# Diffusion Tutorial

compiled by D.Gueorguiev, 6/17/2024

## Introductory Notes

The goal of generative modeling is: given iid samples from unknown distribution , construct a sampler for approximately the same distribution.

*Example*: given a training set of dog images from some underlying distribution , we want a method of producing new images of dogs from this distribution.

One way to solve this problem is to learn a transformation from some easy-to-sample distribution (such as Gaussian noise) to our target distribution . Diffusion models offer a general framework for learning such transformations. We want to reduce the problem of sampling from distribution to a sequence of easier sampling problems.

## Gaussian Diffusion

Let be a random variable in distributed according to the target distribution . Then construct a sequence of r.v.’s by successively adding independent Gaussian noise with some small scale :

, (1)

(1) represents forward process, which transforms the data distribution into a noise distribution. Thus (1) defines a joint distribution over , and we let denote the marginal distributions of each . Notice that at large step count , the distribution is nearly Gaussian, so we can approximate sample from by just sampling a Gaussian.

Now, suppose we can solve the following subproblem –

Given a sample marginally distributed as , produce a sample marginally distributed as .

We will call a method that does this a *reverse sampler*, since it tells us how to sample from assuming we can already sample from . If we had a reverse sampler, we could sample from our target by simply starting with a Gaussian sample from , and iteratively applying the reverse sampling procedure to get samples from , and finally .

The key insight of diffusion is, learning to reverse each step can be easier than learning to sample from target distribution in one step. There are many ways to construct reverse samplers, but for concreteness let us first see the standard diffusion sampler which we will call the *Denoising Diffusion Probabilistic Model* (DDPM) sampler.

The *ideal DDPM sampler* uses an obvious strategy: at time , given input (a sample from ), we output a sample from the conditional distribution

(2)

(2) represents a reverse sample. The problem is, it requires learning a generative model for the conditional distribution for every , which could be complicated. But if the per-step noise is sufficiently small, then it turns out this conditional distribution becomes simple:

Property of Diffusion Reverse Process

For small , and the Gaussian diffusion process defined in (1), the conditional distribution is itself close to Gaussian. That is, for all times and conditionings , there exists some mean parameter such that

(3)

For a given time and conditioning value , learning the mean of is sufficient to learn the full conditional distribution . This not obvious fact enables a drastic simplification – instead of having to learn an arbitrary distribution from scratch, we now know everything about this distribution except its mean, which we denote .

Learning the mean of is a much simpler problem than learning the conditional distribution itself; we can solve it by regression. We have a joint distribution from which we can sample and want to estimate . This is done by minimization of the standard regression loss

(4)

(5)

(6)

where the expectation is taken over samples from our target distribution . We simulate samples of by adding noise to the samples of as defined by (1).

When the target is a distribution on images, then the corresponding regression problem (6) is an *image denoising objective*, which can be approached with CNNs.

### Constructing Diffusion-like Generative Models

Let us now abstract away the Gaussian setting, to define diffusion-like models in a way that will capture their many instantiations (including deterministic samples, discrete domains, and flow-matching).

We start with the target distribution , and we pick some base distribution which is easy to sample from, e.g. a standard Gaussian or i.i.d. bits. We then try to construct a sequence of distributions which interpolate between the target and the base distribution . That is, we construct distributions

(7)

such that is our target, is the base distribution, and adjacent distributions are close enough in some well-defined sense. Then we learn a reverse sampler which transforms to . Formally,

**Definition** (*Reverse Sampler*)

Given a sequence of marginal distributions , a reverse sampler for step t is a potentially stochastic function such that if , then the marginal distribution of is exactly .

(8)

There are many possible reverse samplers; some samplers can be deterministic.

We will consider three possible reverse samplers : the *DDPM sampler*, the *DDIM sampler,* which is deterministic and the family of *flow-matching models* which can be thought as generalization of *DDIM*.

### Discretization

Let us elaborate what it means adjacent distributions to be close. The sequence can be thought of as the discretization of some (well-behaved) time-evolving function , that starts from the target distribution at time and ends at the noisy distribution at time :

, where (9)

The number of steps controls the fineness of the discretization and hence the closeness of adjacent distributions.

In order to ensure that the variance of the final distribution, , is independent of the number of discretization steps, we also need to be more specific about the variance of each increment.

Note that if , then . Therefore, we need to scale the variance of each increment by , that is, choose

(10)

where is the desired terminal variance. The choice (10) ensures that the variance of is always , regardless of .

