Deep learning

深度学习

> 译序
>
> 随着近年来，计算机在多种复杂问题的处理表现上击败人类，无论是科学界还是平民百姓之中，都掀起了人工智能的热潮。而这些问题原来被认为需要高级智能才能正确处理的，它们包括：围棋、组织病理、自动驾驶等等。当前人工智能的基础是深度学习。我一直想寻找一篇深入浅出、具有系统性学习意义，又能帮助大家展望未来的文章来精读一下。Deep Learning 就是这样的好文章。并且我发现它还没有中文版本，也就顺手翻译一下，供大家参考。
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> 这篇文章，不管是对于专业人士，还是普通人，都极具意义。因为不管我们是否愿意，人工智能很快将进入我们生活的方方面面！
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> 计算机专业的人士，可以通过文章中对深度学习的原理解说，以及范例代码，实现快速入门。而作为非专业人士，也能非常形象地了解深度学习的原理，了解一个你必须面对的新生事物，一定不是坏事。
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> 本文是作为开源项目放到我个人的 Github 空间上。一般的用户可以直接下载 PDF 格式的深度学习中英文双语版。
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> 罗峥嵘，2017年6月24日，于广州。

In the last chapter we learned that deep neural networks are often much harder to train than shallow neural networks. That's unfortunate, since we have good reason to believe that *if* we could train deep nets they'd be much more powerful than shallow nets. But while the news from the last chapter is discouraging, we won't let it stop us. In this chapter, we'll develop techniques which can be used to train deep networks, and apply them in practice. We'll also look at the broader picture, briefly reviewing recent progress on using deep nets for image recognition, speech recognition, and other applications. And we'll take a brief, speculative look at what the future may hold for neural nets, and for artificial intelligence.

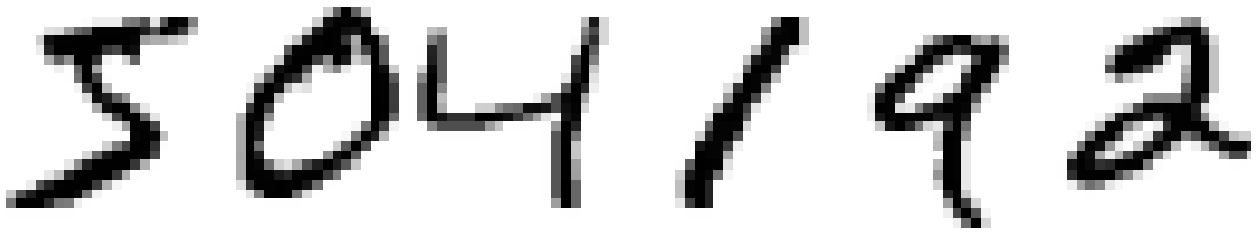
在上一章中，我们研究过训练深度神经网络要比浅度神经网络艰难很多。真是不幸，因为我们有很好的理由相信，*如果*我们可以训练深度网络的话，它将比浅度网络强大很多。尽管上一章的消息的确令人沮丧，我们不会让它阻止我们。在本章中，我们将开发可以用于训练深度网络的技术，并将它们用于实践。我们还要扩大视野，简要地回顾当前深度网络用于图像识别，语音识别，以及其他应用的进展。我们也将简要地展望神经网络的未来，以及它在人工智能上的作用。

The chapter is a long one. To help you navigate, let's take a tour. The sections are only loosely coupled, so provided you have some basic familiarity with neural nets, you can jump to whatever most interests you.

这一章有点长。为了帮助你浏览，让我们先做个参观。段落之间是松散结合的，所以如果你有一定的神经网络的基础，你可以跳到任何你感兴趣的内容中。

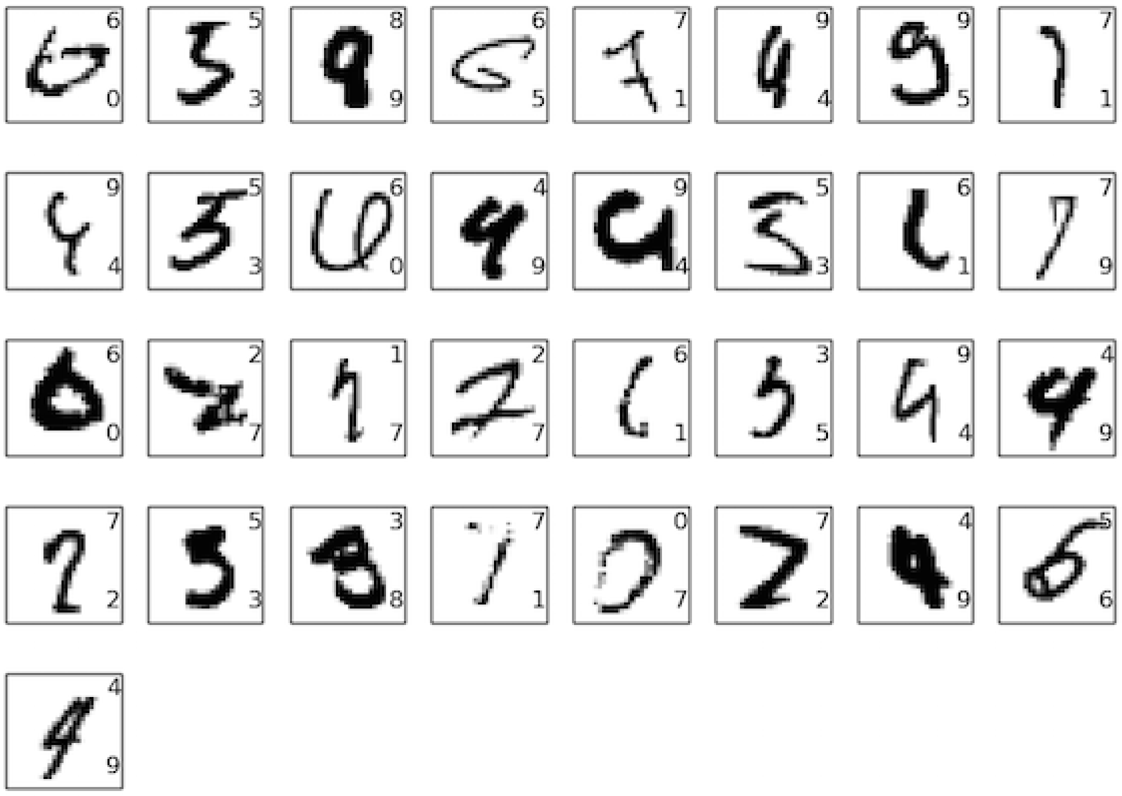
The main part of the chapter is an introduction to one of the most widely used types of deep network: deep convolutional networks. We'll work through a detailed example - code and all - of using convolutional nets to solve the problem of classifying handwritten digits from the MNIST data set:

本章的主要部分是介绍一个最广泛使用的深度网络类型：深度卷积网络。我们的工作将贯穿一个详尽的例子 - 从源代码到方方面面 - 用卷积网络去解决从 MNIST 数据集中分辨手写数字的问题：



We'll start our account of convolutional networks with the shallow networks used to attack this problem earlier in the book. Through many iterations we'll build up more and more powerful networks. As we go we'll explore many powerful techniques: convolutions, pooling, the use of GPUs to do far more training than we did with our shallow networks, the algorithmic expansion of our training data (to reduce overfitting), the use of the dropout technique (also to reduce overfitting), the use of ensembles of networks, and others. The result will be a system that offers near-human performance. Of the 10,000 MNIST test images - images not seen during training! - our system will classify 9,967 correctly. Here's a peek at the 33 images which are misclassified. Note that the correct classification is in the top right; our program's classification is in the bottom right:

我们叙述卷积网络的起点，是本书早前介绍过的以浅度网络解决这个问题的内容。经过多次迭代，我们将构建越来越强大的网络。在我们的历程中，我们将探索许多强大的技术：卷积，池化，使用 GPUs 做相比于浅层网络更多的训练，以算法扩展训练数据（抑制过拟合），使用辍学技术（同样可以抑制过拟合），使用协作网络，等等。最后的结果是系统提供了接近人类的表现。在 10,000 个 MNIST 测试图片中 - 系统在训练期间从来没有看过这些图片 - 我们的系统准确识别 9,967 张。下面是 33 张被错误识别的。请留意，正确的分类标注在右上；程序的分类标注在右下：



Many of these are tough even for a human to classify. Consider, for example, the third image in the top row. To me it looks more like a "9" than an "8", which is the official classification. Our network also thinks it's a "9". This kind of "error" is at the very least understandable, and perhaps even commendable. We conclude our discussion of image recognition with a survey of some of the spectacular recent progress using networks (particularly convolutional nets) to do image recognition.

这堆东西即便是人类来分辨都很艰难。考虑一个例子，第一行的第三个图片。对于我来说，它更像 “9” 而不是 “8”，而官方的分类是 8 。我们的网络当然也将它视为 “9” 。这类的“错误”至少是可以理解的，甚至是可取的。我们通过一个调查来结束我们关于图像识别的讨论，调查中包含了洋洋大观的用网络（特别是卷积网络）进行图像识别的当前进展。

The remainder of the chapter discusses deep learning from a broader and less detailed perspective. We'll briefly survey other models of neural networks, such as recurrent neural nets and long short-term memory units, and how such models can be applied to problems in speech recognition, natural language processing, and other areas. And we'll speculate about the future of neural networks and deep learning, ranging from ideas like intention-driven user interfaces, to the role of deep learning in artificial intelligence.

本章的余下部分，从广义的与宏观远景的方式讨论深度学习。我们将简要地讨论神经网络的其他模型，譬如，循环神经网络和长短期记忆单元，以及这些模型如何应用到语音识别，自然语言处理，与其他领域的问题。并且我们展望神经网络与深度学习的未来，从意念驱动用户界面，到深度学习在人工智能中的角色。

The chapter builds on the earlier chapters in the book, making use of and integrating ideas such as backpropagation, regularization, the softmax function, and so on. However, to read the chapter you don't need to have worked in detail through all the earlier chapters. It will, however, help to have read Chapter 1, on the basics of neural networks. When I use concepts from Chapters 2 to 5, I provide links so you can familiarize yourself, if necessary.

本章建基于书中早前的章节，应用和整合的思想包括反向传播，正则化，softmax 函数，等等。不过，阅读本章你不需要涉及所有早前章节的细节。然而，阅读一下第一章有关神经网络的基础是有帮助的。当我使用的概念来自第二到第五章的时候，我会提供对应的链接，以便你熟悉它们，如果有需要的话。

It's worth noting what the chapter is not. It's not a tutorial on the latest and greatest neural networks libraries. Nor are we going to be training deep networks with dozens of layers to solve problems at the very leading edge. Rather, the focus is on understanding some of the core principles behind deep neural networks, and applying them in the simple, easy-to-understand context of the MNIST problem. Put another way: the chapter is not going to bring you right up to the frontier. Rather, the intent of this and earlier chapters is to focus on fundamentals, and so to prepare you to understand a wide range of current work.

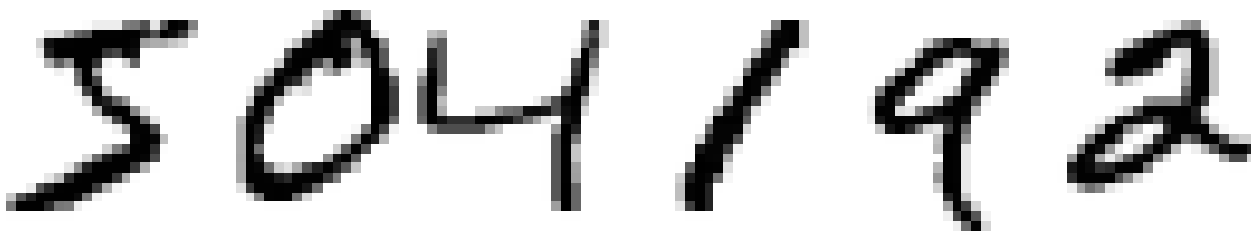
值得注意的是，什么东西不是本章的任务。它不是一个最新和最宏伟的神经网络库的教程。我们也不会去训练几十层的神经网络去解决非常前沿的问题。相反，会聚焦于理解一些深度神经网络背后的核心原理，以及将它们应用到像 MNIST 那样的简单的，易于理解来龙去脉的问题上。从另一面讲：本章不打算把你带到终极解决方案那里去。相反，这一章和早前章节的意愿是聚焦于基本原则，以及让你准备好去理解当前神经网络的方方面面。

Introducing convolutional networks

介绍卷积网络

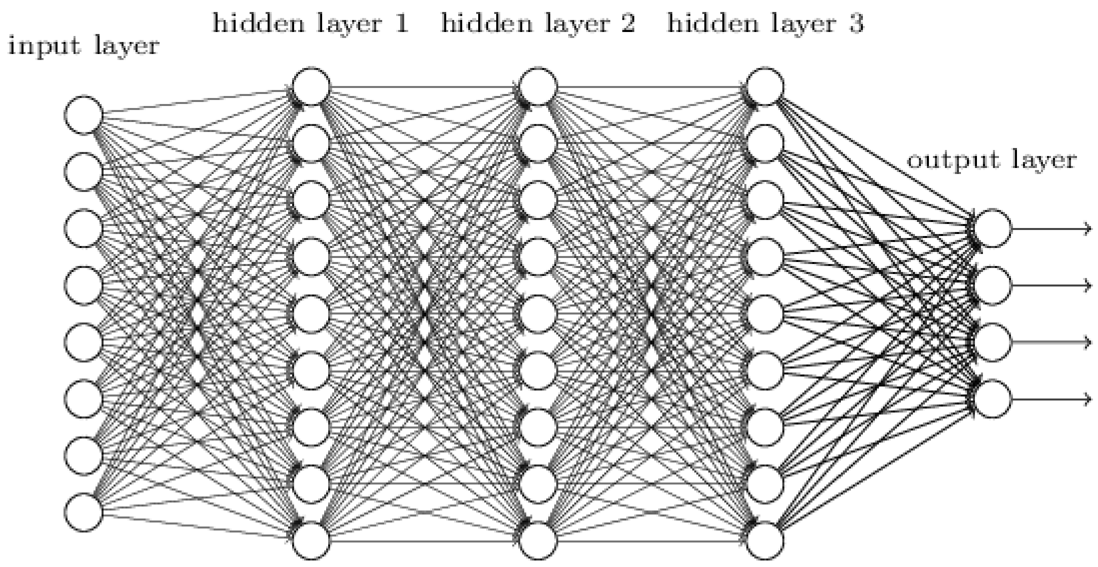
In earlier chapters, we taught our neural networks to do a pretty good job recognizing images of handwritten digits:

在前面的章节中，我们训练了一个工作起来还不错的神经网络，它可以从图片中识别手写的数字：



We did this using networks in which adjacent network layers are fully connected to one another. That is, every neuron in the network is connected to every neuron in adjacent layers:

我们是通过一个相邻的层之间都是全链接的网络来做到这一点的。就是，网络中的每个神经元都与相邻层中的所有神经元链接：



In particular, for each pixel in the input image, we encoded the pixel's intensity as the value for a corresponding neuron in the input layer. For the 28×28 pixel images we've been using, this means our network has 784 (=28×28) input neurons. We then trained the network's weights and biases so that the network's output would - we hope! - correctly identify the input image: '0', '1', '2', ..., '8', or '9'.

