
Methods

In **Part II** we will dive into the six families of generative models, including the theory behind how they work and practical examples of how to build each type of model.

In **Chapter 3** we shall take a look at our first generative deep learning model, the *variational autoencoder*. This technique will allow us to not only generate realistic faces, but also alter existing images—for example, by adding a smile or changing the color of someone’s hair.

Chapter 4 explores one of the most successful generative modeling techniques of recent years, the *generative adversarial network*. We shall see the ways that GAN training has been fine-tuned and adapted to continually push the boundaries of what generative modeling is able to achieve.

In **Chapter 5** we will delve into several examples of *autoregressive models*, including LSTMs and PixelCNN. This family of models treats the generation process as a sequence prediction problem—it underpins today’s state-of-the-art text generation models and can also be used for image generation.

In **Chapter 6** we will cover the family of *normalizing flow models*, including RealNVP. This model is based on a change of variables formula, which allows the transformation of a simple distribution, such as a Gaussian distribution, into a more complex distribution in way that preserves tractability.

Chapter 7 introduces the family of *energy-based models*. These models train a scalar energy function to score the validity of a given input. We will explore a technique for training energy-based models called contrastive divergence and a technique for sampling new observations called Langevin dynamics.

Finally, in **Chapter 8** we shall explore the family of *diffusion models*. This technique is based on the idea of iteratively adding noise to an image and then training a model to remove the noise, giving us the ability to transform pure noise into realistic samples.

By the end of **Part II** you will have built practical examples of generative models from each of the six generative modeling families and be able to explain how each works from a theoretical perspective.