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Reinforcement Learning for background determination in particle physics

Experimental studies of ⊠-hadron decays face significant challenges due to a wide range of backgrounds arising from the numerous possible decay channels with similar final states. For a particular signal decay, the process for ascertaining the most relevant background processes necessitates a detailed analysis of final state particles, potential misidentifications, and kinematic overlaps which, due to computational limitations, is restricted to the simulation of only the most relevant backgrounds. Moreover, this process typically relies on the physicist' s intuition and expertise, as no systematic method exists. This work presents a novel approach that utilises Reinforcement Learning to overcome these challenges by systematically determining the critical backgrounds affecting ⊠-hadron decay measurements. Our method further incorporates advanced Artificial Intelligence models and techniques to enhance background identification accuracy: a transformer model is employed to handle token sequences representing decays, a Graph Neural Network is used for predicting Branching Ratios (BRs), and Genetic Algorithms are utilised as an auxiliary tool to efficiently explore the action space, among others.

AI keywords

Reinforcement Learning; transformers; Graph Neural Networks; Genetic Algorithms;

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Track Classification: Explainability & Theory