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Machine Learning for Efficient and Physically Interpretable Parameter Inference

Global fits in high energy physics and cosmology often face the challenge of exploring high-dimensional parameter spaces with computationally expensive or topologically complex likelihood functions. In this work, we present a Machine Learning framework designed to emulate complex, often non-Gaussian likelihood landscapes using gradient-boosted regression trees (XGBoost). We discuss the advantages of the Machine Learning approach in terms of computational efficiency and the resolution of confidence regions, particularly in scenarios with complex correlations or “curved” degeneracies. We validate this methodology by applying it to a recent analysis on flavour anomalies in semileptonic B meson decays and discussing the adaptability of this framework to other phenomenological systems, such as axion-like particles or cosmology global fits. Finally, we utilise SHAP (Shapley Additive exPlanations) values to provide a transparent analysis of feature importance, ensuring that the Machine Learning predictions remain physically interpretable and consistent with the underlying physics.

Primary author(s) : MIR, Alejandro (Universidad de Zaragoza, CAPA); PENARANDA-RIVAS, Siannah (University of Zaragoza); ASOREY BARREIRO, Jacobo (CAPA - Universidad de Zaragoza); ALDA GALLO, Jorge (Universidad de Zaragoza)

Presenter(s) : MIR, Alejandro (Universidad de Zaragoza, CAPA)

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