

Addressing the Inverse Problem Instability in Plasma Physics Modelling using Stochastic Machine Learning Optimization

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Our understanding of the behaviour of matter in extreme conditions has greatly benefited from the advent of novel laser and free-electron laser facilities, and the growing availability of high-performance supercomputing. Large-scale plasma experiments are now commonly modelled via increasingly detailed simulations, where the agreement between experiment and simulation enables the extraction of physical quantities and the understanding of novel underlying processes. However, simulations with large parameter spaces suffer from the inverse problem instability, where very similar simulated outputs can map back to very different sets of input parameters. While this provides a fundamental problem for interpreting the results from integrated experiments, the effect is seldom comprehensively explored due to the intractably large number of simulations required to fill the parameter space. Here we show how this problem can be addressed using stochastic machine learning optimization together with Markov Chain Monte Carlo techniques. We apply our approach to extract physical information from three common experimental diagnostics: x-ray emission spectroscopy, inelastic x-ray scattering and proton radiography. We find that all three suffer from inverse instabilities, rendering the extraction of physical information from some experimental measurements impossible even when excellent agreement with a simulation can be found. Our method provides a way to quantify the uncertainty due to the unstable nature of reverse physical models, and we describe an approach to experimental design that can mitigate its impact.