# Notes on Variational Autoencoders

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## Introductory Notes

*Generative modeling* is a broad area of machine learning which deals with the models of distributions , defined over datapoints in some potentially high-dimensional space . For instance, images are a popular kind of data for which we might create generative models. Each “datapoint” (image) has thousands or millions of dimensions (pixels), and the generative model’s job is to somehow capture the dependencies between pixels, e.g., that nearby pixels have similar color, and are organized into objects. Exactly what it means to “capture” these dependencies depend on exactly what we want to do with the model. One kind of generative model simply allows us to compute numerically. In the case of images, values which look like real images should get high probability, whereas images that look like random noise should get low probability. However, models like this are not necessarily useful: knowing that one image is unlikely does not help us synthesize one that is likely.

Instead, one often cares about producing more examples that are *like* those already in a database, but not exactly the same. We could start with a database of raw images and synthesize new, unseen images. We could start with database of raw images and synthesize new, unseen images. We might take in a database of 3D models of something like plants and produce more of them to fill a forest in a video game. We could take handwritten text and try to produce more handwritten text. We can formalize this setup by saying that we get examples distributed according to some unknown distribution , and our goal is to learn a model which we can sample from, such that P is as similar as possible to .

Training this type of model has been a long-standing problem in the machine learning community and most approaches before variational autoencoders have had one of three serious drawbacks.

*First*, they might require strong assumptions about the nature of the data. *Second*, they might make severe approximations leading to suboptimal models. *Third*, they might rely on computationally expensive inference procedures like *Markov Chain Monte Carlo*. More recently there has been demonstrated progress using neural nets as function approximators through backpropagation. One such framework is the *Variational Autoencoder*.

## Preliminaries: Latent Variable Models

## Autoencoders

Autoencoders reconstruct high-dimensional data using a NN with a narrow (aka “*bottleneck*”) layer in the middle. Because of the narrow middle layer the phenomenon *dimensionality reduction* takes place which leads to *compressed latent encoding*.

### Latent Space Compression

By compressing data into a compact, information-rich *latent space*, NN can learn representations suitable for variety of classification and forecasting tasks.

Let us compare NN-based dimensionality reduction with alternative method for dimensionality reduction - Principal Component Analysis (PCA).

PCA is a ***linear*** technique which reduces the dimensionality of the data by projecting it onto the principal components which capture the most variance of the data by utilizing appropriately chosen linear transformation.

NN, on the other hand, can learn more complex relationships not limited to linear functions. A common NN architecture for dimensionality reduction is the *Autoencoder architecture* ([1]). The autoencoder is composed of two main components: an encoder that maps the input data to a lower-dimensional latent space representation and a decoder that reconstructs the input data from the latent space.

The autoencoder learns to compress the data in the latent space by minimizing the reconstruction error, which measures the difference between input and output.

Encoder

Decoder

is

reconstructed input

The Encoder network translates the original high-dimension input into a latent lower-dimensional vector encoding represented by . Clearly, .

The Decoder network recovers useful data contained in from the lossy encoding vector .

The model contains an encoder function parametrized by and a decoder function parametrized by . The low-dimensional code learned for inthe narrow layer is and the reconstructed input is .

The parameters are learned together to output a reconstructed data sample as the original input, or in other words, to learn an identity function. The difference between and can be quantified through a variety of metrics. One of those is mean square error loss function:

where is the number of data samples in the data set .

Another metric for the error loss function is the cross entropy, defined below:

### Denoising Autoencoder

## Appendix

### A Tiny Bit of Theory on Bayesian Modeling

**Bayes theorem**

Let is sample space and let be a partition of so that (i) and (ii) for all . Then we have:

**The Prior and Posterior Distributions**

Let be some unknown parameter vector which is random with distribution . This is the *prior distribution,* and it captures our prior uncertainty regarding . There is also a random vector y with PDF (or PMF in discrete case) – this is the *likelihood*. The joint distribution of and and is then given by

and we can integrate the joint distribution to get the *marginal distribution* of , namely

We can compute the *posterior distribution* via the Bayes’ Theorem which will provide us with a distribution for obtained with the new knowledge of the quantity and its statistical properties with respect to :

(1)

The mode of the posterior distribution is called the *maximum a posterior* (MAP) *estimator* while the mean is of course . The *posterior predictive distribution* is the distribution of a new as yet unseen data point , :

(2)

where the final equality follows because the data are assumed i.i.d. given . As its name suggests, the posterior predictive distribution can be used to predict new values of .