具体点说，对于即将被输入的图片中的每个像素，我们都将该像素的灰度，编码为输入层中对应像素的神经元的值。我们采用 28x28 的图片，这意味着我们的网络需要 784(=28x28) 个输入神经元。接着我们训练出网络的权重以及偏至，以便网络能像我们期待的那样区分输入的图片：’0‘，’1‘，’2‘，…’8‘，或者 ’9‘。

Our earlier networks work pretty well: we've obtained a classification accuracy better than 98 percent, using training and test data from the MNIST handwritten digit data set. But upon reflection, it's strange to use networks with fully-connected layers to classify images. The reason is that such a network architecture does not take into account the spatial structure of the images. For instance, it treats input pixels which are far apart and close together on exactly the same footing. Such concepts of spatial structure must instead be inferred from the training data. But what if, instead of starting with a network architecture which is *tabula rasa*, we used an architecture which tries to take advantage of the spatial structure? In this section I describe *convolutional neural networks* *. These networks use a special architecture which is particularly well-adapted to classify images. Using this architecture makes convolutional networks fast to train. This, in turn, helps us train deep, many-layer networks, which are very good at classifying images. Today, deep convolutional networks or some close variant are used in most neural networks for image recognition.

我们早前的网络工作得不错：我们使用 MNIST 手写数字数据集来训练和测试时，取得了高于98%的识别率。不过值得反思的是，以层间全链接的网络来识别图像有点奇怪。理由是，这样的网络架构没有考虑到图像的空间结构。举例来说，该架构对输入像素的处理方式，掩盖了它们的远近关系，然而，训练样本中的数据空间结构关系必须得到体现。我们如何白手起家地搭建一个可以充分利用数据空间结构的网络架构呢？在本章节中，我将介绍*卷积神经网络* *. 这些网络具有非常适合图像分类的特殊架构。应用这些架构使得卷积网络实现快速训练。这样可以帮助我们训练那种深度的多层的网络，这种网络对于图像的分类效果很棒。今天，在神经网络图像识别领域中，*深度卷积网络*以及类似的变体应用得最多。

> The origins of convolutional neural networks go back to the 1970s. But the seminal paper establishing the modern subject of convolutional networks was a 1998 paper, "Gradient-based learning applied to document recognition", by Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. LeCun has since made an interesting remark on the terminology for convolutional nets: "The [biological] neural inspiration in models like convolutional nets is very tenuous. That's why I call them 'convolutional nets' not 'convolutional neural nets', and why we call the nodes 'units' and not 'neurons' ". Despite this remark, convolutional nets use many of the same ideas as the neural networks we've studied up to now: ideas such as backpropagation, gradient descent, regularization, non-linear activation functions, and so on. And so we will follow common practice, and consider them a type of neural network. I will use the terms "convolutional neural network" and "convolutional net(work)" interchangeably. I will also use the terms "[artificial] neuron" and "unit" interchangeably.
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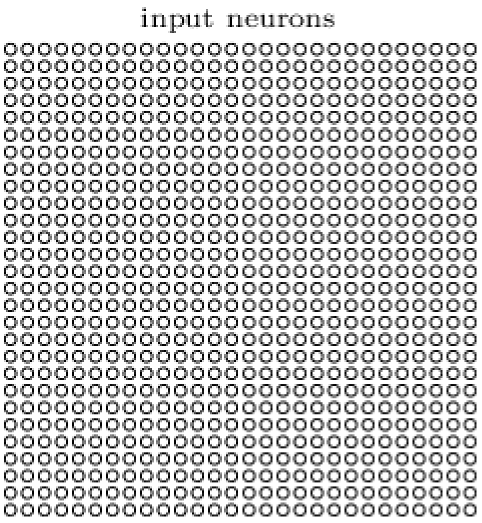
> 卷积神经网络的起源可以追索到20世纪70年代。不过奠定神经网络影响地位的开创性论文是1998年发表的"Gradient-based learning applied to document recognition"，作者是 Yann LeCun, Léon Bottou, Yoshua Bengio, 与 Patrick Haffner。关于卷积网络这个术语，LeCun 曾经做过一个有趣的说明：“在卷积网络模型中，所包含的来自生物神经系统的灵感很少。这就是为什么我叫它们做‘卷积网络’而不是‘卷积神经网络’，以及我们称节点为‘单元’而不是‘神经元’的原因”。尽管如此，卷积网络使用的很多概念，与我们今天研究的神经网络相同：这些概念包括反向传播，梯度下降，正则化，非线性激活函数等等。所以，我们会跟随一般的惯例，都将它们看成是神经网络的一个类型。我会交替使用“卷积神经网络”与“卷积网络”作为术语，我也会交替使用“[人工]神经元”与“单元”作为术语。

Convolutional neural networks use three basic ideas: *local receptive fields*, *shared weights*, and *pooling*. Let's look at each of these ideas in turn.

卷积神经网络使用到三个基本思想：*局部接收域*，*共享权值*，以及*池化*。让我们依次了解一下这些思想。

Local receptive fields: In the fully-connected layers shown earlier, the inputs were depicted as a vertical line of neurons. In a convolutional net, it'll help to think instead of the inputs as a 28×28 square of neurons, whose values correspond to the 28×28 pixel intensities we're using as inputs:

局部接收域： 在早前陈述的全链接层中，输入数据被展开到一个神经元的纵行之中。在卷积网络中，它帮助我们将 28x28 个像素的灰度值的输入，看作是一个由 28x28 个输入点组成的方阵。

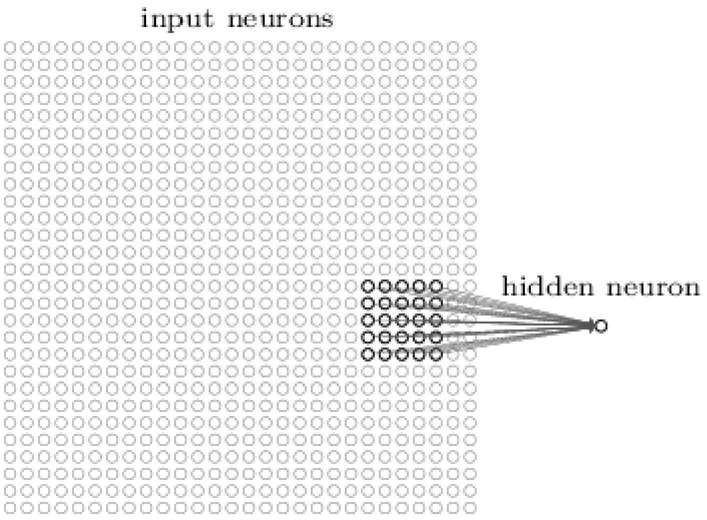


As per usual, we'll connect the input pixels to a layer of hidden neurons. But we won't connect every input pixel to every hidden neuron. Instead, we only make connections in small, localized regions of the input image.

和通常一样，我们将把输入像素链接到一个隐藏层的神经元当中。不过，这次我们不再将所有的输入连接到，所有的隐藏层神经元之中。取而代之的是，我们仅建立对输入图像的小范围的，局部的链接关系。

To be more precise, each neuron in the first hidden layer will be connected to a small region of the input neurons, say, for example, a 5×5 region, corresponding to 25 input pixels. So, for a particular hidden neuron, we might have connections that look like this:

更准确的描述是，每个在第一个隐藏层的神经元，将链接到一个细小的输入区域，譬如说一个 5x5 的区域，对应于 25 个输入像素。所以，对于一个隐藏层神经元，我们的链接看起来如下图：

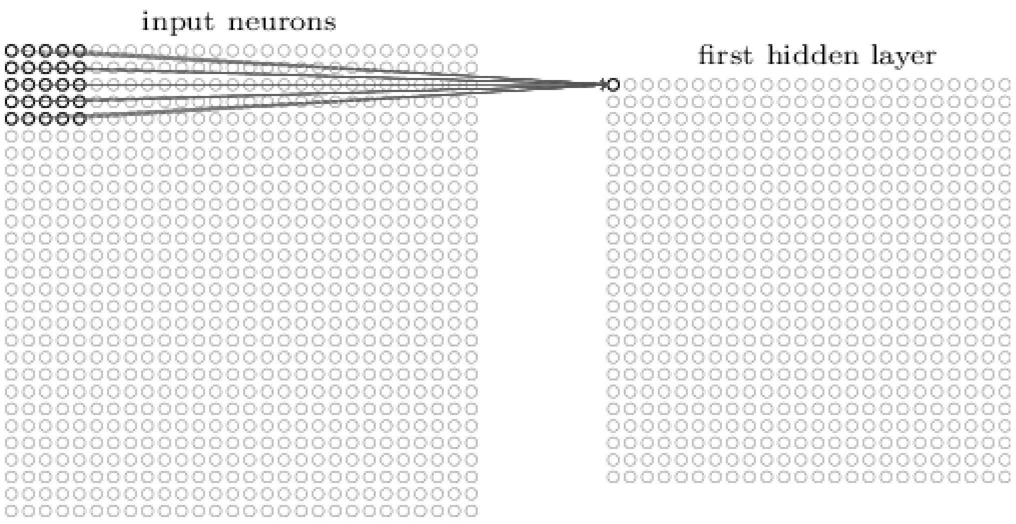


That region in the input image is called the *local receptive field* for the hidden neuron. It's a little window on the input pixels. Each connection learns a weight. And the hidden neuron learns an overall bias as well. You can think of that particular hidden neuron as learning to analyze its particular local receptive field.

对应于隐藏神经元的那个输入图像的细小区域，被称为*局部接收域*。它是一个输入像素的小窗口。它的每个链接都需要通过学习求得权重。同样地每个隐藏层神经元，也要通过学习求出偏至。你可以这样认为，这个特定的隐藏层神经元承担着学习如何分析它所对应的局部接收的任务。

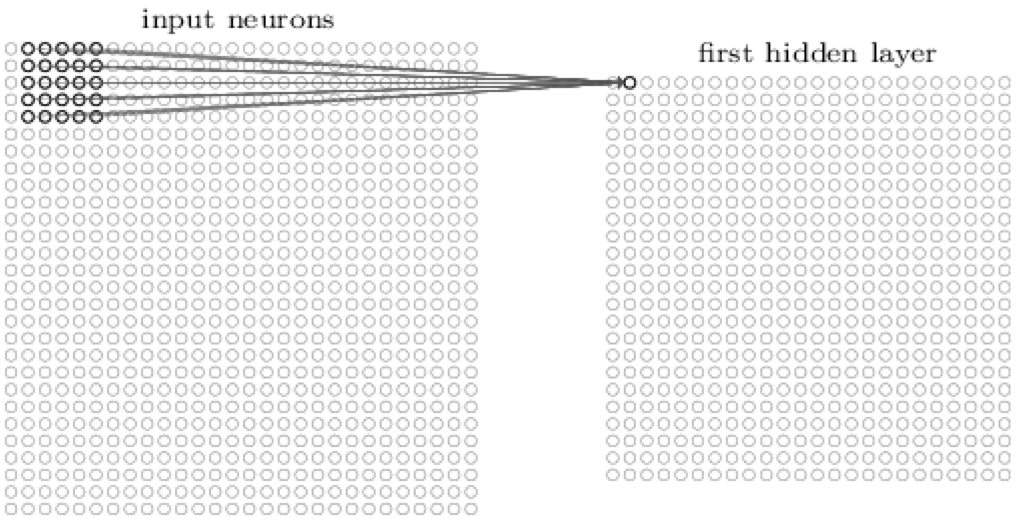
We then slide the local receptive field across the entire input image. For each local receptive field, there is a different hidden neuron in the first hidden layer. To illustrate this concretely, let's start with a local receptive field in the top-left corner:

我们接着将局部接收域滑动扫描过整张输入图片。对于每个局部接收域，都在第一个隐藏层，有一个独立的神经元与之对应。为了具体地说明这个机制，让我们从左上角开始：



Then we slide the local receptive field over by one pixel to the right (i.e., by one neuron), to connect to a second hidden neuron:

我们将局部接收域向右滑动一个像素（这里是一个神经元），并连接到第二个隐藏层神经元：



And so on, building up the first hidden layer. Note that if we have a 28×28 input image, and 5×5 local receptive fields, then there will be 24×24 neurons in the hidden layer. This is because we can only move the local receptive field 23 neurons across (or 23 neurons down), before colliding with the right-hand side (or bottom) of the input image.

如此这般，我们就打造了第一个隐藏层。注意，如果我们的输入图像是 28x28，并且局部接收域是 5x5，那么就有 24x24 个神经元在隐藏层。这是因为我们只能将局部接收域滑动（或者下降 23 个神经元） 23 个像素，之后就会碰到输入图像的右边（或者是下面）。

I've shown the local receptive field being moved by one pixel at a time. In fact, sometimes a different *stride length* is used. For instance, we might move the local receptive field 2 pixels to the right (or down), in which case we'd say a stride length of 2 is used. In this chapter we'll mostly stick with stride length 1, but it's worth knowing that people sometimes experiment with different stride lengths*.

