Contribution ID: **105** Type: **not specified**

Generative diffusion model with inverse renormalization group flows

Monday, 25 August 2025 15:55 (20 minutes)

The renormalization group (RG) framework, which establishes a connection between a microscopic model at short distances and its coarse-grained counterpart at larger scales, has been a pivotal tool for understanding many-body phenomena across vastly different scales, ranging from elementary particles to condensed matter. Central to the RG's success is its multiscale nature, enabling systems with distinct short-scale behaviors to exhibit similar patterns at macroscopic scales.

On another front, recent advances in machine learning have positioned diffusion models [1, 2] as one of the most prominent examples of generative models, achieving a great success across various domains, including computer vision, audio synthesis, and point cloud generation. Nevertheless, diffusion models have so far largely overlooked the inherent multiscale structures of natural data, and their slow generation process remains a bottleneck for expanding their applications to important domains in physics [3].

In our work [4], we introduce a novel class of generative diffusion models inspired by the concept of the RG, which leverage the multiscale properties of natural data to realize efficient and high-quality data generation. Specifically, we establish a connection between the flow equations in the RG framework and the convex diffusion equations underlying diffusion models. This connection allows us to construct a diffusion model that generates data in a coarse-to-fine manner by reversing the RG flows, thereby naturally incorporating the multiscale structures in natural data. To validate the effectiveness and versatility of our approach, we apply the model to real-world problems in two distinct domains: protein structure prediction and image generation. Our numerical results demonstrate that the RG-based diffusion models consistently outperform conventional models across all tested datasets, enhancing sample quality and/or accelerating sampling speed by an order of magnitude.

In the presentation, we first illustrate the theoretical formulation of the RG-based diffusion model, and then, demonstrate the numerical results that support the validity of the model. The framework of our RG-inspired scalable approach to data generation is general and would bear a close connection to machine learning approaches for analyzing, e.g., (Boltzmann) distributions in quantum and classical many-body systems.

[1] J. Sohl-Dickstein, E. Weiss, N. Maheswaranathan and S. Ganguli, Proc. of the ICML, 2256 (2015).
[2] J. Ho, A. Jain, and P. Abbeel, Adv. In NIPS 33, 6840 (2020).
[3] K. A. Dill, S. B. Ozkan, M. S. Shell, and T. R Weikl, Annu. Rev. Biophys. 37, 289 (2008).
[4] **K. Masuki** and Y. Ashida, arXiv:2501.09064 (2025).

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Session Classification: Contributed talks

Track Classification: Invited talk