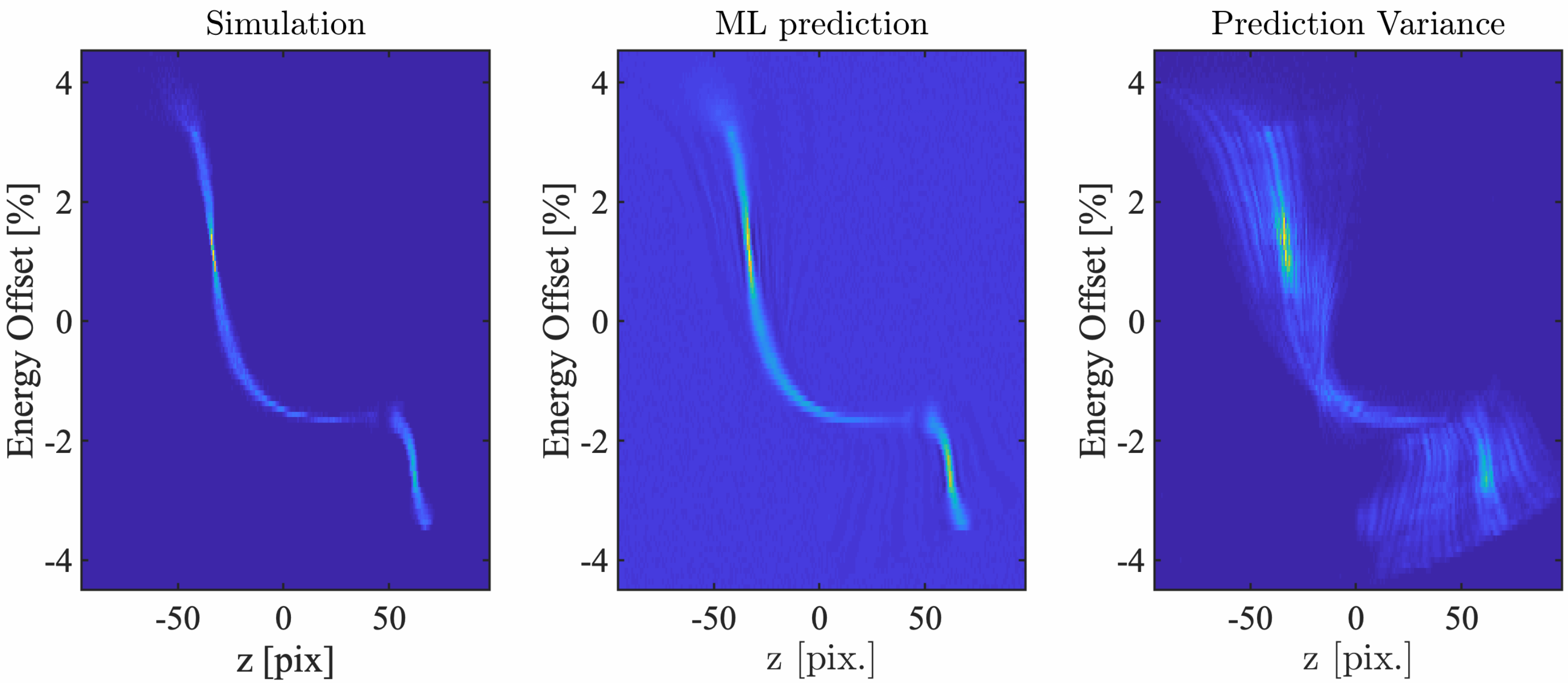




Good measurement region
Bad measurement region

- Correlations between time and/or energy separation and peak current maybe can be used to flag shots where the XTCAV measurement plateaus around 35kA and the actual current at the IP varies between 60 and 100 kA.
- Energy separation can be measured on the SYAG shot-to-shot

Uncertainty prediction



Variance is 2d std of prediction for each pixel value over 10 different ML models initialized with different starting weights