我介绍了将局部接收域每次移动一个像素的情况。事实上，有些时候也会使用不同的步长。例如，我们可以将局部接收域每次向右（或向下）移动 2 个像素，这种情况下我们称为移动 2 个步长。在本章中，我们几乎总是使用 1 个步长，不过值得了解的是，实际应用中，人们会使用不同的步长*。

> As was done in earlier chapters, if we're interested in trying different stride lengths then we can use validation data to pick out the stride length which gives the best performance. For more details, see the earlier discussion of how to choose hyper-parameters in a neural network. The same approach may also be used to choose the size of the local receptive field - there is, of course, nothing special about using a 5×5 local receptive field. In general, larger local receptive fields tend to be helpful when the input images are significantly larger than the 28×28 pixel MNIST images.
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> 正如在早前的章节中所做的那样，如果我们有兴趣尝试不同的步长，那么我们需要用一些可靠的资料来确定步长，以便取得最佳性能。更多的信息，请参阅如何在神经网络中选择超参数的早前讨论。里面同样的方法可以用来选择局部接收域的大小 - 不必总是使用 5x5 的局部接收域的。总的来说，当输入的图像明显大于 MNIST 数据集的 28x28 的图像大小时，更大的局部接收域更加有用。

> > 译注：超参数（hyper-parameters）是指那些凭经验或者调试来确定的参数。譬如，这里讨论的局部接收域的大小是 5x5。有没有想过它或者可以是 8x8 呢？对于本文的 MNIST 数字识别范例，第一个卷积层的结构是 20x24x24，即抽取 20 个特征图等等。就译者所知，目前还没有任何一种成熟的理论体系来指导深度学习的体系架构的设计。

Shared weights and biases: I've said that each hidden neuron has a bias and 5×5 weights connected to its local receptive field. What I did not yet mention is that we're going to use the *same* weights and bias for each of the 24×24 hidden neurons. In other words, for the j, kth hidden neuron, the output is:

共享权值与偏至：我已经谈论过，每个隐藏层神经元有一个偏至以及 5x5 个权重链接到局部接收域。还有一点我没有指出的是，我们将会以相同的权重与偏至应用到 24x24 个隐藏神经元中。换言之，对于第 j, k 个隐藏神经元，它的输出是：

$$\sigma\left(b + \sum_{l=0}^{4}\sum_{m=0}^{4} w_{l,m} a_{j+l,k+m}\right) \tag{125}$$

Here, σ is the neural activation function - perhaps the sigmoid function we used in earlier chapters. b is the shared value for the bias. $w_{l,m}$ is a 5×5 array of shared weights. And, finally, we use $a_{x,y}$ to denote the input activation at position x, y.

这里，σ 是神经激活函数 - 一般就是我们前面说到的 sigmoid 函数。b 是一个共享值，用作偏至。$w_{l,m}$ 是一个 5x5 的共享权值数组。最后，我们用 $a_{x,y}$ 来表示在 x, y 位置的输入值。

This means that all the neurons in the first hidden layer detect exactly the same feature*, just at different locations in the input image.

这样意味着在第一个隐藏层的所有神经元，仅是侦测输入图像的不同位置上的同一个特性。

> I haven't precisely defined the notion of a feature. Informally, think of the feature detected by a hidden neuron as the kind of input pattern that will cause the neuron to activate: it might be an edge in the image, for instance, or maybe some other type of shape.

> 我还没有对特性下过准确的定义。非正式的说法是，通过隐藏神经元抽取的特征，就是足以使神经元激活的某种输入图像所包含的纹理：它也许是图像中的边缘，或者是其他什么形状。

To see why this makes sense, suppose the weights and bias are such that the hidden neuron can pick out, say, a vertical edge in a particular local receptive field. That ability is also likely to be useful at other places in the image. And so it is useful to apply the same feature detector everywhere in the image. To put it in slightly more abstract terms, convolutional networks are well adapted to the translation invariance of images: move a picture of a cat (say) a little ways, and it's still an image of a cat*.

看看个中的道理，假设隐藏层神经元可以通过权值与偏至，能够抽取特定局部接收域中的图像的垂直边缘。那这样的能力在图像的其他位置同样有用。在图像的每个地方都应用相同的特征感测器是很有用的。将它推广为稍微抽象点的概念，卷积网络很适合图像不变性信息的转换：移动一张带猫的照片一点点，它仍然是一张带猫的图片*。

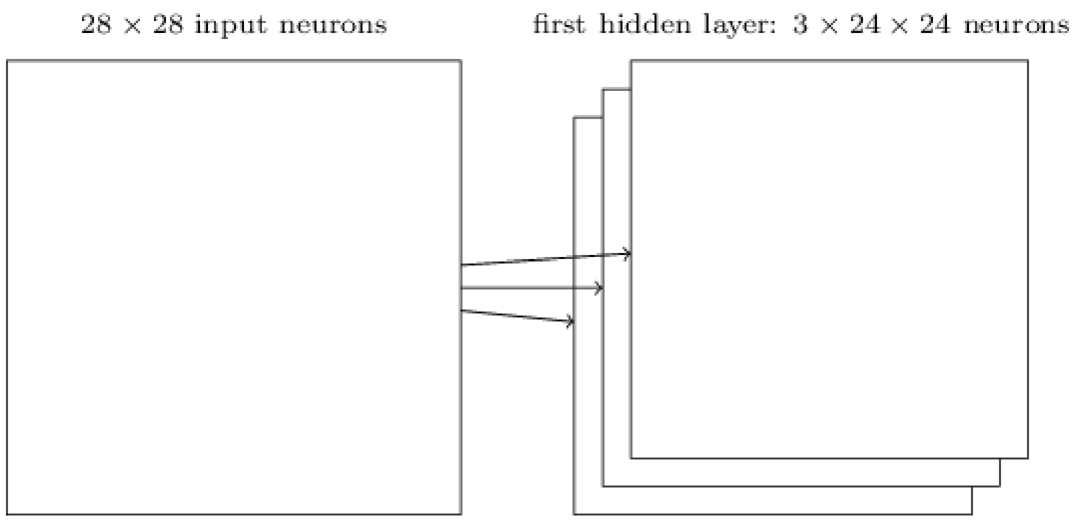
> In fact, for the MNIST digit classification problem we've been studying, the images are centered and size-normalized. So MNIST has less translation invariance than images found "in the wild", so to speak. Still, features like edges and corners are likely to be useful across much of the input space.
>
> 事实上，对于我们正在研究的 MNIST 数字分类问题，图形都是居中以及大小正常的。所以，说起来 MNIST 比那些“野外”的图片具有更少的转换不变性。尽管这样，边缘与转角特征的抽取在整个输入空间中仍然很有用。

For this reason, we sometimes call the map from the input layer to the hidden layer a *feature map*. We call the weights defining the feature map the *shared weights*. And we call the bias defining the feature map in this way the *shared bias*. The shared weights and bias are often said to define a *kernel* or *filter*. In the literature, people sometimes use these terms in slightly different ways, and for that reason I'm not going to be more precise; rather, in a moment, we'll look at some concrete examples.

基于这样的理由，我们有时候将从输入层到隐藏层的映射叫做*特征映射*。我将定义特征映射的权值叫*共享权值*。将定义特征映射的偏至叫做*共享偏至*。共享权值与共享偏至合并在一起通常被称为*内核*或者*滤镜*。在文字上，人们使用这些术语的时候会有一点点差异，因此，我不打算太多计较；在这一刻，我们宁愿看些实际的例子吧。

The network structure I've described so far can detect just a single kind of localized feature. To do image recognition we'll need more than one feature map. And so a complete convolutional layer consists of several different feature maps:

我一路以来介绍的网络结构都是抽取一个局部特征的。要做到图像识别，我们需要不止一个的特征映射。所以完善的卷积层会包含若干个特征图：



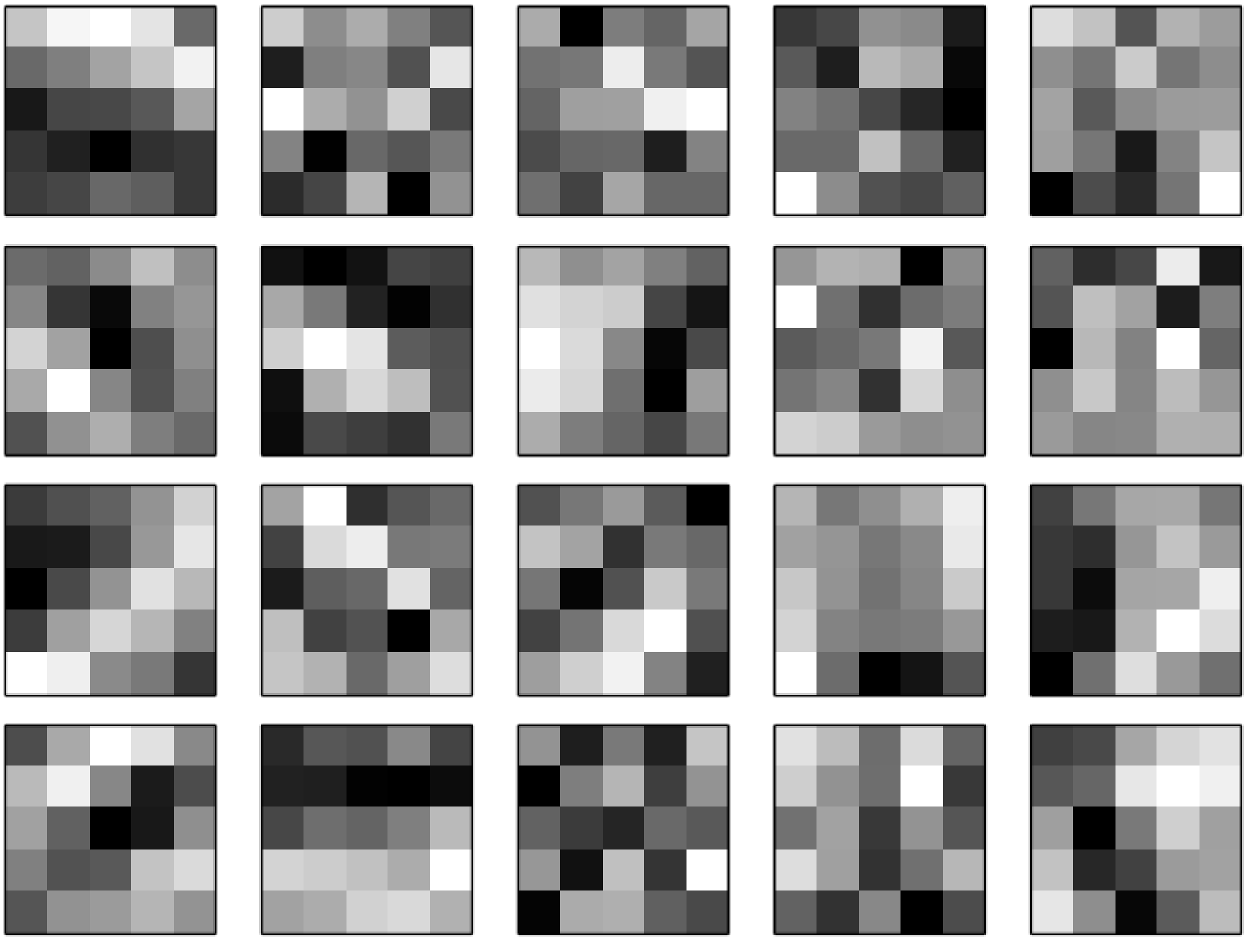
In the example shown, there are 3 feature maps. Each feature map is defined by a set of 5×5 shared weights, and a single shared bias. The result is that the network can detect 3 different kinds of features, with each feature being detectable across the entire image.

在上面的例子中，有三个特征图。每个特征图由 5x5 个共享权值，以及单个共享偏至来定义。结论是网络可以侦测 3 个不同的特征，并且特征的检测历遍了整个图像。

I've shown just 3 feature maps, to keep the diagram above simple. However, in practice convolutional networks may use more (and perhaps many more) feature maps. One of the early convolutional networks, LeNet-5, used 6 feature maps, each associated to a 5×5 local receptive field, to recognize MNIST digits. So the example illustrated above is actually pretty close to LeNet-5. In the examples we develop later in the chapter we'll use convolutional layers with 20 and 40 feature maps. Let's take a quick peek at some of the features which are learned * :

我仅是展示 3 个特征图，是为了保持使得示意图保持简洁。然而，在实际应用中，卷积网络会使用更多的特征图。LeNet-5 是其中一个早期的卷积网络，它使用 6 个特征图，每个关联一个 5x5 的局部接收域，去识别 MNIST 数字。所以上述给大家描述的例子，已经比较接近 LeNet-5 了。在本章后面对这个例子的发展中，我们将在卷积网络中使用 20 至 40 个特征图。现在让我们先窥视一下这些通过训练得到的特征是什么样子的：

> The feature maps illustrated come from the final convolutional network we train, see here.
>
> 这里展示的特征图来自我们最后训练出来的卷积网络，看这里 。



The 20 images correspond to 20 different feature maps (or filters, or kernels). Each map is represented as a 5×5 block image, corresponding to the 5×5 weights in the local receptive field. Whiter blocks mean a smaller (typically, more negative) weight, so the feature map responds less to corresponding input pixels. Darker blocks mean a larger weight, so the feature map responds more to the corresponding input pixels. Very roughly speaking, the images above show the type of features the convolutional layer responds to.

这 20 个图片对应于 20 个不同的特征映射（或者叫滤镜，内核）。每个映射表现为一个 5x5 的方块图像，对应于 5x5 个在局部接收域中的权重。白色的方块表示更小的权重值（更加负面），所以特征映射对输入像素的响应更小。黑色的方块意味着更大的权重值，这样特征映射对于输入像素的响应更大。大体来说，上面的图型展示了卷积层对不同特征类型的响应。

So what can we conclude from these feature maps? It's clear there is spatial structure here beyond what we'd expect at random: many of the features have clear sub-regions of light and dark. That shows our network really is learning things related to the spatial structure. However, beyond that, it's difficult to see what these feature detectors are learning. Certainly, we're not learning (say) the Gabor filters which have been used in many traditional approaches to image recognition. In fact, there's now a lot of work on better understanding the features learnt by convolutional networks. If you're interested in following up on that work, I suggest starting with the paper Visualizing and Understanding Convolutional Networks by Matthew Zeiler and Rob Fergus (2013).

