Physics-inspired learning on graphs

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The message-passing paradigm has been the "battle horse" of deep learning on graphs for several years, making graph neural networks a big success in a wide range of applications, from particle physics to protein design. From a theoretical viewpoint, it established the link to the Weisfeiler-Lehman hierarchy, allowing to analyse the expressive power of GNNs. We argue that the very "node-and-edge"-centric mindset of current graph deep learning schemes may hinder future progress in the field. As an alternative, we propose physics-inspired "continuous" learning models that open up a new trove of tools from the fields of differential geometry, algebraic topology, and differential equations so far largely unexplored in graph ML.