Learning the Local Physics of Quenched Disorder with Generative Models

Stefano Bae[1]

[1]Sapienza Universita' Di Roma, Roma, Italy

We introduce a generative discrete diffusion model designed for the sampling of disordered spin systems. The proposed architecture utilizes graph neural networks based on local message passing. This design ensures that the network's receptive field intrinsically mirrors the local interactions of the underlying Hamiltonian, allowing the model to capture the fundamental local physics of the system. The framework is evaluated using the random field Ising model (RFIM), which serves as a computational bridge between simple ferromagnetic systems and highly frustrated spin glasses. While pure models lack the quenched disorder necessary to simulate complex energy landscapes, the random field Ising model incorporates local random fields that create deep metastable states. Unlike fully frustrated spin glasses, this model—particularly on sparse topologies—can exhibit a well-behaved, smooth macroscopic response to disorder.

By operating on node-level features, the model is trained to process unseen instances of both the graph topology and the quenched random fields. This methodology effectively bypasses the need for computationally demanding Markov Chain Monte Carlo equilibration runs, which are traditionally required for every new realization of disorder. We evaluate the generative fidelity of the framework against ground-truth datasets across a range of disorder strengths and finite temperatures. The model accurately reconstructs macroscopic probability distributions for unseen instances, including the joint distribution of magnetization and energy as well as the local magnetizations of individual spins. Furthermore, we demonstrate the model's capacity for size extrapolation by training on smaller systems and successfully predicting thermodynamic observables for significantly larger system sizes. By establishing that the architecture learns the local rules of quenched disorder, this work provides a scalable foundation for the future application of generative diffusion to the complex, competing interactions required for fully frustrated systems.