通过这些特征图，我们会有什么收获呢？很明显，这些空间结构超出了我们最大胆的想象：大部分的特征都有黑白分明的子区域。那就表明了我们的网络，的确是在学习一些与空间结构相关的东西。无论如何，除此之外，我们很难通过其他途径来看到特征感测器正在学习。十分肯定的是，我们并不是在训练 Gabor 滤镜，它在传统的图像识别技术中被广泛使用。事实上，要更好地理解卷积网络的特征学习，还需要做很多工作。如果你对接下来的这些工作有兴趣，我建议从这篇论文 Visualizing and Understanding Convolutional Networks 开始，它由 Matthew Zeiler 和 Rob Fergus 在 2013 年发表。

A big advantage of sharing weights and biases is that it greatly reduces the number of parameters involved in a convolutional network. For each feature map we need 25=5×5 shared weights, plus a single shared bias. So each feature map requires 26 parameters. If we have 20 feature maps that's a total of 20×26=520 parameters defining the convolutional layer. By comparison, suppose we had a fully connected first layer, with 784=28×28 input neurons, and a relatively modest 30 hidden neurons, as we used in many of the examples earlier in the book. That's a total of 784×30 weights, plus an extra 30 biases, for a total of 23,550 parameters. In other words, the fully-connected layer would have more than 40 times as many parameters as the convolutionual layer.

共享权值和偏至的优势是它们可以极大地节省构建卷积网络的参数数量。对于每个特征图，我们仅需要 25=5x5 个共享权值，外加一个共享偏至。所以每个特征图需要 26 个参数。如果我们需要 20 个特征图，你定义这个卷积网络的参数就是 20x26=520。相比较而言，假如我们在第一个层使用全链接网络，则需要 784=28x28 个输入神经元，大致用 30 个隐藏神经元比较恰当，就如本书之前的很多例子那样。那样一共需要 784x30 个权值，外加 30 个偏至，总共 23,550 个参数。换言之，全链接网络使用的参数是卷积网络的 40 倍。

Of course, we can't really do a direct comparison between the number of parameters, since the two models are different in essential ways. But, intuitively, it seems likely that the use of translation invariance by the convolutional layer will reduce the number of parameters it needs to get the same performance as the fully-connected model. That, in turn, will result in faster training for the convolutional model, and, ultimately, will help us build deep networks using convolutional layers.

当然，我们不能机械地比较参数数量的差别，毕竟两个模型本质上采用不同的方法学。不过，直觉上，对于实现转换不变性这样的目的来说，卷积网络可以节省不少的参数而获得与全链接网络同等的性能。进一步讲，卷积网络能够有更快的训练速度，最终有利于我们以卷积层构建深度网络。

Incidentally, the name *convolutional* comes from the fact that the operation in Equation (125) is sometimes known as a *convolution*. A little more precisely, people sometimes write that equation as $a^1 = \sigma(b + w * a^0)$, where a^1 denotes the set of output activations from one feature map, a^0 is the set of input activations, and $*$ is called a convolution operation. We're not going to make any deep use of the mathematics of convolutions, so you don't need to worry too much about this connection. But it's worth at least knowing where the name comes from.

顺带说明一下，*卷积*这个词来自于算式（125），它有时候被当作是*卷积*运算。更精确地，大家有时候将算式写成 $a^1 = \sigma(b + w * a^0)$，这里 a^1 表示其中一个特征图的激活输出值的集合，a^0 表示有效输入值的集合，而 $*$ 被称为卷积运算符。我们将不会对数学意义上的卷积涉及太深，所以你也无需对它们之间的关联担心太多。不过，知道这个名称的由来总是有好处的。

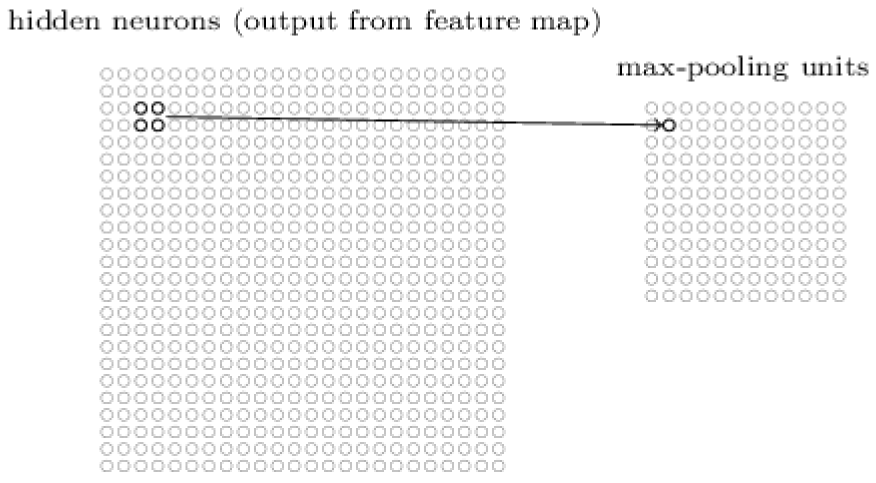
Pooling layers: In addition to the convolutional layers just described, convolutional neural networks also contain *pooling layers*. Pooling layers are usually used immediately after convolutional layers. What the pooling layers do is simplify the information in the output from the convolutional layer.

池化层：除了刚刚介绍过的卷积层之外，卷积神经网络通常也包含*池化层*。卷积层之后通常立即使用池化层。池化层的作用就是简化卷积层中输出的信息。

In detail, a pooling layer takes each feature map* output from the convolutional layer and prepares a condensed feature map. For instance, each unit in the pooling layer may summarize a region of (say) 2×2 neurons in the previous layer. As a concrete example, one common procedure for pooling is known as *max-pooling*. In max-pooling, a pooling unit simply outputs the maximum activation in the 2×2 input region, as illustrated in the following diagram:

详细地说，池化层将卷积层中的输出再浓缩到一个特征图*中。例如，每个池化层中的单元都是对前面一个层的某个区域（譬如，2x2 个像素）的汇总。举个实际的例子，一个常见的池化处理是*极值池化（max-pooling）*。在极值池化中，一个池化单元就只是简单地将 2x2 输入区域中的最大激活值输出。

> The nomenclature is being used loosely here. In particular, I'm using "feature map" to mean not the function computed by the convolutional layer, but rather the activation of the hidden neurons output from the layer. This kind of mild abuse of nomenclature is pretty common in the research literature.
>
> 这个术语在这里用得有点随意。特别地，相比于使用激活值这个术语，我会用“特征图”来表示通过卷积层来的计算方法获得的结果。这种术语的随意使用的情况，在科研类文章中很常见。

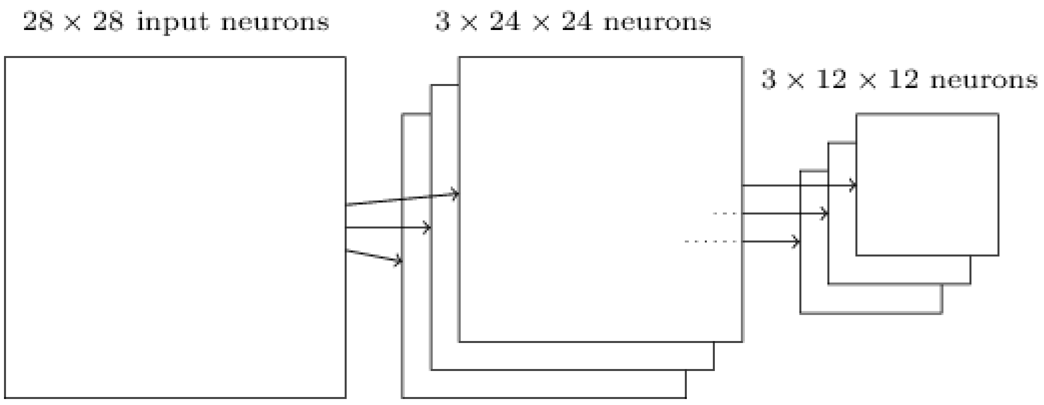


Note that since we have 24×24 neurons output from the convolutional layer, after pooling we have 12×12 neurons.

注意，当我们有一个 24x24 个输出神经元的卷积层时，经过池化处理之后，我们会得到一个 12x12 的神经元。

As mentioned above, the convolutional layer usually involves more than a single feature map. We apply max-pooling to each feature map separately. So if there were three feature maps, the combined convolutional and max-pooling layers would look like:

正如上面提及的那样，卷积网络通常包含一个以上的特征图。我们分别对每个特征图应用极值池化。所以，如果我们有三个特征图，卷积层和池化层结合后的样子应该像这样：



28×28 input neurons
$3 \times 24 \times 24$ neurons
$3 \times 12 \times 12$ neurons

We can think of max-pooling as a way for the network to ask whether a given feature is found anywhere in a region of the image. It then throws away the exact positional information. The intuition is that once a feature has been found, its exact location isn't as important as its rough location relative to other features. A big benefit is that there are many fewer pooled features, and so this helps reduce the number of parameters needed in later layers.

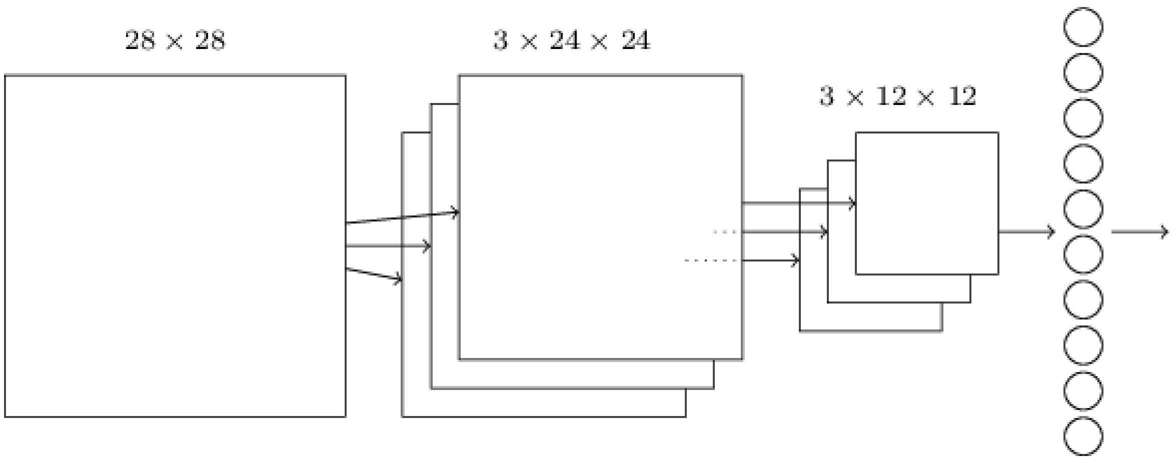
我们可以将极值池化看作是一个查证的方法，它说明了在图像的某个区域中是否有某种给定的特征存在。它还会给出准确的位置信息。在直觉上就可知，一旦某个特征被发现，重要的是它与其他特征的大致的位置关联性，而不是它自己的确切位置。这样的一大好处是，形成了数量较小的被池化后的特征，并且帮助后续的层节省参数的数量。

Max-pooling isn't the only technique used for pooling. Another common approach is known as *L2 pooling*. Here, instead of taking the maximum activation of a 2×2 region of neurons, we take the square root of the sum of the squares of the activations in the 2×2 region. While the details are different, the intuition is similar to max-pooling: L2 pooling is a way of condensing information from the convolutional layer. In practice, both techniques have been widely used. And sometimes people use other types of pooling operation. If you're really trying to optimize performance, you may use validation data to compare several different approaches to pooling, and choose the approach which works best. But we're not going to worry about that kind of detailed optimization.

极值池化并非唯一的池化技术。常用的方法还有 *L2 池化*。这里，替代取 2x2 区域中激活值的最大值，我们取 2x2 区域中激活值的平方和的方根作为池化值。尽管细节上有不同，直觉上它与极值池化类似：L2 池化也是一个将卷积层的信息浓缩的方法。在实践中，两种技术都应用广泛。有时大家还会使用其他的池化操作。当你已经准备优化性能的话，你也许需要用些可靠的资料来比较不同的池化方法，以便取得最佳的方案。不过，在这里我们不打算纠结于各种优化的细节。

Putting it all together: We can now put all these ideas together to form a complete convolutional neural network. It's similar to the architecture we were just looking at, but has the addition of a layer of 10 output neurons, corresponding to the 10 possible values for MNIST digits ('0', '1', '2', *etc*):

总体集成：我们现在可以将所有的构思集结到一起形成完整的卷积神经网络了。它看起来很像我们刚刚看过的架构，不过还附加了 10 个神经元，对应于 MNIST 数字可能的值。



The network begins with 28×28 input neurons, which are used to encode the pixel intensities for the MNIST image. This is then followed by a convolutional layer using a 5×5 local receptive field and 3 feature maps. The result is a layer of 3×24×24 hidden feature neurons. The next step is a max-pooling layer, applied to 2×2 regions, across each of the 3 feature maps. The result is a layer of 3×12×12 hidden feature neurons.

网络开始时有 28x28 个输入神经元，它用于编码 MNIST 图像的像素灰度。接着会跟随着一个使用 5x5 局部接受域以及 3 个特征图的卷积层。结果是形成一个 3x24x24 个隐藏特征神经元的层。下一步就是一个极值池化层，使用 2x2 的区块，历遍 3 个特征图。这样再形成一个 3x12x12 个隐藏特征神经元。

The final layer of connections in the network is a fully-connected layer. That is, this layer connects *every* neuron from the max-pooled layer to every one of the 10 output neurons. This fully-connected architecture is the same as we used in earlier chapters. Note, however, that in the diagram above, I've used a single arrow, for simplicity, rather than showing all the connections. Of course, you can easily imagine the connections.

