Generative, Explainable Artificial Intelligence for Nuclear Physics and HEP

Letter of Interest for Snowmass 2021

We propose to leverage novel setups of Generative Adversarial Networks (GANs) [1] to accelerate and broaden the progress in the understanding of the underlying dynamics of parton showers in vacuum and their interactions with quark-gluon plasma created in high-energy heavy ion collisions. The new methodology will enable comparisons of measurements from the LHC (and RHIC) to various theoretical descriptions using full event information. In addition, it will enable new experimental approaches by introducing novel observables at future colliders (EIC and LHC).

The nuclear and heavy-ion physics contain a large volume of data that are difficult to understand and model from first principles with today's theoretical knowledge, e.g. containing non-perturbative or many body dynamics [2–3]. Similar considerations can be made about high-energy proton-proton collisions — in particular those generating high-particle multiplicities. The application of novel artificial intelligence/machine learning (AI/ML) techniques is attractive, both to automatically deduce and hypothesize new theoretical models, and also develop novel observables not yet humanly envisioned. Moreover, our proposed approach utilizing GANs accompanied by human understandable construction of the neural network systems [4–5] may be used to other experiment-theory Monte Carlo feedback frameworks allowing for rapid progress in understanding the underlying physics.

References

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