Machine Learning Meets the Challenges of HEP Research and Development

B. D. O'Shea[1], A. Edelen[1], C. Emma[1], A. Hanuka [1], R. Lehe[3], D. Ratner[1], R. Roussel[2]
[1]SLAC National Accelerator Laboratory
[2]University of Chicago
[3]Lawrence Berkeley National Laboratory

Machine Learning is a vast landscape of techniques, and application to accelerators is growing rapidly. We regret that we are unable to reference many excellent works and look forward to reading the other Letters of Interest that will certainly be submitted on this topic.

Future HEP programs will require beam quality beyond state of the art in order to provide the needed luminosity for experiments. Additionally, in order to reduce backgrounds in the high intensity frontier [i] and utilize cost cutting technologies in the energy frontier [ii, iii] unprecedented precision and control of accelerators is required. Finally, the scale of proposed HEP flagship scientific facilities requires fiscally untenable operational and maintenance costs. All together, these next generation HEP machines are a radical shift in accelerator technology and scale that require new methods of design, study and control. Machine learning provides tools to push the design, study and control of accelerators beyond the state of the art. Deploying ML to increase the capabilities of existing accelerators is an essential, guiding step to the successful application of ML to the challenges of future accelerators. To encourage continued support, this Letter of Interest outlines how ML has begun to meet critical HEP needs by summarizing successful research employing machine learning in control, diagnostics and design and modeling of accelerators.

Future discovery HEP accelerators will require machine control beyond the present state of the art to enable novel technologies with challenging alignment and placement tolerances [iv, v, vi, vii]. The goal is to improve performance by global control across the entire accelerator as opposed to the traditional technique of local control of a subset of parameters [viii]. Machine learning is ideally capable of handling high-dimensional, nonlinear and data intensive systems in real time, as is necessary for global control. This capability means that ML excels at solving problems involving systems that are impractical to model, such as compensating for tuning changes throughout an accelerator due to thermal effects [ix, x].

Luminosity of the proposed CLIC accelerator has been increased in simulation using ML based optimization to handle the high dimensional space of an entire family of magnets at once [xi]. Increased tuning performance and reduced downtime of the LCLS free-electron laser is routinely demonstrated by using ML to compensate for uncertainty in input beam parameters in matching quadrupole sections [xii]. Necessary RF efficiency improvements [RF roadmap] have been demonstrated using ML-based control of the temperature of RF systems [xiii, xiv]. These techniques are all directly applicable to HEP priority technologies like advanced phase space manipulation methods, such as emittance exchange [xv] and the challenges of beam combination in wakefield accelerators [xvi]. Current efforts seek to incorporate physics models directly into ML models to improve interpretability and robustness of ML models [xvii], in some cases, eliminating the need for prior data [xviii].

Maintaining luminosity through advanced machine control requires diagnostics capable of providing quantification of beam parameters on the order of 1 Hz or faster. Additionally, future colliders are expected to produce beam quality sufficient to destroy intercepting diagnostics that rely on material close to the beam [xix]. “Virtual diagnostics” are a class of diagnostic which use a machine learning model to enhance and replicate the output of a traditional, intercepting diagnostic. As one example, a deflecting cavity bunch length measurement system can be enhanced using coherent radiation to increase the resolution [xx] or increase the functional repetition rate [xxi]. Furthermore, replication of an existing diagnostic using a virtual diagnostic is necessary when use of the traditional diagnostic would interrupt beam delivery [xxii, xxiii, xxiv]. Finally, machine learning models can be used to determine beam parameters from radiation interference patterns in real-time, [xxv, xxvi] providing non-intercepting beam measures at repetition rates relevant for machine control.

The next generation of linear colliders are designed at the limit of longitudinal and transverse beam focusing technologies. Development of beyond state-of-the-art accelerator technology will require incorporation of nonlinear and collective effects into design processes. “Surrogate models” (SM) based on machine learning can be used to increase simulation capacity for iterative tasks [xxvii] and to find novel solutions in high-dimensional spaces to meet collider needs. For example, it was demonstrated in [xxviii] that applying Bayesian optimization to a plasma accelerator enabled unexpected physics relationships to be uncovered. Similarly, reinforcement learning has been used to discover a counter-intuitive undulator taper profile that doubled the pulse energy of the LCLS X-ray laser [xxix].

Early results have demonstrated the promise of using ML techniques to meet critical HEP goals. These early results were enabled by the many tools that have been developed in the past decade for implementing ML in a manner that is fast and efficient. Beyond meeting traditional HEP goals, application of ML to physical systems requires research that addresses general challenges of uncertainty quantification to guide data fusion, safety boundaries for machine protection and behavior interpretation to understand how to improve control. Meeting these challenges requires dedicated efforts aimed at current HEP operational and design interests while developing knowhow and experience to meet future HEP goals. Concerted efforts beyond HEP with agencies that employ accelerators, such as BES and Nuclear Physics, to enhance capacity and generate robust solutions should be encouraged.

