ABSTRACT

The intersection of physics and machine learning (ML) is a highly active area of research [1, 2, 3, 4, 5, 6]. ML plays an important role within large-scale physics applications, and physics has inspired many popular techniques in ML [3, 2]. Furthermore, physics may offer explanations as to why certain ML techniques, especially deep neural networks, work as well as they do [2]. Others are exploring the use of ML to guide the "physical reasoning process" [5] not only to aid in analyzing data [5, 6]. The goal of this capstone is to introduce ML practitioners to relevant physics concepts, and vice-versa, so as to enable further investigation into each of the above areas of intersection. Specifically, this capstone will focus on restricted Boltzmann machines, a type of neural network, the renormalization group (RG), a set of techniques from theoretical physics, and the relation between them. There is disagreement as to the particulars of this comparison [2, 7, 4, 5, 6], and it is our aim to clarify the points of contention. Building on a thorough literature review, we provide an open-source implementation of the real-space mutual information (RSMI) algorithm as conceived by Koch-Janusz and Ringel [5]: this algorithm learns optimal transformations, most notably, in an unsupervised fashion. We leverage machine learning to predict critical exponents of the Ising model in two dimensions and describe a novel generalization of this algorithm to arbitrary lattice systems. This extends the RSMI algorithm to an antire family of RG transformations with implications extending beyond physics. By building a better understanding of the relations between physics and ML, we hope to enable and inspire more interdisciplinary research towards better understanding of physical systems and ML algorithms but also to building more efficient and rigorous algorithms [5].

***K*eywords** Machine Larning, Restricted Boltzmann Machines, The Renormalization Group, Information Theory, Mutual Information