网络的最后一个链接层是一个全链接层。该层将所有的极值池化层中的所有神经元，都全链接到 10 个输出神经元中的每一个之中。这个全链接架构与我们之前的章节中使用的相同。注意，上面的示意图，我使用了单个箭头，这比画出所有的链接更简洁。当然了，你应该很容易想像这些链接的样子。

This convolutional architecture is quite different to the architectures used in earlier chapters. But the overall picture is similar: a network made of many simple units, whose behaviors are determined by their weights and biases. And the overall goal is still the same: to use training data to train the network's weights and biases so that the network does a good job classifying input digits.

这个卷积架构与之前章节中使用的完全不同。不过总体的场景是那么熟悉：一个有许多简单单元构成的网络，它的行为表现决定于它们的权值与偏至。总体的目标仍然相同：以样本数据去训练出网络的权值与偏至，使得网络对输入数字的分辨工作良好。

In particular, just as earlier in the book, we will train our network using stochastic gradient descent and backpropagation. This mostly proceeds in exactly the same way as in earlier chapters. However, we do need to make a few modifications to the backpropagation procedure. The reason is that our earlier derivation of backpropagation was for networks with fully-connected layers. Fortunately, it's straightforward to modify the derivation for convolutional and max-pooling layers. If you'd like to understand the details, then I invite you to work through the following problem. Be warned that the problem will take some time to work through, unless you've really internalized the earlier derivation of backpropagation (in which case it's easy).

特别是，我们将使用随机梯度下降以及反向传播来训练我们的网络，这就会像本书前面所介绍的内容那样容易。绝大部分的步骤都和早前的章节介绍的一样。不过，我们需要对反向传播做一些调整。理由是我们之前的反向传播算法的推导是面向全链接网络的。幸运的是，对于卷积和极值池化层的反向传播推导修改起来很简单易懂。要是你希望了解详情，那么我邀请你为下面的问题做点事。下面提及的问题，需要花点时间才能搞定，除非你已经深入了解

过早前的反向传播的推导（在这种情况下就很容易了）。

Problem

问题

- **Backpropagation in a convolutional network** The core equations of backpropagation in a network with fully-connected layers are (BP1)-(BP4) (link). Suppose we have a network containing a convolutional layer, a max-pooling layer, and a fully-connected output layer, as in the network discussed above. How are the equations of backpropagation modified?

  卷积网络中的反向传播 全链接网络中的反向传播的核心公式是 (BP1)-(BP4) (link)。假设我们有一个网络，它包含一个卷积层，以及极值池化层，一个用于输出的全链接层，就像我们在上面讨论过的网络一样。如何调整反向传播的公式呢？

  > BP1: $\delta_j^L = \frac{\partial C}{\partial a_j^L}\sigma'(z_j^L)$
  >
  > BP4: $\frac{\partial C}{\partial w_{jk}^l} = a_k^{l-1}\delta_j^l$

Convolutional neural networks in practice

实战中的卷积神经网络

We've now seen the core ideas behind convolutional neural networks. Let's look at how they work in practice, by implementing some convolutional networks, and applying them to the MNIST digit classification problem. The program we'll use to do this is called `network3.py`, and it's an improved version of the programs `network.py` and `network2.py` developed in earlier chapters *. If you wish to follow along, the code is available on GitHub. Note that we'll work through the code for `network3.py` itself in the next section. In this section, we'll use `network3.py` as a library to build convolutional networks.

我们现在已经看过卷积神经网络后面的核心思想。下面让我们通过实现一些卷积网络，以及将它们用于解决 MNIST 数字分辨的问题，看看它在实战中如何运作。我们将要使用到的程序叫 `network3.py`，以及它一个改进版本 `network.py` 与在早前的章节*中发展起来的 `network2.py`。要是你希望跟踪这些程序，可以在 on GitHub 得到它们的源代码。在下一个段落中，我们将介绍 `network3.py` 源码本身。而在本段落中，我们将以 `network3.py` 作为一个函数库来构建一个卷积网络。

> Note also that `network3.py` incorporates ideas from the Theano library's documentation on convolutional neural nets (notably the implementation of LeNet-5), from Misha Denil's implementation of dropout, and from Chris Olah.
>
> 提示一下，`network3.py` 的实现思想来自卷积神经网络函数库 Theano 的文档（特别是 LeNet-5 的实现部分），以及 Misha Denil 的论文 implementation of dropout，还有 Chris Olah。

The programs `network.py` and `network2.py` were implemented using Python and the matrix library Numpy. Those programs worked from first principles, and got right down into the details of backpropagation, stochastic gradient descent, and so on. But now that we understand those details, for `network3.py` we're going to use a machine learning library known as Theano*. Using Theano makes it easy to implement backpropagation for convolutional neural networks, since it automatically computes all the mappings involved. Theano is also quite a bit faster than our earlier code (which was written to be easy to understand, not fast), and this makes it practical to train more complex networks. In particular, one great feature of Theano is that it can run code on either a CPU or, if available, a GPU. Running on a GPU provides a substantial speedup and, again, helps make it practical to train more complex networks.

程序 `network.py` 和 `network2.py` 都是基于 Python 以及矩阵库 Numpy 来实现的。程序从最基本的原则开始，直至一路展开各种细节，像反向传播，随机梯度下降等等。不过在我们已经明白了详情之后，对于程序 `network3.py` ，我们将会直接调用机器学习库 Theano*。使用 Theano 可使卷积神经网络的反向传播更加容易实现，因为它能够自动计算所有被包含的映射。Theano 在速度上完胜我们早前的代码（那份代码是为了容易理解而写，不是追求速度），并且这使得更复杂的网络在训练上更有实效。特别是，Theano 的一个了不起的特性是它可以运行于 CPU 上，或者是 GPU 上。运行在 GPU 上使程序得到实质性的加速，这同样有助于训练更加复杂的网络。

> See Theano: A CPU and GPU Math Expression Compiler in Python, by James Bergstra, Olivier Breuleux, Frederic Bastien, Pascal Lamblin, Ravzan Pascanu, Guillaume Desjardins, Joseph Turian, David Warde-Farley, and Yoshua Bengio (2010). Theano is also the basis for the popular Pylearn2 and Keras neural networks libraries. Other popular neural nets libraries at the time of this writing include Caffe and Torch.
>
> 参考 Theano: A CPU and GPU Math Expression Compiler in Python, 它由 James Bergstra, Olivier Breuleux, Frederic Bastien, Pascal Lamblin, Ravzan Pascanu, Guillaume Desjardins, Joseph Turian, David Warde-Farley, 与 Yoshua Bengio 在 2010 年发表。Theano 是流行的神经网络库 Pylearn2 与 Keras 的基础。其他流行的神经网络库在本文撰写的时候也开始支持 Theano，包括 Caffe 和 Torch。

If you wish to follow along, then you'll need to get Theano running on your system. To install Theano, follow the instructions at the project's homepage. The examples which follow were run using Theano 0.6*. Some were run under Mac OS X Yosemite, with no GPU. Some were run on Ubuntu 14.04, with an NVIDIA GPU. And some of the experiments were run under both. To get `network3.py` running you'll need to set the `GPU` flag to either `True` or `False` (as appropriate) in the `network3.py` source. Beyond that, to get Theano up and running on a GPU you may find the instructions here helpful. There are also tutorials on the web, easily found using Google, which can help you get things working. If you don't have a GPU available locally, then you may wish to look into Amazon Web Services EC2 G2 spot instances. Note that even with a GPU the code will take some time to execute. Many of the experiments take from minutes to hours to run. On a CPU it may take days to run the most complex of the experiments. As in earlier chapters, I suggest setting things running, and continuing to read, occasionally coming back to check the output from the code. If you're using a CPU, you may wish to reduce the number of training epochs for the more complex experiments, or perhaps omit them entirely.

如果你打算跟着一起玩，那么你需要部署 Theano，让它运行在你的系统上。可以根据项目主页上的指引安装 Theano。接下来的范例需要运行在 Theano 0.6* 上。有些需要运行在 Mac OS X Yosemite 上，无需 GPU 支持。有些运行在 Ubuntu 14.04 上，需要 NVIDIA GPU。而有些实习可以运行在上述两个系统上。要使 `network3.py` 正确运行，你需要在 `network3.py` 源码中（恰当地）将 `GPU` 这个标志设置为 `True` 或者 `False`。除此之外，要在 GPU 上正确配置和运行 Theano，你会发现 这里的指引 非常有用。网上还有很多的教程，很容易通过 Google 找到，它们会帮助你搞定很多事情。如果你自己没有可用的 GPU，你或者可以看看 Amazon Web Services 的 EC2.G2 套餐。值得注意的是，即使使用 GPU，代码的执行还是会挺费时的。许多实验的运行时间长达几分钟到几个小时，仅是以 CPU 来运行复杂的实验的话，可能要花费数天的时间。就像在前面，我建议的那样，先配置运行某些作业，然后继续阅读文献，偶尔回头看看程序的输出。如果你只是使用 CPU，对于复杂的实验，你可能会希望减少训练的时间片段，或者宁愿整个忽略它们。

> As I release this chapter, the current version of Theano has changed to version 0.7. I've actually rerun the examples under Theano 0.7 and get extremely similar results to those reported in the text.

> 当我发表这个文章的时候，Theano 已经升级到 0.7 版本。我在 Theadno 0.7 上重新运行过那些例子，并且得到与官方的汇报非常近似的结果。

To get a baseline, we'll start with a shallow architecture using just a single hidden layer, containing 100 hidden neurons. We'll train for 60 epochs, using a learning rate of $\eta = 0.1$, a mini-batch size of 10, and no regularization. Here we go*:

先搞个入门级的，我们将以仅包含一个隐藏层的浅层网络作为起点，它包含100个隐藏神经元。我们将训练60个轮次，学习步长 $\eta = 0.1$，微批量大小是 10 ，不考虑正则化。我们这就开始*：

> > 译注：mini-batch size，每次梯度下降训练抽取的样本数据数量

```
>>> import network3
>>> from network3 import Network
>>> from network3 import ConvPoolLayer , FullyConnectedLayer , SoftmaxLayer
>>> training_data , validation_data , test_data = network3.load_data_shared()
>>> mini_batch_size = 10
>>> net = Network([
        FullyConnectedLayer(n_in=784, n_out=100),
        SoftmaxLayer(n_in=100, n_out=10)], mini_batch_size)
>>> net.SGD(training_data , 60, mini_batch_size , 0.1,
            validation_data , test_data)
```

> Code for the experiments in this section may be found in this script. Note that the code in the script simply duplicates and parallels the discussion in this section.
>
> Note also that throughout the section I've explicitly specified the number of training epochs. I've done this for clarity about how we're training. In practice, it's worth using early stopping, that is, tracking accuracy on the validation set, and stopping training when we are confident the validation accuracy has stopped improving.
>
> 这一段中的实习代码可以在这个脚本里面找到。脚本中的代码与本段完全一致，并且与本段的讨论顺序是并行对应的。
>
> 还要注意，在整个段落中，我都明确定义了训练的轮次。我这样做是为了标明我们是如何训练的。事实上，提前终止是很有用。就是说，密切跟踪通过使用验证数据集测试得到的准确率，当我们确信验证的准确率不会再改善的时候，就可以停止训练了。

I obtained a best classification accuracy of 97.80 percent. This is the classification accuracy on the `test_data`, evaluated at the training epoch where we get the best classification accuracy on the `validation_data`. Using the validation data to decide when to evaluate the test accuracy helps avoid overfitting to the test data (see this earlier discussion of the use of validation data). We will follow this practice below. Your results may vary slightly, since the network's weights and biases are randomly initialized*.

我取得了最高 97.80% 的最佳分类精度。这个是在`测试数据`上取得的分类精度，我们以`验证数据`在训练轮次中对网络进行评估，以便确定在哪里获得最佳的分类精度。使用验证数据来决定何时检测分类精度，以帮助避免出现对测试数据的过拟合（请参考有关验证数据的使用的早前讨论）。我们会伴随后续的内容进行练习，你得到的结果可能略有不同，原因是网络的权值和偏至是随机初始化*的。

> In fact, in this experiment I actually did three separate runs training a network with this architecture. I then reported the test accuracy which corresponded to the best validation accuracy from any of the three runs. Using multiple runs helps reduce variation in results, which is useful when comparing many architectures, as we are doing. I've followed this procedure below, except where noted. In practice, it made little difference to the results obtained.
>
> 事实上，在这个实验当中，我是在相同架构下的一个网络上分开三个进程来训练。我给大家报告的那个最佳的分类率，就是在这三个进程中对应于最佳核实分类准确度的那个。多进程训练，有助于降低结果的不确定性，从而有利于比较各种架构，就如我们正在做的（各种深度学习的架构探索）那样。

This 97.80 percent accuracy is close to the 98.04 percent accuracy obtained back in Chapter 3, using a similar network architecture and learning hyper-parameters. In particular, both examples used a shallow network, with a single hidden layer containing 100 hidden neurons. Both also trained for 60 epochs, used a mini-batch size of 10, and a learning rate of $\eta = 0.1$.

这里的 97.80% 的分辨精度已经接近第三章所取得的 98.04% 的分辨精度，两者用的是类似的架构以及学习参数。事实上，两个例子使用的都是浅层网络，包含一个 100 个隐藏神经元的隐藏层。两者都训练 60 个轮次，微批量大小为 10，以及学习步长 $\eta = 0.1$ 。

There were, however, two differences in the earlier network. First, we regularized the earlier network, to help reduce the effects of overfitting. Regularizing the current network does improve the accuracies, but the gain is only small, and so we'll hold off worrying about regularization until later. Second, while the final layer in the earlier network used sigmoid activations and the cross-entropy cost function, the current network uses a softmax final layer, and the log-likelihood cost function. As explained in Chapter 3 this isn't a big change. I haven't made this switch for any particularly deep reason - mostly, I've done it because softmax plus log-likelihood cost is more common in modern image classification networks.

