# Notes on Probabilistic Diffusion Models

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## Introductory Notes

Diffusion models are generative models which implies that they model/generate data similar to the data on which they were trained. Fundamentally, the diffusion models work by removing information from the training data in iterative fashion through the successive addition of Gaussian noise and then learning to approximate some of the lost information by reversing the noising process.

After training, the diffusion model can be used to generate data by simply passing randomly sampled noise through the denoised process with learned parameters.

In mathematical terms, a diffusion model is a latent variable model which maps to the latent space using a fixed Markov chain. This chain adds noised to the data in order to obtain the approximate posterior , where are latent variables of the same dimensionality as .



Figure: Markov chain constructed from image as data source

After state transitions, as shown on the Figure above the source image is transformed into Gaussian noise asymptotically. The goal of training diffusion model is to learn the reverse process – that is training to recover as much as possible



Figure: training the diffusion model to discover the original image from the noise

The diffusion model consists of a forward process (aka diffusion process) in which a datum which is generally an image is progressively noised, and a reverse process (aka reverse diffusion process), in which noise is transformed back into a sample from the target distribution.

The sampling chain transitions in the forward process can be set to conditional Gaussians when the noise level is sufficiently low.

//TODO: finish this section

## The Basics: Variational Auto-Encoder (VAE)

The simplest approach to build a generator that generates images from a latent code is to consider an encoder-decoder pair shown below (aka *variational autoencoder*)

## References

[Introduction to Diffusion Models for Deep Learning, Ryan O'Connor, 2022 (online blog)](https://www.assemblyai.com/blog/diffusion-models-for-machine-learning-introduction/)

[Deep Unsupervised Learning Using Nonequilibrium Thermodynamics, Jascha Sohl-Dickstein et al, Stanford U., 2015](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Deep_Unsupervised_Learning_using_Nonequilibrium_Thermodynamics_Sohl-Dickstein_2015.pdf)

[Tutorial on Diffusion Models for Imaging and Vision, Stanley Chan, 2024](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Tutorial_on_Diffusion_Models_for_Imaging_and_Vision_Chan_2024.pdf)

[Understanding Diffusion Models: Unified Perspective, Calvin Luo, Google Brain, 2022](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/generative_models/Understanding_Diffusion_Models-A_Unified_Perspective_Luo_GoogleBrain_2022.pdf)