Much of the Bayesian analysis is concerned with “understanding” the posterior . Note that

which is what we often work with in practice. Sometimes we can recognize the form of the posterior by simply inspecting . But typically we cannot recognize the posterior and cannot compute the denominator of (1) either. In such cases approximate inference techniques such as MCMC are required.

**Beta Distribution**

The beta distribution is applied to model the behavior of random variables limited to intervals of finite lengths.

In Bayesian inference, the beta distribution is the conjugate prior probability distribution for the Bernoulli, binomial, negative binomial, and geometric distributions.

The PDF of the beta distribution is defined for random variable with range and shape parameters . It is a power function of and its reflection as shown below:

where is the Gamma function. The beta function, , is a normalization constant to ensure the total probability is 1.

**Example 1**: A Beta Prior and Binomial Likelihood

Let represents some unknown stochastic parameter. We assume a prior so that:

.

We also assume that so that . The posterior then satisfies

which is another beta distribution with parameters and . Notice how the only dependence on y in the posterior is through the shape parameters of the newly formed beta distribution. This result indicates that the beta distribution is *conjugate prior* of the binomial likelihood. More formal definition of conjugate prior below.

**Conjugate Priors**

Consider the following probabilistic model. The parameter vector has prior while the data is distributed as . As we saw earlier, the posterior distribution satisfies:

.

We say that the prior is a conjugate prior for the likelihood if the posterior satisfies

so that the observations influence the posterior only via a parameter change . In particular, the form or type of the distribution is unchanged. In the earlier Example we saw that the beta distribution is conjugate for the binomial likelihood. Two more examples below.

**Example 2**. Conjugate Prior for Mean of a Normal Distribution

Suppose that and for with is assumed known. In this case we have . If we have

### Markov Chain Monte Carlo

## References

[1] [Transforming Auto-encoders, G. Hinton, A. Krizhevsky, S.D. Wang, 2011](https://github.com/dimitarpg13/deep_learning_and_neural_networks/blob/main/literature/articles/TransformingAutoencodersHinton.pdf)

[2] [Autoencoders, Dor Bank, 2021](https://github.com/dimitarpg13/deep_learning_and_neural_networks/blob/main/literature/articles/Autoencoders.pdf)

[3] [Autoencoders, Unsupervised Learning, and Deep Architectures, Pierre Baldi, 2012](https://github.com/dimitarpg13/deep_learning_and_neural_networks/blob/main/literature/articles/Autoencoders_Unsupervised_Learning_and_Deep_Architectures_Baldi_2012a.pdf)

[4] [Neural Networks and Principal Component Analysis: Learning from Examples Without Local Minima, Pierre Baldi, Kurt Hornik, 1988](https://github.com/dimitarpg13/deep_learning_and_neural_networks/blob/main/literature/articles/Neural_Networks_and_Principal_Component_Analysis-Learning_from_Examples_Without_Local_Minima_Baldi_Hornik-89.pdf)

[5] [Tutorial on Variational Autoencoders, Carl Doersch, Carnegie Mellon, UC Berkeley, 2021](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/variational_autoencoders/Tutorial_on_Variational_Autoencoders_Doersch_2021.pdf)

[6] [Introduction to Variational Autoencoders, Diedrik P. Kingma, Max Welling, 2019](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/variational_autoencoders/An_Introduction_to_Variational_Autoencoders_Kingma_2019.pdf)

[7] [Auto-Encoding Variational Bayes, Diedrik P. Kingma, Max Welling, 2022](https://github.com/dimitarpg13/information_theory_and_statistical_mechanics/blob/main/literature/articles/variational_autoencoders/Auto-Encoding_Variational_Bayes_Kingma_2022.pdf)