Learning Renormalization Group Flows for Lattices

Jay Shen*
Department of Physics
University of Chicago †

Real space renormalization is a powerful and theoretically fascinating, albeit difficult technique for investigating scale and phase behavior in physical systems. For even the simplest problems, formulating the so-called renormalization group (RG) flow involves incredibly tedious, intuition-dependent work that can drag on for years. However, once accurately described, RG flows have a number of uses, from describing phase behaviors to speeding up simulations. Accordingly, any information at all about their properties is highly valued and sought after by physicists. Here, we review and assess a novel approach to real space renormalization initially proposed by [Hou et al. , 1]. The so-called Machine Learning Renormalization Group (MLRG) algorithm automatically determines approximate RG flows of translationally-invariant Ising models, given only the symmetry description of the lattice. It has the potential to effectively characterize a wide range of interesting systems, and also demonstrates an elegant synthesis of both new and old machine learning techniques with statistical physics. In the first section of the review, we will first give some background for real space renormalization and the Ising model. In the second section, we will describe the MLRG algorithm and demonstrate its use. In the third section, we will discuss the algorithmic design space and suggest modifications for greater efficacy and efficiency.

I. BACKGROUND

A. Real Space Renormalization

Real space renormalization is a theory of scaling in physical systems. That is, it asks how the apparent behavior of a system changes when considered from different length scales.

Consider, as a toy example, the task of modeling some volume of water. At the smallest scale, field theories form our understanding of the particulate structures within atoms. Zooming out and changing our scale of consideration, theories such as quantum mechanics and classical mechanics provide well-developed frameworks for modeling subatomic and atomic dynamics. Zooming out all the way out, fluid mechanics elegantly describes the hydrodynamic behaviors of human-scale systems.

Somehow, all these loosely-related theories must be related, for they all model the same system. Real space renormalization is a theoretical framework for systematically linking these theories.

B. The Ising Model

II. THE MLRG ALGORITHM

A. Algorithm Description

B. Demonstration of Results

III. THE MLRG DESIGN SPACE

A. Learning the Flow versus the Monotone

B. RBM Hyperparameters

C. Sampler Hyperparameters

* My gratitude goes out to Professor Kao at NTU for his guidance, the NTU physics buddies and my group mates for their friendship and hospitality, the other UCTS fellows for their companionship, and Professor Chin and all the UCTS donors for making my summer in Taiwan possible.

† jshe@uchicago.edu