Notes on Flow Matching and Diffusion Models

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# Introductory Remarks

We will be discussing two widely used generative AI algorithms: denoising diffusion models, and flow matching.

These generative models generate objects by iteratively converting noise into data with the help of ordinary or stochastic differential equation (ODEs/SDEs) models. Flow matching and denoising diffusion models are a family of techniques that allow us to construct, train, and simulate such ODEs/SDEs at large scale with Deep Neural Nets (DNNs).

Before delving into the models, we will list the different data types (aka *modalities*) which we will consider and their numerical representations

**Image**: consider images with pixels where describes the height and the width of the image, each with three color channels (RGB). For every pixel and every color channel, it is given an intensity value in . Thus, the image can be represented by an element .

**Video**: video is viewed as a series of images in time. If we have time points (aka *frames*), a video would therefore be represented by an element .

**Molecular structure**: A naïve way would be to represent the structure of a molecule by a matrix where is the number of atoms in the molecule and each describes the location of that atom.

In all of the above example the object we want to generate can be represented as a vector. Therefore in our further model discussion the object being generated will be referred as vectors .

# Generative Modeling as Sampling

There is a spectrum of images that fit better or worse a predefined concept.

# References

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[2] MIT Class 6.S184 website: <https://diffusion.csail.mit.edu/>

[3] [Score-Based Generative Modeling through Stochastic Differential Equations, Yang Song et al, Stanford U., 2021](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Score-Based_Generative_Modeling_through_Stochastic_Differential_Equations_Song_2021.pdf)

[4] [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)

[5] [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)

[6] [Stochastic Interpolants: A Unifying Framework for Flows and Diffusions, Michael S. Albergo et al, 2023](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Stochastic_Interpolants-A_Unifying_Framework_for_Flows_and_Diffusions_Albergo_NYU_2023.pdf)

[7] [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)

[8] flow\_matching library at <https://github.com/facebookresearch/flow_matching>