Automation, optimization and machine learning in modern plasma diagnostics

Sam M. Vinko
1) Department of Physics, Clarendon Laboratory, University of Oxford
E-mail : sam.vinko@physics.ox.ac.uk

The development of large-scale facilities tailored to the study of dense plasmas is having a transformative effect on experimental high-energy-density and astrophysical plasma research, enabling a host of new exploration avenues that were hitherto beyond our reach. High-repetition rate facilities such as the Extreme Light Infrastructure (ELI), the Extreme Photonics Applications Centre (EPAC), the Linac Coherent Light Source (LCLS), the European XFEL free-electron laser, and others, are heralding a new era of research into the physics of extreme states of matter. However, more capable computational tools will be needed to fully exploit these opportunities, given both the substantial rise in experimental complexity and the rapidly growing diversity of fielded diagnostics. These tools will be invaluable in supporting all stages of experimental research, from the planning through to data acquisition and all the way to data analysis and interpretation. The tools required for the interpretation of experimental diagnostics and related analysis workflows are perhaps where most development is needed today. Here, three areas stand out: 1) the requirement for near-real-time inverse optimization of complex data using non-invertible models; 2) the need for efficient large-scale simulation support to enable information extraction; and 3) the seamless use of statistical sampling tools that allow for robust uncertainty prediction in the presence of low signals, random noise, systematic errors, and inaccurate computational models. Modern machine learning tools and algorithms have an important role to play in supporting this effort – efficient stochastic optimization algorithms can be used to quickly sample very large spaces and tackle inverse problems for fast data interpretation, Bayesian inference sampling techniques can provide uncertainty propagation and an un-biased assessment of just how informative certain diagnostics really are [1], and active deep learning can build on-the-fly surrogate models to accelerate computational workflows [2]. Here I will present some examples of what can be done today to tackle these issues, describe what directions are being taken to develop future capabilities, and speculate on how these capabilities will evolve over the next decade.

References

[1] Kasim et al., Physics of Plasmas **26**, 112706 (2019).
[2] Kasim et al., arXiv:2001.08055 (2020).