Note on Energy Matching and Energy Based Models for Generative Modeling

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# Introduction

Energy Matching is a unifying framework that combines the advantages of Flow Matching and Energy-Based Models, parameterized by a time-independent scalar potential field.

It explicitly encodes data likelihood information for controllable generation while keeping curvature low off-data for curl-free, efficient sampling.

The Claim: Energy Matching achieves SOTA performance among likelihood-based methods, on par with Diffusion and Flow Matching, unlocking exciting new inference-time capabilities.

A diagram of energy and energy

AI-generated content may be incorrect.

Figure 1: Trajectories (green lines) of samples traveling from a noise distribution (black dots; here, a

Gaussian mixture model) to a data distribution (blue dots; here, two moons as in [Tong et al., 2023])

under four different methods: Action Matching [Neklyudov et al., 2023], Flow Matching (OT-CFM)

[Tong et al., 2023], EBMs trained via contrastive divergence [Hinton, 2002], and our proposed Energy

Matching. We highlight several individual trajectories in red to illustrate their distinct behaviors.

Both Action Matching and Flow Matching learn time-dependent transports and are not trained for

traversing the data manifold. Conversely, EBMs and Energy Matching are driven by time-independent

fields that can be iterated indefinitely, allowing trajectories to navigate across modes. While samples

from EBMs often require additional steps to equilibrate (see, e.g., the visible mode collapses that

slow down sampling from the data manifold), Energy Matching directs samples toward the data

distribution in “straight” paths, without hindering the exploration of the data manifold.

# References

[1] [Energy Matching: Unifying Flow Matching and Energy-Based Models for Generative Modeling, Michal Balcerak et al, U of Zurich, 2025](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Energy_Matching-Unifying_Flow_Matching_and_Energy-Based_Models_for_Generative_Modeling_Balcerak_2025.pdf)

[2] github repo: <https://github.com/m1balcerak/EnergyMatching>

[] [An Introduction to Flow Matching and Diffusion Models, Peter Holderrieth and Ezra Erives, Notes from MIT Class 6.S184, 2025](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/An_Introduction_to_Flow_Matching_and_Diffusion_Models_Holderrieth_MIT_2025.pdf)

[] [Flow Matching for Generative Modeling, Yaron Lipman et al, Meta FAIR, 2023](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Flow_Matching_for_Generative_Modeling_Lipman_Meta_2023.pdf)

[] [Flow Straight and Fast: Learning to Generate and Transfer Data with Rectified Flow, X. Liu et al, 2022](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Flow_Straight_and_Fast-Learning_to_Generate_and_Transfer_Data_with_Rectified_Flow_Liu_2022.pdf)

[] [Flow Matching Guide and Code, Yaron Lipman et al, 2024](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Flow_Matching_Guide_and_Code_Lipman_2024.pdf)