Notation Adjustment

From here on, will represent a continuous value in the interval ; it will be taking over the values . Subscripts will indicate *time* rather than *index*, so for example will now denote at a discretized time . That is, (1) becomes:

, (11)

which also implies that

, where (12)

since the total noise added up to time (i.e. ) is also Gaussian with mean zero and variance .

## Stochastic Sampling: DDPM

We will review DDPM-like reverse sampler and heuristically prove its correctness.

This sampler is similar as the sampler discussed in [3] and was originally introduced in [1]. The main difference with [3] is that we use the “Variance Exploding” diffusion forward process. We also use constant noise schedule and we do not discuss how to parametrize the predictor (predicting vs vs noise ).

Let us consider the same setup as before – a target distribution and a joint distribution of noisy samples defined in (11). The DDPM sampler will require estimates of the following conditional expectations:

(13)

This is a set of functions , one for every time step . In *the training phase*, we estimate these functions from i.i.d. samples of , by optimizing the denoising regression objective

(14)

Typically a neural network is used to parametrize . In practice, it is common to share parameters when learning the different regression functions ,

Then, in *the inference phase*, we use the estimated functions in the following reverse sampler.

Algorithm 1: Stochastic Reverse Sampler (DDPM-like)

For input sample , and timestep , output:

(15)

To actually generate a sample, say , we first sample as an isotropic Gaussian , and then run the iteration of Algorithm 1 down to , to produce a generated sample . Here , as our discretized notation (12) indicates, is the noise-only terminal distribution, and the iteration takes steps of size .

Question: why does iterating Algorithm 1 produce a sample from (approximately) the target distribution ? The key missing piece is, we need to prove the property of the diffusion processes given with (3) – that is , the true conditional can be approximated by a Gaussian and this approximation converges to the true conditional distribution if we discretize in smaller steps .

Here we continue with the discussion on the property of the diffusion processes-

Statement 1: Let be an arbitrary, sufficiently smooth density over . Consider the joint distribution of where and . Then, for sufficiently small , the following holds: for all conditionings , there exists such that

(16)

for some constant depending only on . Moreover, it suffices to take

(17)

(18)

where is the marginal distribution of .

One can recognize that the second term in (18) is the scaled by variance statistical score (aka informant) ([13], Appendix 1).

Tweedie’s formula ([14], [15], Appendix 2) implies that this mean is exactly correct even for large , with no approximation required. However, the distribution may deviate from Gaussian for larger ’s.

Statement 1 implies that to sample from , it suffices first to sample from , then sample from the Gaussian distribution centered around (ref to (15)). (18) shows that exists.

Discussion of a proof of Statement 1:

Heuristic argument why statistical score appears in the reverse process.

By Bayes theorem:

//TODO: finish this paragraph

Lemma 1: Let be an arbitrary density over with bounded 1st to 4th order derivates. Consider the joint distribution , where and . Then for any conditioning , we have

(21)

where (22)

### Appendix

### Statistical Score / Informant

Score (aka Informant) is the gradient of the log-likelihood function with respect to the parameter vector . Evaluated at a particular point of the parameter vector, the score indicates the steepness of the log-likelihood function and thereby the sensitivity to infinitesimal changes to the parameter values.

Linear score

The likelihood of an observation is given by a density of the form

### Tweedie’s Formula

Let us assume that has been sampled from a prior density and then is observed, where is known:

and (A2.1)

Let denote the marginal distribution of ,

where (A2.2)

Tweedie’s formula calculates the posterior expectation of given as

where (A2.3)

All of the observations can be used to obtain a smooth estimate of , yielding

(A2.4)

(A2.4) represents an estimate which corrects for the selection bias.

Here is an example which we will analyze for evidence that indeed such correction occurs.

Let us suppose there is some large number of possibly correlated normal variates each with its own unobserved mean parameter

for (A2.5)

We are looking into the 100 largest ’s. *Selection bias* is the tendency of the corresponding 100 ’s to be less extreme, that is to lie closer to the center of the observed distribution, an example of regression to the mean. Figure 1 shows a data set with independent values obeying (A2.5) with . The largest ’s are indicated by blue dashes.

Question: How can we undo the effects of selection bias and estimate the corresponding values?

A green and blue graph

Description automatically generated

Figure 1: independent values obeying (A2.5) with . The largest ’s are indicated by blue dashes.