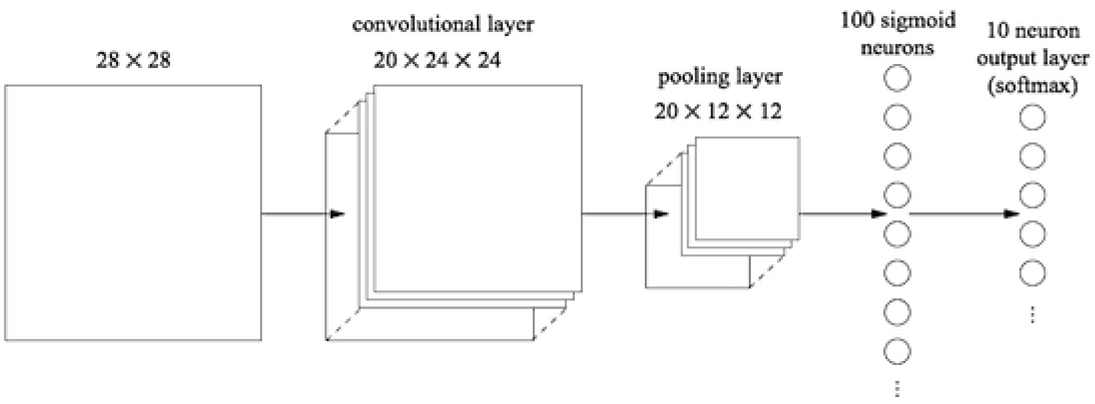
无论如何，前面的两个网络还是存在两个差别。首先，我们正则化过更早的那个网络，以改善过拟合的影响。正则化的确是提高了准确率，不过所得很有限，所以在后面我们不要为正则化过于分心。第二，在更早的网络中，最后一层是使用 sigmoid（反曲函数） 激活函数，以及 cross-entropy（交叉熵）代价函数，当前的这个网络中，最后一层使用的是 softmax（逻辑多分类）以及 log-likelihood（对数似然函数）代价函数。正如在第三章中说明的那样，这并不是什么大的改变。我其实并没有什么特别深入的理由来做这个转变的，我之所以这样做，只是因为在当代的图像分类网络中，softmax 比 log-likelihood 使用得更为广泛。

Can we do better than these results using a deeper network architecture?

我们能够通过更深的网络架构得到更好的结果吗？

Let's begin by inserting a convolutional layer, right at the beginning of the network. We'll use 5 by 5 local receptive fields, a stride length of 1, and 20 feature maps. We'll also insert a max-pooling layer, which combines the features using 2 by 2 pooling windows. So the overall network architecture looks much like the architecture discussed in the last section, but with an extra fully-connected layer:

让我们从插入一个卷积层开始，亦即在网络开始处的右边插入。我们将使用一个 5 乘 5 的局部接收域，步长为 1，以及 20 个特征图。我们当然还需要插入一个极值池化层，它以一个 2 乘 2 的池化窗口进行特征合并。网络的整体架构，看起来就像我们在上一段讨论的那样，除了还外挂了一个全链接层之外。



In this architecture, we can think of the convolutional and pooling layers as learning about local spatial structure in the input training image, while the later, fully-connected layer learns at a more abstract level, integrating global information from across the entire image. This is a common pattern in convolutional neural networks.

在这个架构中，我们可以认为卷积层和池化层承担着学习输入图像的空间结构的任务，紧接着，全链接层承担着更抽象的任务，抽取整张图片的全局信息。这个就是卷积神经网络的大体脉络。

Let's train such a network, and see how it performs*:

让我们来训练这样一个网络吧，看看它的表现如何*：

```
>>> net = Network([
        ConvPoolLayer(image_shape=(mini_batch_size, 1, 28, 28),
                      filter_shape=(20, 1, 5, 5),
                      poolsize=(2, 2)),
        FullyConnectedLayer(n_in=20*12*12, n_out=100),
        SoftmaxLayer(n_in=100, n_out=10)], mini_batch_size)
>>> net.SGD(training_data, 60, mini_batch_size, 0.1,
            validation_data, test_data)
```

> I've continued to use a mini-batch size of 10 here. In fact, as we discussed earlier it may be possible to speed up training using larger mini-batches. I've continued to use the same mini-batch size mostly for consistency with the experiments in earlier chapters.
>
> 我继续使用 10 作为微型批量。事实上，就如我们的早前的讨论，相比于更大尺寸的微型批量，它可能会加速训练速度。我会一直使用与前面的实验中一样大小的微型批量尺寸。

That gets us to 98.78 percent accuracy, which is a considerable improvement over any of our previous results. Indeed, we've reduced our error rate by better than a third, which is a great improvement.

现在我们取得了 98.78% 的准确率，相比之前的结果，这是一个可观的进步。事实上，我们将错误率降低了三分之一，这是一个巨大的进步。

In specifying the network structure, I've treated the convolutional and pooling layers as a single layer. Whether they're regarded as separate layers or as a single layer is to some extent a matter of taste. `network3.py` treats them as a single layer because it makes the code for `network3.py` a little more compact. However, it is easy to modify `network3.py` so the layers can be specified separately, if desired.

在规划网络结构时，我将卷积层和池化层当成一个单层来处理了。是否将它们分层处理还是单层处理，纯粹就是因为外部因素的考虑。`network3.py` 将它们视为单层，是因为这样可以使得 `network3.py` 的源码更加紧凑。如果需要的话，通过修改 `network3.py` 的源码，将它进行分层处理，也是很容易的。

> 译注：在后面，当卷积层和池化层作为一个层来看待时，我们将“convolutional-pooling layer”简称做“卷积池”。

Exercise

练习

- What classification accuracy do you get if you omit the fully-connected layer, and just use the convolutional-pooling layer and softmax layer? Does the inclusion of the fully-connected layer help?

  如果忽略全链接层，仅使用卷积池和逻辑多分类层（softmax），你会得到什么样的分类精度呢？包含全链接层有帮助吗？

Can we improve on the 98.78 percent classification accuracy?

我们还能进一步改进 98.78% 的分类精度吗？

Let's try inserting a second convolutional-pooling layer. We'll make the insertion between the existing convolutional-pooling layer and the fully-connected hidden layer. Again, we'll use a 5×5 local receptive field, and pool over 2×2 regions. Let's see what happens when we train using similar hyper-parameters to before:

让我们试试插入第二个卷积池。我们将它插入到现存的卷积池和全链接隐藏层之间。再次使用 5x5 的局部接收域，以及 2x2 的池化窗口。让我们看看用与之前类似的超参数进行训练时，会发生什么：

```
>>> net = Network([
        ConvPoolLayer(image_shape=(mini_batch_size, 1, 28, 28),
                      filter_shape=(20, 1, 5, 5),
                      poolsize=(2, 2)),
        ConvPoolLayer(image_shape=(mini_batch_size, 20, 12, 12),
                      filter_shape=(40, 20, 5, 5),
                      poolsize=(2, 2)),
        FullyConnectedLayer(n_in=40*4*4, n_out=100),
        SoftmaxLayer(n_in=100, n_out=10)], mini_batch_size)
>>> net.SGD(training_data, 60, mini_batch_size, 0.1,
            validation_data, test_data)
```

Once again, we get an improvement: we're now at 99.06 percent classification accuracy!

我们再一次取得了进步：现在我们取得了 99.06% 的分类精度！

There's two natural questions to ask at this point. The first question is: what does it even mean to apply a second convolutional-pooling layer? In fact, you can think of the second convolutional-pooling layer as having as input 12×12 "images", whose "pixels" represent the presence (or absence) of particular localized features in the original input image. So you can think of this layer as having as input a version of the original input image. That version is abstracted and condensed, but still has a lot of spatial structure, and so it makes sense to use a second convolutional-pooling layer.

关于这一点，很自然需要提两个问题。第一个问题是：采用第二个卷积池意味著什么？事实上，你可以将第二个卷积池当作它具有一个 12x12 的输入“图像”，它的“像素”表示了原始输入图像的某个局部特征是否存在（或者缺失）。所以，你可以将这个层视为具有一个来自原始图像的输入版本。这个版本含有很多空间结构的抽象与浓缩信息，这个就是使用第二个卷积池的理由。

That's a satisfying point of view, but gives rise to a second question. The output from the previous layer involves 20 separate feature maps, and so there are 20×12×12 inputs to the second convolutional-pooling layer. It's as though we've got 20 separate images input to the convolutional-pooling layer, not a single image, as was the case for the first convolutional-pooling layer. How should neurons in the second convolutional-pooling layer respond to these multiple input images? In fact, we'll allow each neuron in this layer to learn from *all* 20×5×5 input neurons in its local receptive field. More informally: the feature detectors in the second convolutional-pooling layer have access to *all* the features from the previous layer, but only within their particular local receptive field *.

这是一个令人满意的观点，不过也带出了第二个问题。上一层的输出包含 20 个分立的特征图，也就是有 20x12x12 个输入到第二个卷积池。亦即我们有 20 个分立的图像输入到卷积池，不像是第一个卷积池那样，只有一个图像输入。那么，在第二个卷积池中的神经元，应该如何应对这些并列的输入图像呢？事实上，我们容许每个在这一层中的神经元，从所有它自己的局部接收域中的 20x5x5 个输入神经元中学习。非正式的说法是：在第二个卷积池中的特征探测器，将会访问来自前一个层中的所有特征，不过仅限于他们专有的局部接收域*。

> This issue would have arisen in the first layer if the input images were in color. In that case we'd have 3 input features for each pixel, corresponding to red, green and blue channels in the input image. So we'd allow the feature detectors to have access to all color information, but only within a given local receptive field.
>
> 如果输入的图像是彩色的，我们在第一层就引发这样的问题。在这样的情形下，对于每个像素，我们将有三个特征，对应于输入图像的红，绿，蓝通道。我们允许特征侦测器访问所有的颜色信息，不过仅限于给定的局部接收域。

Problem

问题

- **Using the tanh activation function** Several times earlier in the book I've mentioned arguments that the tanh function may be a better activation function than the sigmoid function. We've never acted on those suggestions, since we were already making plenty of progress with the sigmoid. But now let's try some experiments with tanh as our activation function. Try training the network with tanh activations in the convolutional and fully-connected layers *.

  使用 **tanh** 激活函数 在前面的章节中，我多次提到以 tanh 函数作为激活函数，要比 sigmoid 函数要好。我们仍然没有按这些建议行动起来，是因为采用 sigmoid 我们已经取得了很大的进步。不过，现在让我们尝试在一些练习中使用 tanh 作为激活函数。并且在卷积层和全连层中都尝试以 tanh 激活函数来训练*。

- > Note that you can pass `activation_fn=tanh` as a parameter to the `ConvPoolLayer` and `FullyConnectedLayer` classes.
  >
  > 你可以以 `activation_fn=tanh` 作为参数传递给 `ConvPoolLayer` 和 `FullyConnectedLayer` 类。

  Begin with the same hyper-parameters as for the sigmoid network, but train for 20 epochs instead of 60. How well does your network perform? What if you continue out to 60 epochs? Try plotting the per-epoch validation accuracies for both tanh- and sigmoid-based networks, all the way out to 60 epochs. If your results are similar to mine, you'll find the tanh networks train a little faster, but the final accuracies are very similar. Can you explain why the tanh network might train faster? Can you get a similar training speed with the sigmoid, perhaps by changing the learning rate, or doing some rescaling * ?

开始时，就像 sigmoid 网络一样，以相同的超参数训练 20 个轮次而不是 60 个轮次。你的网络表现得还好吗？要是连续训练至 60 个轮次呢？试着描述出 tanh 与 sigmoid 网络的全部 60 个训练轮次的验证精度，如果你的结果与我的近似，你会发现 tanh 网络的训练速度要快一点，不过最终的精度是非常相似的。你可以解释为什么 tanh 网络会训练的更快一些呢？你可以在 sigmoid 网络中取得类似的训练速度吗？应该改变学习步长，还是做点其他的什么调整呢* ?

> You may perhaps find inspiration in recalling that $\sigma(z) = \frac{1+\tanh(\frac{z}{2})}{2}$
>
> 你也许会发现重新调整的秘笈是这个 $\sigma(z) = \frac{1+\tanh(\frac{z}{2})}{2}$

Try a half-dozen iterations on the learning hyper-parameters or network architecture, searching for ways that tanh may be superior to the sigmoid. *Note: This is an open-ended problem. Personally, I did not find much advantage in switching to tanh, although I haven't experimented exhaustively, and perhaps you may find a way. In any case, in a moment we will find an advantage in switching to the rectified linear activation function, and so we won't go any deeper into the use of tanh*.

尝试对超参数或者网络进行六次迭代训练，发掘一下 tanh 可能优于 sigmoid 的各种理由。*注意一下：这是一个没完没了的问题。就个人而言，我还找不到切换到 tanh 的很多好处，尽管我还没有尽全力试验过，或者你能发现一些东西吧。无论如何，我们都可以在切换到修正线性激活函数（rectified linear activation function）中找到好处，所以我们不会再在 tanh 上探讨太多。*

Using rectified linear units: The network we've developed at this point is actually a variant of one of the networks used in the seminal 1998 paper* introducing the MNIST problem, a network known as LeNet-5. It's a good foundation for further experimentation, and for building up understanding and intuition. In particular, there are many ways we can vary the network in an attempt to improve our results.

