mappings from $\boldsymbol{x}$ to $\boldsymbol{y}$ that lack feedback connections. Other models presented later will apply these principles to learning stochastic mappings, learning functions with feedback, and learning probability distributions over a single vector.

We begin this chapter with a simple example of a feedforward network. Next, we address each of the design decisions needed to deploy a feedforward network. First, training a feedforward network requires making many of the same design decisions as are necessary for a linear model: choosing the optimizer, the cost function, and the form of the output units. We review these basics of gradient-based learning, then proceed to confront some of the design decisions that are unique to feedforward networks. Feedforward networks have introduced the concept of a hidden layer, and this requires us to choose the **activation functions** that will be used to compute the hidden layer values. We must also design the architecture of the network, including how many layers the network should contain, how these layers should be connected to each other, and how many units should be in each layer. Learning in deep neural networks requires computing the gradients of complicated functions. We present the **back-propagation** algorithm and its modern generalizations, which can be used to efficiently compute these gradients. Finally, we close with some historical perspective.

6.1 Example: Learning XOR

To make the idea of a feedforward network more concrete, we begin with an example of a fully functioning feedforward network on a very simple task: learning the XOR function.

The XOR function ("exclusive or") is an operation on two binary values, x_1 and x_2. When exactly one of these binary values is equal to 1, the XOR function returns 1. Otherwise, it returns 0. The XOR function provides the target function $y = f^*(\boldsymbol{x})$ that we want to learn. Our model provides a function $y = f(\boldsymbol{x};\boldsymbol{\theta})$ and our learning algorithm will adapt the parameters $\boldsymbol{\theta}$ to make f as similar as possible to f^*.

In this simple example, we will not be concerned with statistical generalization. We want our network to perform correctly on the four points $\mathbb{X} = \{[0,0]^\top, [0,1]^\top, [1,0]^\top, \text{and } [1,1]^\top\}$. We will train the network on all four of these points. The only challenge is to fit the training set.

We can treat this problem as a regression problem and use a mean squared error loss function. We choose this loss function to simplify the math for this example as much as possible. In practical applications, MSE is usually not an