finding these transformations; they're merely searching through a predefined set of operations, called a *hypothesis space*.

So that's what machine learning is, technically: searching for useful representations of some input data, within a predefined space of possibilities, using guidance from a feedback signal. This simple idea allows for solving a remarkably broad range of intellectual tasks, from speech recognition to autonomous car driving.

Now that you understand what we mean by *learning*, let's take a look at what makes *deep learning* special.

1.1.4 The "deep" in deep learning

Deep learning is a specific subfield of machine learning: a new take on learning representations from data that puts an emphasis on learning successive *layers* of increasingly meaningful representations. The *deep* in *deep learning* isn't a reference to any kind of deeper understanding achieved by the approach; rather, it stands for this idea of successive layers of representations. How many layers contribute to a model of the data is called the *depth* of the model. Other appropriate names for the field could have been *layered representations learning* and *hierarchical representations learning*. Modern deep learning often involves tens or even hundreds of successive layers of representations—and they're all learned automatically from exposure to training data. Meanwhile, other approaches to machine learning tend to focus on learning only one or two layers of representations of the data; hence, they're sometimes called *shallow learning*.

In deep learning, these layered representations are (almost always) learned via models called *neural networks*, structured in literal layers stacked on top of each other. The term *neural network* is a reference to neurobiology, but although some of the central concepts in deep learning were developed in part by drawing inspiration from our understanding of the brain, deep-learning models are *not* models of the brain. There's no evidence that the brain implements anything like the learning mechanisms used in modern deep-learning models. You may come across pop-science articles proclaiming that deep learning works like the brain or was modeled after the brain, but that isn't the case. It would be confusing and counterproductive for newcomers to the field to think of deep learning as being in any way related to neurobiology; you don't need that shroud of "just like our minds" mystique and mystery, and you may as well forget anything you may have read about hypothetical links between deep learning and biology. For our purposes, deep learning is a mathematical framework for learning representations from data.

What do the representations learned by a deep-learning algorithm look like? Let's examine how a network several layers deep (see figure 1.5) transforms an image of a digit in order to recognize what digit it is.

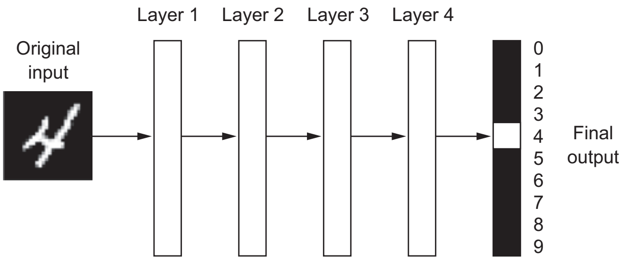


Figure 1.5 A deep neural network for digit classification

As you can see in figure 1.6, the network transforms the digit image into representations that are increasingly different from the original image and increasingly informative about the final result. You can think of a deep network as a multistage information-distillation operation, where information goes through successive filters and comes out increasingly *purified* (that is, useful with regard to some task).