使用纠正线性单元：我们现在在这里开发的网络，实际上是那篇 1998 年的开创性的论文*在介绍 MNIST 问题时所使用的网络的变体，它叫做 LeNet-5。无论对于进一步练习，理解深度学习，还是建立直觉来说，它都是很好的基础。特别是，还存在很多途径调整我们的网络，以改善我们的结果。

> "Gradient-based learning applied to document recognition", by Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner (1998). There are many differences of detail, but broadly speaking our network is quite similar to the networks described in the paper.
>
> "Gradient-based learning applied to document recognition", 由 Yann LeCun, Léon Bottou, Yoshua Bengio, 与 Patrick Haffner 在1998年发布。 尽管有很多细节不同，但是广义来说，我们的网络与论文所述的非常类似。

As a beginning, let's change our neurons so that instead of using a sigmoid activation function, we use rectified linear units. That is, we'll use the activation function $f(z) = \max(0, z)$. We'll train for 60 epochs, with a learning rate of $\eta = 0.03$. I also found that it helps a little to use some l2 regularization, with regularization parameter $\lambda = 0.01$:

作为起点，让我们改变神经元的激活函数 sigmoid，代之以纠正线性单元。亦即，我们以 $f(z) = \max(0, z)$ 作为激活函数。我们将训练 60 个轮次，学习步长 $\eta = 0.03$。我还发现使用 l2 正则化 会有一点帮助，所以设定正则化参数 $\lambda = 0.01$ ：

```
>>> from network3 import ReLU
>>> net = Network([
        ConvPoolLayer(image_shape=(mini_batch_size, 1, 28, 28),
                      filter_shape=(20, 1, 5, 5),
                      poolsize=(2, 2),
                      activation_fn=ReLU),
        ConvPoolLayer(image_shape=(mini_batch_size, 20, 12, 12),
                      filter_shape=(40, 20, 5, 5),
                      poolsize=(2, 2),
                      activation_fn=ReLU),
        FullyConnectedLayer(n_in=40*4*4, n_out=100, activation_fn=ReLU),
        SoftmaxLayer(n_in=100, n_out=10)], mini_batch_size)
>>> net.SGD(training_data, 60, mini_batch_size, 0.03,
            validation_data, test_data, lmbda=0.1)
```

I obtained a classification accuracy of 99.23 percent. It's a modest improvement over the sigmoid results (99.06). However, across all my experiments I found that networks based on rectified linear units consistently outperformed networks based on sigmoid activation functions. There appears to be a real gain in moving to rectified linear units for this problem.

我又取得了 99.23% 的分类精度。相比于 sigmoid 的结果（99.06%），这是一个恰当的进展。无论如何，贯通我的所有实践当中，我发现基于纠正线性单元的网络，总是优于基于 sigmoid 激活函数的网络。在激活函数的选择这个问题上，这带来了一个真正的收获，就是迁移到纠正线性单元。

What makes the rectified linear activation function better than the sigmoid or tanh functions? At present, we have a poor understanding of the answer to this question. Indeed, rectified linear units have only begun to be widely used in the past few years. The reason for that recent adoption is empirical: a few people tried rectified linear units, often on the basis of hunches or heuristic arguments*.

是什么使得纠正线性激活函数比 sigmoid 和 tanh 函数更好呢？从表象上，我们对这个问题缺乏理解。事实上，纠正线性单元被广泛使用也就是近几年的事情。采纳它的理由都是经验性的：有些人尝试使用纠正线性单元，经常是以促进或者启发讨论作为出发点。

> A common justification is that $\max(0, z)$ doesn't saturate in the limit of large z, unlike sigmoid neurons, and this helps rectified linear units continue learning. The argument is fine, as far it goes, but it's hardly a detailed justification, more of a just-so story. Note that we discussed the problems with saturation back in Chapter 2.
>
> 一个常见的正当理由是 $\max(0, z)$ 在大 z 值的限制中不饱和，这一点与 sigmoid 神经元不同，这将有助于纠正线性单元继续学习。这个论点很好，但是它不足以成为具体的理由，而更象是一个传说。请注意，我们在第二章中讨论过神经元的饱和问题。

They got good results classifying benchmark data sets, and the practice has spread. In an ideal world we'd have a theory telling us which activation function to pick for which application. But at present we're a long way from such a world. I should not be at all surprised if further major improvements can be obtained by an even better choice of activation function. And I also expect that in coming decades a powerful theory of activation functions will be developed. Today, we still have to rely on poorly understood rules of thumb and experience.

他们已经取得了良好的分类基准数据集，并且实验已经开展。在理想的世界当中，我们应该有一个理论来告诉我们，哪一个激活函数针对哪一个应用。不过，现实情况是，我们还有很长的路要走。如果深度学习通过选择更好的激活函数，而进一步取得重大进展，我不会感到惊讶。我期待未来的十年内，能够发展出强大的激活函数理论。今天，我们仍然需要依赖对它贫乏的理解和经验。

Expanding the training data: Another way we may hope to improve our results is by algorithmically expanding the training data. A simple way of expanding the training data is to displace each training image by a single pixel, either up one pixel, down one pixel, left one pixel, or right one pixel. We can do this by running the program `expand_mnist.py` from the shell prompt*:

扩展训练数据：另外一个我们可以期待改进结果的方法是通过算法来扩展训练数据。最简单的扩展训练数据的方法是将训练图片移动一个像素，不是上下移动一个像素，就是左右移动一个像素。你可以通过在 shell 命令行提示符下运行程序 `expand_mnist.py` 来实现：

> The code for `expand_mnist.py` is available here.
>
> `expand_mnist.py` 的源码可以在这里获得。

```
$ python expand_mnist.py
```

Running this program takes the 50,000 MNIST training images, and prepares an expanded training set, with 250,000 training images. We can then use those training images to train our network. We'll use the same network as above, with rectified linear units. In my initial experiments I reduced the number of training epochs - this made sense, since we're training with 5 times as much data. But, in fact, expanding the data turned out to considerably reduce the effect of overfitting. And so, after some experimentation, I eventually went back to training for 60 epochs. In any case, let's train:

运行程序取得 50,000 个 MNIST 训练数据，并且形成一个扩展训练集，内含 250,000 个训练图像。接下来我们就可以用它们来训练我们的网络了。我们使用上述同一个网络，以修正线性单元作为激活函数。在初始的实验中，我缩减了训练的轮次。这是有道理的，因为我们的训练数据扩大了 5 倍。的确，扩展数据极大地抑制了过拟合的影响。然而，经过一番试验之后，我最终还是回到了 60 个轮次的训练节奏。无论如何，我们训练吧：

```
>>> expanded_training_data , _, _ = network3.load_data_shared (
        "../data/mnist_expanded.pkl.gz" )
>>> net = Network([
        ConvPoolLayer (image_shape =(mini_batch_size , 1, 28, 28),
                      filter_shape =(20, 1, 5, 5),
                      poolsize =(2, 2),
                      activation_fn =ReLU),
        ConvPoolLayer (image_shape =(mini_batch_size , 20, 12, 12),
                      filter_shape =(40, 20, 5, 5),
                      poolsize =(2, 2),
                      activation_fn =ReLU),
        FullyConnectedLayer (n_in=40*4*4, n_out=100, activation_fn =ReLU),
        SoftmaxLayer (n_in=100, n_out=10)], mini_batch_size )
>>> net.SGD(expanded_training_data , 60, mini_batch_size , 0.03,
            validation_data , test_data , lmbda=0.1)
```

Using the expanded training data I obtained a 99.37 percent training accuracy. So this almost trivial change gives a substantial improvement in classification accuracy. Indeed, as we discussed earlier this idea of algorithmically expanding the data can be taken further. Just to remind you of the flavour of some of the results in that earlier discussion: in 2003 Simard, Steinkraus and Platt* improved their MNIST performance to 99.6 percent using a neural network otherwise very similar to ours, using two convolutional-pooling layers, followed by a hidden fully-connected layer with 100 neurons. There were a few differences of detail in their architecture - they didn't have the advantage of using rectified linear units, for instance - but the key to their improved performance was expanding the training data. They did this by rotating, translating, and skewing the MNIST training images. They also developed a process of "elastic distortion", a way of emulating the random oscillations hand muscles undergo when a person is writing. By combining all these processes they substantially increased the effective size of their training data, and that's how they achieved 99.6 percent accuracy.

使用扩展训练数据，我取得了 99.37% 的训练精度。就是这样一个微不足道的改变，就给分类精度带来了如此显著的提高。实际上，正如我们早前讨论的那样，以算法来扩展数据还可以取得更大的成绩。告诉你一点在早前讨论的结果中的一些趣事：在 2003 年，Simard, Steinkraus 和 Platt* 将 MNIST 的分类表现提高到 99.6% 时，所用的网络架构与我们非常相似，使用两个卷积池，紧跟一个 100 个神经元的全连隐藏层。在他们的架构中稍微有点不同 - 他们没有利用修正线性单元的优势，实际上 - 他们改进表现的关键是扩展训练数据。他们将 MNIST 训练图像进行旋转，变形，和倾斜。他们甚至还开发了一种叫“弹性变形”的方法，这个方法模拟人类手部肌肉在书写过程中的震颤。结合所述的各种方法，他们极大地增加了他们的有效训练数据，这就是为什么他们可以取得 99.6% 的精度的原因。

> Best Practices for Convolutional Neural Networks Applied to Visual Document Analysis, by Patrice Simard, Dave Steinkraus, and John Platt (2003).

Problem

问题

- The idea of convolutional layers is to behave in an invariant way across images. It may seem surprising, then, that our network can learn more when all we've done is translate the input data. Can you explain why this is actually quite reasonable?

  卷积层的设计思想是历遍所有图像，而保持行为的一致性。当我们转变输入数据时，我们的网络可以学习到更多的东西，这听起来很奇怪。你能解释这个现象的确切理由吗？

Inserting an extra fully-connected layer: Can we do even better? One possibility is to use exactly the same procedure as above, but to expand the size of the fully-connected layer. I tried with 300 and 1,000 neurons, obtaining results of 99.46 and 99.43 percent, respectively. That's interesting, but not really a convincing win over the earlier result (99.37 percent).

插入一个额外的全连层： 我们还可以做得更好吗？一个可能的途径是应用上面的相同处理方式，不过，只扩展全连层的大小。我试过用 300 和 1,000 个神经元的，分别取得 99.46% 和 99.43% 的结果。这有点意思，但完全不能令人信服地击败之前的结果（99.37）。

What about adding an extra fully-connected layer? Let's try inserting an extra fully-connected layer, so that we have two 100-hidden neuron fully-connected layers:

多增加一个全连层又如何呢？让我们插入一个额外的全连层，亦即我们有两个 100 个隐藏神经元的全连层：

```
>>> net = Network([
        ConvPoolLayer(image_shape=(mini_batch_size, 1, 28, 28),
                      filter_shape=(20, 1, 5, 5),
                      poolsize=(2, 2),
                      activation_fn=ReLU),
        ConvPoolLayer(image_shape=(mini_batch_size, 20, 12, 12),
                      filter_shape=(40, 20, 5, 5),
                      poolsize=(2, 2),
                      activation_fn=ReLU),
        FullyConnectedLayer(n_in=40*4*4, n_out=100, activation_fn=ReLU),
        FullyConnectedLayer(n_in=100, n_out=100, activation_fn=ReLU),
        SoftmaxLayer(n_in=100, n_out=10)], mini_batch_size)
>>> net.SGD(expanded_training_data, 60, mini_batch_size, 0.03,
            validation_data, test_data, lmbda=0.1)
```

Doing this, I obtained a test accuracy of 99.43 percent. Again, the expanded net isn't helping so much. Running similar experiments with fully-connected layers containing 300 and 1,000 neurons yields results of 99.48 and 99.47 percent. That's encouraging, but still falls short of a really decisive win.

这样做之后，我取得了 99.43% 的测试精度。扩展的网络并不能带来很大的帮助。在包含 300 和 1,000 个神经元的全链接层中运行类似的实验，也取得了 99.48% 和 99.47% 的结果。也算是一个鼓励吧，不过我们仍然缺少一个决定性的胜利。

What's going on here? Is it that the expanded or extra fully-connected layers really don't help with MNIST? Or might it be that our network has the capacity to do better, but we're going about learning the wrong way? For instance, maybe we could use stronger regularization techniques to reduce the tendency to overfit. One possibility is the dropout technique introduced back in Chapter 3. Recall that the basic idea of dropout is to remove individual activations at random while training the network. This makes the model more robust to the loss of individual pieces of evidence, and thus less likely to rely on particular idiosyncracies of the training data. Let's try applying dropout to the final fully-connected layers:

这里到底发生了什么呢？是扩展或者是新增的全连层对 MNIST 没有帮助吗？还是可能我们的网络其实是有能力做得更好，但是我们在探索的过程中走错路了？例如，也许我们可以用更强的正则化技术去抑制过拟合的趋势。其中一个可选项，就是在第三章中介绍过的辍学技术。回顾一下辍学的基本思想，就是在网络训练的过程中，随机地移除单个的活动单元。这将使得我们的模型在面对数据的小片表征缺损时，表现得更加强健，并且尽可能少地脱离训练数据的个体特征的影响。让我们尝试一下将辍学应用到最后的全连层：

> > 译注：暂时用“辍学”来作为 dropout 的中文术语吧。我觉得也挺形象，毕竟那些神经元就是退出学习了。

```
>>> net = Network([
        ConvPoolLayer (image_shape =(mini_batch_size , 1, 28, 28),
                       filter_shape =(20, 1, 5, 5),
                       poolsize =(2, 2),
                       activation_fn =ReLU),
        ConvPoolLayer (image_shape =(mini_batch_size , 20, 12, 12),
                       filter_shape =(40, 20, 5, 5),
                       poolsize =(2, 2),
                       activation_fn =ReLU),
        FullyConnectedLayer (
            n_in=40*4*4, n_out=1000, activation_fn =ReLU, p_dropout =0.5),
        FullyConnectedLayer (
            n_in=1000, n_out=1000, activation_fn =ReLU, p_dropout =0.5),
        SoftmaxLayer (n_in=1000, n_out=10, p_dropout =0.5)],
        mini_batch_size )
>>> net.SGD(expanded_training_data , 40, mini_batch_size , 0.03,
            validation_data , test_data )
```

Using this, we obtain an accuracy of 99.60 percent, which is a substantial improvement over our earlier results, especially our main benchmark, the network with 100 hidden neurons, where we achieved 99.37 percent.

应用这个技巧，我们取得了 99.60% 的精度，这相比于我们早前的结果是一个巨大的进步，尤其是我们以基准方法应用 100 个隐藏神经元的时候，我仅取得 99.37% 的成绩。

There are two changes worth noting.

有两个改变值得注意。

First, I reduced the number of training epochs to 40: dropout reduced overfitting, and so we learned faster.

第一，我们缩减训练的轮次为 40：辍学会抑制过拟合，并且使我们加速了学习。

Second, the fully-connected hidden layers have 1,000 neurons, not the 100 used earlier. Of course, dropout effectively omits many of the neurons while training, so some expansion is to be expected. In fact, I tried experiments with both 300 and 1,000 hidden neurons, and obtained (very slightly) better validation performance with 1,000 hidden neurons.

