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Author(s): Connor Pecar, Anselm Vossen

Title: Reconstructing the kinematics of semi-inclusive deep inelastic scattering at the EIC utilizing the hadronic final state and machine learning

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Editor report

This work proposes a method involving regression to the q-vector in DIS using neural networks (particle-flow networks, in particular). Previous published works by Diefenthaler et al. (Ref[14]), Arratia et al. (Ref[15]), Fanelli et al. (Mach.Learn.Sci.Tech. 5 (2024) 1, 015017), use similar approach, and by Aggarwal et al. (JINST 17 (2022) 09, P09035) is also similar although using a Bayesian approach rather than neural networks. It should be noted that Fanelli et al. and Aggarwal et al. are not cited, as they should be. The authors claim that their work is distinct from these previous studies, as it focuses on semi-inclusive DIS rather than DIS.

The main difference between DIS and SIDIS, as described by the authors, is that the former involves regression to all the q-vector components rather than to some derived quantities from it, such as the magnitude of qˆ2, the Bjorken x variable, or the inelasticity variable y. Thus, this work is incremental at best, in principle. However, it should be noted that the components of the vector q can be derived from other quantities already considered in the regression work in Ref[15] and also in Aggarwal. et al. Therefore, it raises questions regarding whether this approach is fundamentally different from previous published work in practice. On the technical AI/ML side, the application of PFN is indeed an extension of previous work, as it provides a method to incorporate the variable number of particles in each event, rather than simply combining all particles.

Leaving those issues aside, this work faces a major challenge in neglecting the effects of QED radiation. All previous work (Ref[14,15], Fanelli et al., Aggarwal et al.) has directly addressed the issue of QED radiation. This is not a peripheral issue or something that can be ignored or left for future work—it significantly alters the problem. Specifically, in the presence of QED, the relations of Q^2, x, and y are not as straightforward as assumed in this paper. More importantly, it entirely changes the "truth" or "target" of the AI. It is well-known that the "truth" depends on the particular reconstruction method used. In particular, in HERA, the various methods employed had different sensitivities to QED effects, and a comprehensive approach in selecting a specific method quantified the impact of the corrections in assessing the overall performance. The AI/ML methods pose another key challenge. What "truth" would be the target of the PFN? This is straightforward in the case of no QED radiation, but that is not useful. For reference, Ref[14] used a definition previously employed in the ZEUS Collaboration at HERA; Ref[15] used a newly proposed method to define truth; and Fanelli et al. used the same definition as Ref[15]. The impact of QED is critical, both conceptually and practically, as it affects the resolution of the method. Therefore, I do not believe this can be published as is, given the state of the art. I do not think that the conclusions of this paper are supported, given this deficiency.

I would suggest revising this work to include proper MC samples incorporating QED radiative effects, and ensuring that the authors clearly define the target of the PFN regression in the presence of QED radiative effects. They could follow either the methodology outlined in Ref [14] or Ref [15] regarding how truth is defined. The method proposed by the authors (using PFN with all particles as input) might indeed improve upon DNNs used in other papers, but it is not possible to claim that at the moment given the lack of quantification of the QED radiation.