A review of explainable Machine Learning accelerating Fusion science

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It has become widely accepted that Machine Learning (ML) accelerated research can enable reactor-relevant solutions for a broad spectrum of fusion challenges [1]. Both inertial and magnetic confinement fusion need to address complex multi-scale, multi-physics systems whose integrated modelling implies extremely expensive computations, and ML can assist via surrogate modelling for accelerating such demanding simulation loops [2, 3]. Further relevant examples of ML applications in fusion include enhancing the analysis of instrumentation data, optimizing experimental design and performance [4, 5], and real-time monitoring of proximity to boundaries of plasma stability [6, 7].

This keynote talk will review ML techniques that guarantee an explainable and interpretable predictive output, thus enabling effective controllers for magnetically confined fusion plasmas [8]. Several examples will be provided of data-driven applications tailored for pre-disruptive instabilities and time-to-event predictions to provide early disruption warnings and actionable information. Transfer learning and domain adaptation techniques will also be discussed, highlighting the need to understand how to extrapolate knowledge to devices yet to be built or to experiments with different physical and statistical properties [9].

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