Machine Learning Accelerated Discovery and Design

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Advances in high performance computing and data analytics are rapidly accelerating the pace of inertial confinement fusion research at Lawrence Livermore National Laboratory. Design studies are becoming more expansive, experimental post-mortems more rigorous, and analyses more insightful. As a complement to in-depth high-fidelity studies (e.g. [1]), we have combined high frequency simulation, automated computational workflows and machine learning to advance ICF research at the National Ignition Facility. Our application of these machine learning based techniques to NIF experimental design has already led to the discovery of a novel robust class of asymmetric implosions [2] (Fig. 1) and enabled quantitative multivariate post-shot analysis [3]. We will discuss these results, as well as the technical advances regarding the generation and analysis of large (multi-petabyte) simulation datasets that made them possible. Finally, we will highlight how machine learning could permeate many other aspects of ICF scientific inquiry, from enabling rapid hypothesis testing and rigorous uncertainty-based pre-shot predictions, to the inference of unmeasurable physical quantities from experimental observations alone.

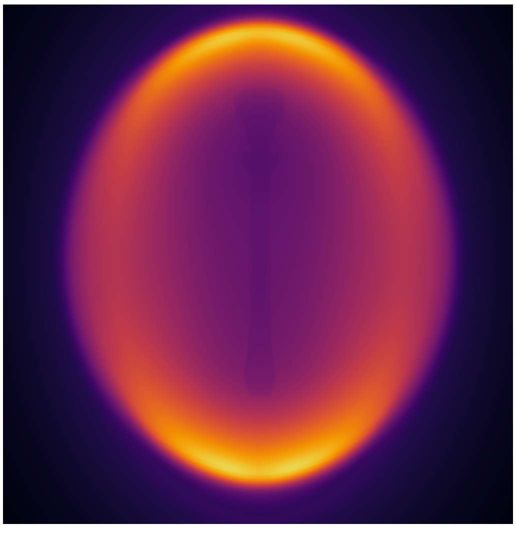

Figure 1: Simulation of the robust ovoid NIF design [2], which was discovered by a machine learning algorithm.

References

[1] D. S. Clark *et al.*, Physics of Plasmas **22**, 022703 (2015)
[2] J. L. Peterson *et al.*, Physics of Plasmas **24**, 032702 (2017)
[3] R. Nora *et al.*, Bulletin of the American Physical Society **61** (18), 287 (2016)

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