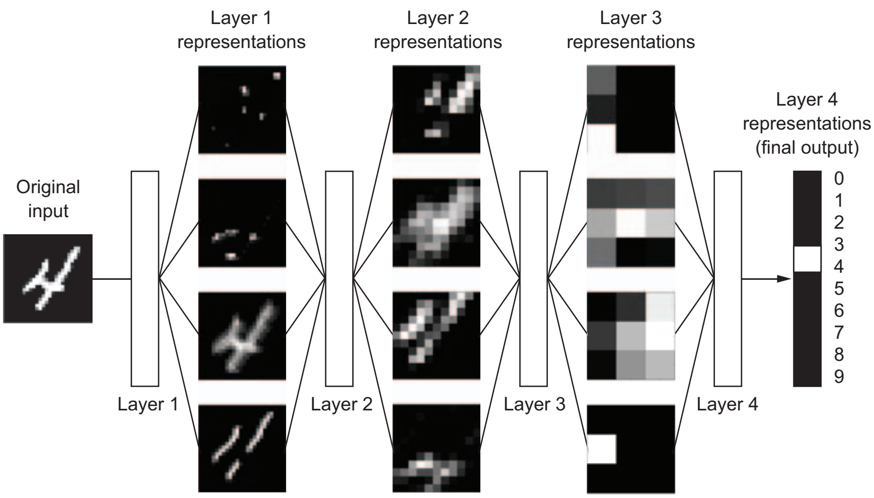


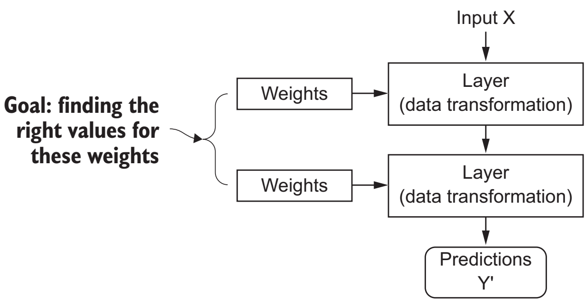
Figure 1.6 Deep representations learned by a digit-classification model

So that's what deep learning is, technically: a multistage way to learn data representations. It's a simple idea—but, as it turns out, very simple mechanisms, sufficiently scaled, can end up looking like magic.

1.1.5 Understanding how deep learning works, in three figures

At this point, you know that machine learning is about mapping inputs (such as images) to targets (such as the label "cat"), which is done by observing many examples of input and targets. You also know that deep neural networks do this input-to-target mapping via a deep sequence of simple data transformations (layers) and that these data transformations are learned by exposure to examples. Now let's look at how this learning happens, concretely.

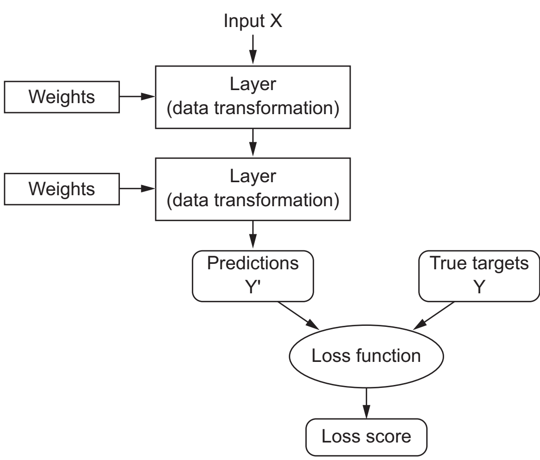
The specification of what a layer does to its input data is stored in the layer's *weights*, which in essence are a bunch of numbers. In technical terms, we'd say that the transformation implemented by a layer is *parameterized* by its weights (see figure 1.7). (Weights are also sometimes called the *parameters* of a layer.) In this context, *learning* means finding a set of values for the weights of all layers in a network, such that the network will correctly map example inputs to their associated targets. But here's the thing: a deep neural network can contain tens of millions of parameters. Finding the correct value for all of them may seem like a daunting task, especially given that modifying the value of one parameter will affect the behavior of all the others!



multiple layers with the data transformation

Figure 1.7 A neural network is parameterized by its weights.

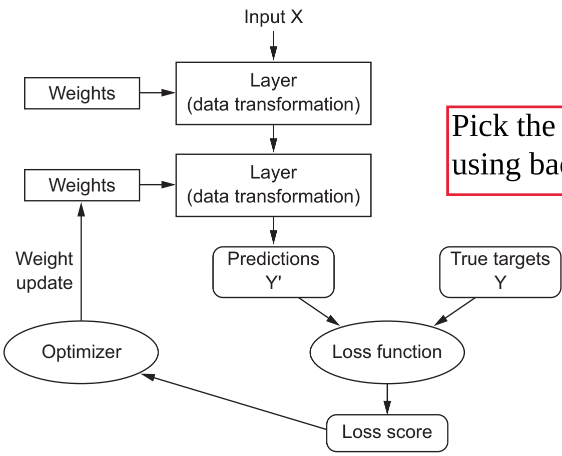
To control something, first you need to be able to observe it. To control the output of a neural network, you need to be able to measure how far this output is from what you expected. This is the job of the *loss function* of the network, also called the *objective function*. The loss function takes the predictions of the network and the true target (what you wanted the network to output) and computes a distance score, capturing how well the network has done on this specific example (see figure 1.8).



goodness of the transformation (weights) ?

