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Building physics into neural networks to improve predictions and reduce uncertainty[1] BRIAN SPEARS, JIM GAFFNEY, SCOTT BRANDON, KELLI HUMBIRD, MICHAEL KRUSE, BOGDAN KUSTOWSKI, RYAN NORA, LUC PETERSON, RUSHIL ANIRUDH, JAY THIAGARAJAN, TIMO BREMER, Lawrence Livermore Natl Lab — Comparison of precision experiments and numerical simulations, like those at the National Ignition Facility (NIF), are increasingly reliant on statistical analyses to quantify uncertainty and to explore correlations among key diagnostic signatures. These methods typically rely on a high-fidelity surrogate model, for example a deep neural network, that can emulate the simulation output. However, for physics applications, we demand that these emulated outputs respect key physical laws. We demonstrate in this talk multiple new methods to force neural network surrogates to respect physics-based constraints. These include demanding that the surrogate model be consistent with its own inverse and adjusting regularizing terms in loss functions to drive solutions to physical consistency. We apply our techniques to ICF simulations based on BigFoot and HDC implosion campaigns at the NIF. We will show, absent these physics enforcements, correlations among multiple physics outputs are broken and physics analyses can break down. With the physics enforcements, analyses obey physics principles and lead to more robust inferences with reduced uncertainty.

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