Machine Learning Experiments at FACET-II

C. Emma
FACET-II Science Workshop, October 2019, SLAC
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
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.

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

**Current Profile Prediction**

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

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

<table>
<thead>
<tr>
<th>Simulation parameter scanned</th>
<th>Range</th>
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<tbody>
<tr>
<td>L1 &amp; L2 phase [deg]</td>
<td>±0.25</td>
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<tr>
<td>L1 &amp; L2 voltage [%]</td>
<td>±0.1</td>
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<tr>
<td>Bunch charge [%]</td>
<td>±1</td>
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Input to ML model Accuracy
| L1 & L2 phase [deg]          | ±0.1           |
| L1 & L2 voltage [%]          | ±0.05          |
| I_{pk} at BC (11,14,20) [kA] | ±(0.25, 1.5)   |
| e_n at BC (11,14) [μm]       | ±1             |

Beam centroid BC (11,14) [m]
Experimental proof-of-concept at LCLS

LCLS Experiment:

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

Successful ML prediction of LPS from five scalar inputs
Experimental proof-of-concept at LCLS

LCLS Experiment:

Machine parameters scanned:
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Inputs to ML model:
- L1s voltage & phase readbacks,
- BC1 and BC2 current

Successful ML prediction of LPS from five scalar inputs

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**

**Current calculated from simulated particle distribution**

**TCAV Resolution**

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

\[ I_{pk,max} \approx 35kA \quad \text{(drive beam)} \]

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
Good agreement in between ML prediction and simulated TCAV measurement

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Parameter scans with simulated TCAV

Single shots

All shots

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.

**Two Bunch Mode**

- No simple correlation in two-bunch mode
- Spectral data may be used to bracket high $I_{pk}$ shots

Correlation between BC20 & BC14 current can be used to bracket high current shots
Tagging high $I_{pk}$ shots using spectral measurements

- 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.
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

Flow diagram for the NN + feedback

1. Target LPS
2. Neural Net
3. New machine settings
4. Actual LPS
5. Feedback (calculate difference)

Feedback + ML
Feedback no ML

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 Edelean,2 Dorian Bohler,2 Claudio Emma,2 and Alberto Lutman2
1Los Alamos National Laboratory, P.O. Box 1663, Los Alamos, New Mexico 87545, USA
2SLAC National Accelerator Laboratory, 2575 Sand Hill Road, Menlo Park, California 94025, USA

PHYSICAL REVIEW LETTERS 121, 044801 (2018)
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)
### Timeline for first ML experiments at FACET-II

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- Integration with controls software:
  - Write software links from DAQ to ML code

- ML LPS diagnostic (starting with injector TCAV)
  - ML model development
  - Testing and evaluating prototypes
  - Implement prediction GUI in control system
  - Test ML-based optimization with feedbacks

- ML emittance diagnostic
  - Install cameras and optics
  - Offline development of CNN
  - Install online Computing
  - Online Emittance Measurements

- 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. Kirchner et al., ICFA ML workshop 2019

**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.
• Non-invasive diagnostics are critical for monitoring and controlling the performance of PWFA.

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

Guess machine parameters and simulate with LiTrack.

Measure energy spectrum on SYAG.

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

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

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

- Convergence Rate/Accuracy sensitive to initial parameter guess
- 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

- 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.

ML prediction of LPS can be used for accelerator tuning (e.g. set linac phases)
**Parameter scans with simulated TCAV**

**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.

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Spectrometer input for improved confidence in LPS prediction

\[
\frac{dU}{d\Omega d\omega} \Bigg|_N = \begin{cases} 
N_e \frac{dU}{d\Omega d\omega} & \omega > 1/\sigma_t \\
N_e f(\omega) \frac{dU}{d\Omega d\omega} & \omega < 1/\sigma_t
\end{cases}
\]

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

S - VD:
- Spectrum
- NN (Ground Truth: TCAV)
Spectral measurements

\[ \frac{dU}{d\Omega d\omega} \bigg|_{N} = \begin{cases} \frac{N}{d\omega} \frac{dU}{d\Omega d\omega} \bigg|_{1} & \omega > 1/\sigma_t \\ \frac{N^2 f(\omega)}{d\omega} \frac{dU}{d\Omega d\omega} \bigg|_{1} & \omega < 1/\sigma_t \end{cases} \]

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

**VD:**
- Input scalers
- NN (Ground Truth: TCAV)

**Example:**

- Simulation
- Neural Net - scalers
- Neural Net - spectrum

\[ |VD-SVD| < tol \]
Control / Tuning: Safety Constraints

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)
FACET-II Two-bunch simulations with TCAV

Single:

2 Bunch:

Real
Focus at 10 GeV

<table>
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<tr>
<th>Single Bunch</th>
<th>Drive $I_{pk}$</th>
<th>Witness $I_{pk}$</th>
<th>Charge ratio</th>
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<tbody>
<tr>
<td></td>
<td>65 kA</td>
<td>31 kA</td>
<td>1.5/0.5 nC</td>
</tr>
<tr>
<td>2 Bunch:</td>
<td></td>
<td></td>
<td>1.503/0.497</td>
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Correlations in two-bunch simulations

• 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