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QFT inspired learning

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We present a fully information theoretic approach to renormalization inspired by Bayesian statistical inference, which we refer to as Bayesian renormalization. The main insight of Bayesian renormalization is that the Fisher metric defines a correlation length that plays the role of an emergent renormalization group (RG) scale quantifying the distinguishability between nearby points in the space of probability distributions. This RG scale can be interpreted as a proxy for the maximum number of unique observations that can be made about a given system during a statistical inference experiment. The role of the Bayesian renormalization scheme is subsequently to prepare an effective model for a given system up to a precision which is bounded by the aforementioned scale. In applications of Bayesian renormalization to physical systems, the emergent information theoretic scale is naturally identified with the maximum energy that can be probed by current experimental apparatus, and thus Bayesian renormalization coincides with ordinary renormalization. However, Bayesian renormalization is sufficiently general to apply even in circumstances in which an immediate physical scale is absent, and thus provides an ideal approach to renormalization in data science contexts. To this end, we provide insight into how the Bayesian renormalization scheme relates to existing methods for data compression and data generation such as the information bottleneck and the diffusion learning paradigm. We conclude by designing an explicit form of Bayesian renormalization inspired by Wilson's momentum shell renormalization scheme in quantum field theory. We apply this Bayesian renormalization scheme to a simple neural network and verify the sense in which it organizes the parameters of the model according to a hierarchy of information theoretic importance.

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