Figure 1.8 A loss function measures the quality of the network's output.

The fundamental trick in deep learning is to use this score as a feedback signal to adjust the value of the weights a little, in a direction that will lower the loss score for the current example (see figure 1.9). This adjustment is the job of the *optimizer*, which implements what's called the *Backpropagation* algorithm: the central algorithm in deep learning. The next chapter explains in more detail how backpropagation works.



Pick the best function (weights) using back propagation

Figure 1.9 The loss score is used as a feedback signal to adjust the weights.

Initially, the weights of the network are assigned random values, so the network merely implements a series of random transformations. Naturally, its output is far from what it should ideally be, and the loss score is accordingly very high. But with every example the network processes, the weights are adjusted a little in the correct direction, and the loss score decreases. This is the *training loop*, which, repeated a sufficient number of times (typically tens of iterations over thousands of examples), yields weight values that minimize the loss function. A network with a minimal loss is one for which the outputs are as close as they can be to the targets: a trained network. Once again, it's a simple mechanism that, once scaled, ends up looking like magic.

1.1.6 What deep learning has achieved so far

Although deep learning is a fairly old subfield of machine learning, it only rose to prominence in the early 2010s. In the few years since, it has achieved nothing short of a revolution in the field, with remarkable results on perceptual problems such as seeing and hearing—problems involving skills that seem natural and intuitive to humans but have long been elusive for machines.

In particular, deep learning has achieved the following breakthroughs, all in historically difficult areas of machine learning:

- Near-human-level image classification
- Near-human-level speech recognition
- Near-human-level handwriting transcription
- Improved machine translation

- Improved text-to-speech conversion
- Digital assistants such as Google Now and Amazon Alexa
- Near-human-level autonomous driving
- Improved ad targeting, as used by Google, Baidu, and Bing
- Improved search results on the web
- Ability to answer natural-language questions
- Superhuman Go playing

We're still exploring the full extent of what deep learning can do. We've started applying it to a wide variety of problems outside of machine perception and natural-language understanding, such as formal reasoning. If successful, this may herald an age where deep learning assists humans in science, software development, and more.

1.1.7 Don't believe the short-term hype

Although deep learning has led to remarkable achievements in recent years, expectations for what the field will be able to achieve in the next decade tend to run much higher than what will likely be possible. Although some world-changing applications like autonomous cars are already within reach, many more are likely to remain elusive for a long time, such as believable dialogue systems, human-level machine translation across arbitrary languages, and human-level natural-language understanding. In particular, talk of *human-level general intelligence* shouldn't be taken too seriously. The risk with high expectations for the short term is that, as technology fails to deliver, research investment will dry up, slowing progress for a long time.

This has happened before. Twice in the past, AI went through a cycle of intense optimism followed by disappointment and skepticism, with a dearth of funding as a result. It started with symbolic AI in the 1960s. In those early days, projections about AI were flying high. One of the best-known pioneers and proponents of the symbolic AI approach was Marvin Minsky, who claimed in 1967, "Within a generation … the problem of creating 'artificial intelligence' will substantially be solved." Three years later, in 1970, he made a more precisely quantified prediction: "In from three to eight years we will have a machine with the general intelligence of an average human being." In 2016, such an achievement still appears to be far in the future—so far that we have no way to predict how long it will take—but in the 1960s and early 1970s, several experts believed it to be right around the corner (as do many people today). A few years later, as these high expectations failed to materialize, researchers and government funds turned away from the field, marking the start of the first *AI winter* (a reference to a nuclear winter, because this was shortly after the height of the Cold War).

It wouldn't be the last one. In the 1980s, a new take on symbolic AI, *expert systems*, started gathering steam among large companies. A few initial success stories triggered a wave of investment, with corporations around the world starting their own in-house AI departments to develop expert systems. Around 1985, companies were spending over $1 billion each year on the technology; but by the early 1990s, these systems had proven expensive to maintain, difficult to scale, and limited in scope, and interest died down. Thus began the second AI winter.