[i] Ultra-short-z Linear Collider Parameters, arXiv:1811.11782

[ii] Advanced Accelerator Development Strategy Report, DOI: 10.2172/1358081

[iii] Radiofrequency Accelerator R&D Strategy Report DOI: 10.2172/1631119

[iv] White, G. R., and T. O. Raubenheimer. *Transverse Jitter Tolerance Issues for Beam-Driven Plasma Accelerators*. No. thpgw087. SLAC National Accelerator Lab., Menlo Park, CA (United States), 2019.

[v] Thévenet, Maxence, et al. "Emittance growth due to misalignment in multistage laser-plasma accelerators." *Physical Review Accelerators and Beams* 22.5 (2019): 051302.

[vi] CERN-ACC-2018-0051; CLIC-Note-1138 and reference therein

[vii] Li, C., et al. "High gradient limits due to single bunch beam breakup in a collinear dielectric wakefield accelerator." *Physical Review Special Topics-Accelerators and Beams* 17.9 (2014): 091302.

[viii] Qiang, Ji. "Fast longitudinal beam dynamics optimization in x-ray free electron laser linear accelerators." *Physical Review Accelerators and Beams* 22.9 (2019): 094401.

[ix] Huang, Xiaobiao. *Development and application of online optimization algorithms*. No. SLAC-PUB-16831. SLAC National Accelerator Lab., Menlo Park, CA (United States), 2017.

[x] Leemann, S. C., et al. "Demonstration of Machine Learning-Based Model-Independent Stabilization of Source Properties in Synchrotron Light Sources." *Physical review letters* 123.19 (2019): 194801.

[xi] J. Ogren, ”Machine Learning and Tuning of the CLIC 380 GeV Final-Focus System”, Presentation February 21st, 2019.

[xii] Duris, Joseph, et al. "Bayesian optimization of a free-electron laser." *Physical Review Letters* 124.12 (2020): 124801.

[xiii] Edelen, A. L., et al. "Neural network model of the PXIE RFQ cooling system and resonant frequency response." *arXiv preprint arXiv:1612.07237* (2016).

[xiv] Cruz, Jorge Alberto Diaz, et al. "Studies in Applying Machine Learning to LLRF and Resonance Control in Superconducting RF Cavities." *arXiv preprint arXiv:1910.07648* (2019).

[xv] Ha, Gwanghui, et al. "Precision control of the electron longitudinal bunch shape using an emittance-exchange beam line." *Physical review letters* 118.10 (2017): 104801.

[xvi] Adli, Erik. "Plasma wakefield linear colliders—opportunities and challenges." *Philosophical Transactions of the Royal Society A* 377.2151 (2019): 20180419.

[xvii] Hanuka, Adi, et al. "Online tuning and light source control using a physics-informed Gaussian process Adi." *arXiv preprint arXiv:1911.01538* (2019).

[xviii] Ivanov, Andrei, and Ilya Agapov. "Physics-based deep neural networks for beam dynamics in charged particle accelerators." *Physical Review Accelerators and Beams* 23.7 (2020): 074601.

[xix] Yakimenko, V., et al. "FACET-II facility for advanced accelerator experimental tests." *Physical Review Accelerators and Beams* 22.10 (2019): 101301.

[xx] A. Hanuka, *in preparation*.

[xxi] Sanchez-Gonzalez, A., et al. "Accurate prediction of X-ray pulse properties from a free-electron laser using machine learning." *Nature communications* 8.1 (2017): 1-9.

[xxii] Emma, C., et al. "Machine learning-based longitudinal phase space prediction of particle accelerators." *Physical Review Accelerators and Beams* 21.11 (2018): 112802.

[xxiii] Edelen, A. L., et al. "First steps toward incorporating image based diagnostics into particle accelerator control systems using convolutional neural networks." *arXiv preprint arXiv:1612.05662* (2016).

[xxiv] Scheinker, Alexander, and Spencer Gessner. "Adaptive method for electron bunch profile prediction." *Physical Review Special Topics-Accelerators and Beams* 18.10 (2015): 102801.

[xxv] O.V. Chubar, "Determining electron beam parameters from edge radiation measurement results on Siberia-1 storage ring", *Particle Accelerator Conference 1995. Proceedings of the 1995*, vol. 4, pp. 2402-2404 vol.4, 1995.

[xxvi] R. Fiorito, *et al. Physical Review Special Topics-Accelerators and Beams* 17.12 (2014): 122803.

[xxvii] Edelen, Auralee, et al. "Machine learning for orders of magnitude speedup in multiobjective optimization of particle accelerator systems." *Physical Review Accelerators and Beams* 23.4 (2020): 044601.

[xxviii] R.J. Shalloo, Automation and control of laser wakefield accelerators using Bayesian optimisation, arXiv:2007.14340

[xxix] Wu, Juhao, et al. "Multi-dimensional optimization of a terawatt seeded tapered free electron laser with a multi-objective genetic algorithm." *Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment* 846 (2017): 56-63.