A graph of a curve

Description automatically generated

Figure 2: Empirical Bayes estimation curve . Blue dashes indicate the 100 largest ’s and their corresponding . Small green dots show the actual Bayes estimation curve.

Robbins ([15]) presents Tweedie’s formula as an [exponential family](https://en.wikipedia.org/wiki/Exponential_family) generalization of (A2.1)

and (A2.6)

Here is the natural or canonical parameter of the family, the [cumulant generating function](https://www.statlect.com/fundamentals-of-probability/cumulant-generating-function) or (which makes integrate to 1), and the density when .

The choice where is given with (A2.2) i.e. , yields the normal translation family , with . In this case .

Bayes rule provides the posterior density of given ,

(A2.7)

where is the marginal density

(A2.8)

is the sample space of the exponential family. Then (A2.6) gives

where (A2.9)

(A2.9) represents an exponential family with canonical parameter and .

Proof of (A2.9):

Recall ([16]) that of is defined as:

where

Therefore

Substituting (A2.6) into the last equation leads to

. Substituting (A2.8) in the latter leads to . Thus

Differentiation of yields the posterior cumulants of given ,

, var (A2.10)

Let’s compute the first derivative of :

. (A2.11)

, (A2.12)

(A2.13)

(A2.14)

(A2.14) in (A2.13) leads to

(A2.15)

(A2.15) and (A2.12) in (A2.11) leads to

(A2.16)

Since the last two terms cancel out and using (A2.7) becomes

Let’s compute the second derivate of :

References

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

[2] [Step-By-Step Diffusion: An Elementary Tutorial, P. Nakkiran et al, 2024](https://github.com/dimitarpg13/deep_learning_for_image_processing/blob/main/literature/articles/generative_models/StepByStepDiffusionAnElementaryTutorial_Nakkiran_2024.pdf)

[3] [Denoising Diffusion Probabilistic Models, J. Ho et al, UC Berkeley, 2020](https://github.com/dimitarpg13/deep_learning_for_image_processing/blob/main/literature/articles/generative_models/Denoising_Diffusion_Probabilistic_Models_Ho_UCBerkeley_2020.pdf)

[4] [Introduction to Flow Matching, Tor Fjelde, Emile Mathieu, Vincent Dutordoir, 2024 (online blog)](https://mlg.eng.cam.ac.uk/blog/2024/01/20/flow-matching.html)

[5] [Building Diffusion Model's theory from ground up, Ayan Das, ICRL blogposts, 2024](https://iclr-blogposts.github.io/2024/blog/diffusion-theory-from-scratch/)

[6] [Perspectives on Diffusion, Sander Dieleman, 2023](https://sander.ai/2023/07/20/perspectives.html)

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

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

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

[10] [Sampling, Diffusion, and Stochastic Localization, Andrea Montanari, 2023](https://github.com/dimitarpg13/deep_learning_for_image_processing/blob/main/literature/articles/generative_models/Sampling_diffusions_and_stochastic_localization_Montanari_2023.pdf)

[11] [Demystifying Variational Diffusion Models, Fabio De Sousa Ribeiro et al, Imperial College, 2024](https://github.com/dimitarpg13/deep_learning_for_image_processing/blob/main/literature/articles/generative_models/Demystifying_Variational_Diffusion_Models_Ribeiro_2024.pdf)

[12] [Lightweight Diffusion Models: A Survey, W. Song et al, 2024](https://github.com/dimitarpg13/deep_learning_for_image_processing/blob/main/literature/articles/generative_models/Lightweight_Diffusion_Models_A_Survey_Song_2024.pdf)

[13] [Score, Wikipedia](https://en.wikipedia.org/wiki/Informant_(statistics))

[14] [Tweedie's Formula and Selection Bias, Bradley Efron, Stanford U., 2011](https://github.com/dimitarpg13/probabilistic_machine_learning/blob/main/applied_statistics/articles/Tweedies_Formula_and_Selection_Bias_Effron_Stanford_2011.pdf)

[15] [Empirical Bayes Approach to Statistics, Herbert Robbins, Columbia U., 1956](https://github.com/dimitarpg13/probabilistic_machine_learning/blob/main/applied_statistics/articles/Empirical_Bayes_Approach_to_Statistics_Robbins_Columbia_1956.pdf)

[16] [Cumulant Generating Function, Marco Taboga, statlect.com](https://www.statlect.com/fundamentals-of-probability/cumulant-generating-function)

[17] [Exponential Family, Wikipedia](https://en.wikipedia.org/wiki/Exponential_family)