第二，全链接隐藏层有 1,000 个神经元，不是早前的 100 个。当然，辍学有效地在训练中忽略了其中的大多数，所以我们可以预测一些扩展的结果。事实上，我尝试过 300 至 1,000 个隐藏神经元，并且在 1,000 个隐藏神经元的时候获得更好的（非常轻微）表现。

Using an ensemble of networks: An easy way to improve performance still further is to create several neural networks, and then get them to vote to determine the best classification. Suppose, for example, that we trained 5 different neural networks using the prescription above, with each achieving accuracies near to 99.6 percent. Even though the networks would all have similar accuracies, they might well make different errors, due to the different random initializations. It's plausible that taking a vote amongst our 5 networks might yield a classification better than any individual network.

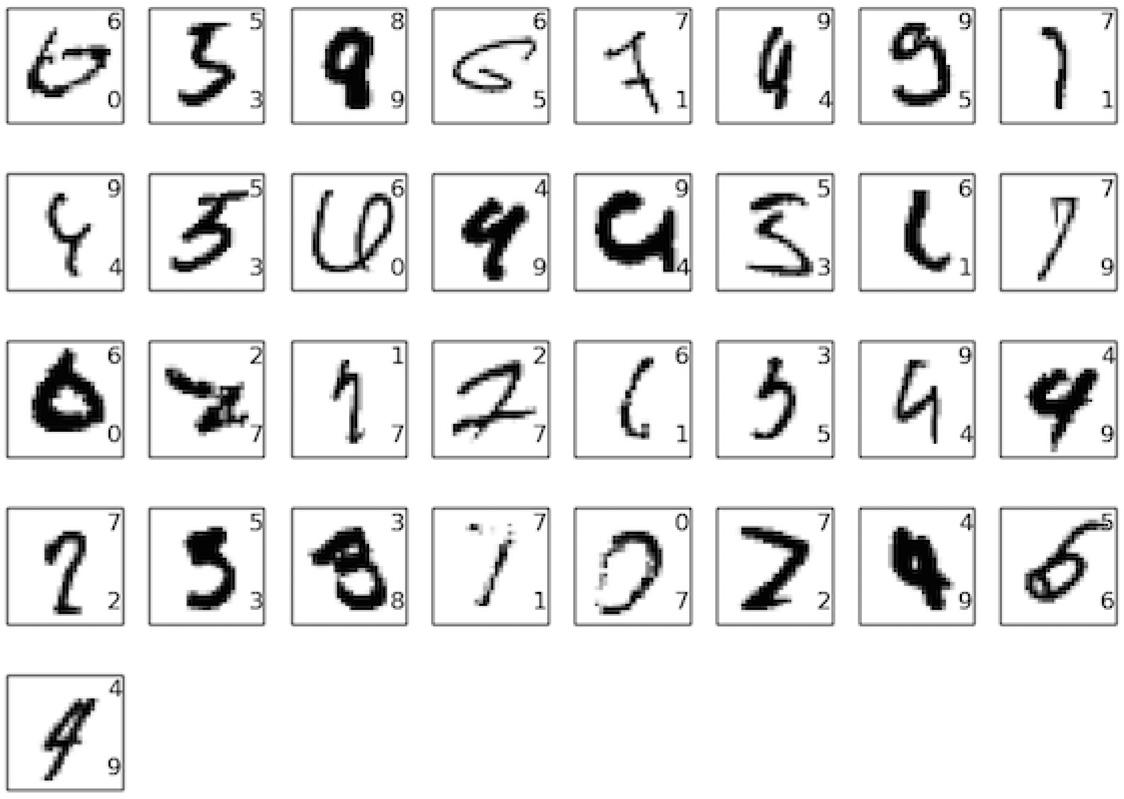
使用网络的协作： 一个简单的进一步推进网络表现的途径，就是创建多个神经网络，并且从它们当中般选最佳的分类结果。假设，我们用上述的技巧，训练 5 个不同的神经网络，每个网络大致都会取得 99.6% 的成绩。尽管它们都有相似的精度，而他们产生的错误可能是不同的，这是由于它们是被随机初始化的。从 5 个网络分类结果中选择，会比单一网络的结果更佳，这样更加合理一些。

This sounds too good to be true, but this kind of ensembling is a common trick with both neural networks and other machine learning techniques. And it does in fact yield further improvements: we end up with 99.67 percent accuracy. In other words, our ensemble of networks classifies all but 33 of the 10,000 test images correctly.

听起来实现了很好的结果，这种在两个神经网络和机器学习中协调的方法，是一种常用的技巧。而它并不会产生实质性的改进：我们最终停止在 99.67% 的精度。换言之，我们的网络协作正确地识别了所有的 10,000 个图像，除了 33 个之外。

The remaining errors in the test set are shown below. The label in the top right is the correct classification, according to the MNIST data, while in the bottom right is the label output by our ensemble of nets:

测试集中还留下的错误都在下面显示了。右上的标签是 MNIST 数据中标定的正确分类，而右下是我们的多个网络的协作分类的输出：



It's worth looking through these in detail. The first two digits, a 6 and a 5, are genuine errors by our ensemble. However, they're also understandable errors, the kind a human could plausibly make. That 6 really does look a lot like a 0, and the 5 looks a lot like a 3. The third image, supposedly an 8, actually looks to me more like a 9. So I'm siding with the network ensemble here: I think it's done a better job than whoever originally drew the digit. On the other hand, the fourth image, the 6, really does seem to be classified badly by our networks.

值得查看一下这些细节。头两个数字，6 和 5，这的确是网络协作出错了。不过，他们都是可以理解的错误，人类也会产生这样的错误。那个 6 看起来非常像 0，还有那个 5 看起来很像 3 。第三个图，据说是 8 ，实际上看起来很像 9 。所以，到这里，我的立场和网络协作的结果是一致的：我认为现在的工作已经比那些画这些数字的人做得更好了。另一个方面，我们的网络分类的确是有明显出错的地方，譬如地四个图片，那个是 6 。

And so on. In most cases our networks' choices seem at least plausible, and in some cases they've done a better job classifying than the original person did writing the digit. Overall, our networks offer exceptional performance, especially when you consider that they correctly classified 9,967 images which aren't shown. In that context, the few clear errors here seem quite understandable. Even a careful human makes the occasional mistake. And so I expect that only an extremely careful and methodical human would do much better. Our network is getting near to human performance.

如此等等。在大多数情况下，我们的网络的选择看起来至少是合情合理的，还有一些情况下，它们做得比描画这些数字图片的人类原创者做得更好。总体来说，我们的网络提供了令人期待的表现，尤其是你试想一下，它们正确地分辨了 9,967 张图片。在这样的表现之中，有个别明显的错误也是可以理解的。即使是一个谨慎的人也会偶尔犯这样的错误。在我看来，只有那些极端谨小慎微和很有条理的人才会做得更好。我们的网络正在接近人类的表现。

Why we only applied dropout to the fully-connected layers: If you look carefully at the code above, you'll notice that we applied dropout only to the fully-connected section of the network, not to the convolutional layers. In principle we could apply a similar procedure to the convolutional layers. But, in fact, there's no need: the convolutional layers have considerable inbuilt resistance to overfitting. The reason is that the shared weights mean that convolutional filters are forced to learn from across the entire image. This makes them less likely to pick up on local idiosyncracies in the training data. And so there is less need to apply other regularizers, such as dropout.

为什么我们仅将辍学应用到全连层： 如果你仔细查看上面的源代码，你会注意到我们仅将辍学应用到网络的全链接层中，而没有应用到卷积层。从原理上，我们也可以将类似的处理应用到卷积层。不过，事实上，没有这个必要：卷积层对于过拟合具有相当大的内在抗性。理由是，共享权值意味着卷积滤镜被强制从整张图片中学习。这使得他们极少可能在训练数据中拾取到局部的个体特征。因而，极少需要应用额外的正则化处理，譬如辍学。

Going further: It's possible to improve performance on MNIST still further. Rodrigo Benenson has compiled an informative summary page, showing progress over the years, with links to papers. Many of these papers use deep convolutional networks along lines similar to the networks we've been using. If you dig through the papers you'll find many interesting techniques, and you may enjoy implementing some of them. If you do so it's wise to start implementation with a simple network that can be trained quickly, which will help you more rapidly understand what is going on.

更上一层楼： 继续推进对 MNIST 的分类表现是可能的。Rodrigo Benenson 编订过一个信息摘要页，列举了各个年份的进展，以及论文的链接。大部分这些论文所使用的卷积网络的技术线路与我们使用的类似。如果你深入发掘这些论文，你会发现很多有趣的技术，并且你也许能享受这些技术的实现过程。如果你要动手干了，明智的方法是以一个可以让你快速训练的网络作为实现的起点，它能让你更快速地理解事情的发展。

For the most part, I won't try to survey this recent work. But I can't resist making one exception. It's a 2010 paper by Cireșan, Meier, Gambardella, and Schmidhuber *. What I like about this paper is how simple it is. The network is a many-layer neural network, using only fully-connected layers (no convolutions). Their most successful network had hidden layers containing 2,500, 2,000, 1,500, 1,000, and 500 neurons, respectively. They used ideas similar to Simard *et al* to expand their training data. But apart from that, they used few other tricks, including no convolutional layers: it was a plain, vanilla network, of the kind that, with enough patience, could have been trained in the 1980s (if the MNIST data set had existed), given enough computing power. They achieved a classification accuracy of 99.65 percent, more or less the same as ours. The key was to use a very large, very deep network, and to use a GPU to speed up training. This let them train for many epochs. They also took advantage of their long training times to gradually decrease the learning rate from 10^{-3} to 10^{-6}. It's a fun exercise to try to match these results using an architecture like theirs.

大多数情况下，我不太想去评定这些工作。不过，我还是不能抗拒一个例外。它是 Cireșan, Meier, Gambardella, 和 Schmidhuber 在 2010 年发表的一篇论文。我之所以喜欢这篇论文，是因为它是那么的简洁。这个网络是一个多层神经网络，仅用全链接层（无卷积）。他们最成功的网络，各个隐藏层分别拥有 2,500, 2,000, 1,500, 以及 500 个神经元。他们使用的思想类似于 Simard *et al* 的扩展训练数据。不过，除此之外，他们还使用了其他的一些技巧，包括无卷积层：从类型来说，它是一个简单平常的网络，在足够的耐心和计算资源的支持下，在 20 世纪 80 年代完成了训练（如果那个时候 MNIST 数据集就已经存在的话）。他们取得了 99.65% 的分类精度，跟我们的结果出入不大。关键是使用非常大，非常深的网络，并且使用 GPU 加速训练。这使得他们需要训练很多轮次。他们还利用他们有大量的时间来训练的好处，将学习速率从 10^{-3} 下降到 10^{-6} 。以他们类似的架构，尝试达成他们那些结果，是一个有趣的练习。

> Deep, Big, Simple Neural Nets Excel on Handwritten Digit Recognition, by Dan Claudiu Cireșan, Ueli Meier, Luca Maria Gambardella, and Jürgen Schmidhuber (2010).

Why are we able to train? We saw in the last chapter that there are fundamental obstructions to training in deep, many-layer neural networks. In particular, we saw that the gradient tends to be quite unstable: as we move from the output layer to earlier layers the gradient tends to either vanish (the vanishing gradient problem) or explode (the exploding gradient problem). Since the gradient is the signal we use to train, this causes problems.

我们凭什么去训练？ 我们在上一章中，看到过对于深度，多层网络的训练存在着根本障碍。我们看到过梯度训练趋于完全失稳：当我们从输出层向早前的层推算时，梯度要么趋于消失（梯度消失问题），要么趋于爆炸（梯度爆炸问题）。梯度是我们赖以训练网络的信号，因而会造成问题。

How have we avoided those results?

我们如何避开这些坑？

Of course, the answer is that we haven't avoided these results. Instead, we've done a few things that help us proceed anyway. In particular: (1) Using convolutional layers greatly reduces the number of parameters in those layers, making the learning problem much easier; (2) Using more powerful regularization techniques (notably dropout and convolutional layers) to reduce overfitting, which is otherwise more of a problem in more complex networks; (3) Using rectified linear units instead of sigmoid neurons, to speed up training - empirically, often by a factor of 3-5; (4) Using GPUs and being willing to train for a long period of time. In particular, in our final experiments we trained for 40 epochs using a data set 5 times larger than the raw MNIST training data. Earlier in the book we mostly trained for 30 epochs using just the raw training data. Combining factors (3) and (4) it's as though we've trained a factor perhaps 30 times longer than before.

诚然，答案是我们其实无法避免这些坑。替代的办法是，我们做了些事情来帮助我们继续前进。具体来说：（1）使用卷积层极大地缩减了层中的参数，使得训练容易了很多；（2）使用更加有力的正则化技术（特别是辍学和卷积层）抑制过拟合，否则在越复杂的网络中，问题越严重；（3）使用修正线性单元替代 sigmoid 神经元，以加速训练速度 - 经验上通常快 3-5 倍；（4）使用 GPU 以及耐心地进行长时间的训练。在我们最后的实验中，我们以 MNIST 的原始数据 5 倍的扩展数据训练了 40 个轮次。在本书的前期联系中，我们几乎都是使用原始数据训练 30 个轮次。结合（3）和（4）它相当于我们的训练比之前多了 30 倍。

Your response may be "Is that it? Is that all we had to do to train deep networks? What's all the fuss about?"

你的回应可能是“这有什么呢？我们不就是要训练个深度网络吗？有什么大不了的？”

Of course, we've used other ideas, too: making use of sufficiently large data sets (to help avoid overfitting); using the right cost function (to avoid a learning slowdown); using good weight initializations (also to avoid a learning slowdown, due to neuron saturation); algorithmically expanding the training data. We discussed these and other ideas in earlier chapters, and have for the most part been able to reuse these ideas with little comment in this chapter.

当然，我们还想了其他的办法：使用大数据集（帮助避免过拟合）；使用正确的代价函数（避免学习降速）；使用良好的权值初始化（避免神经元饱和而导致学习降速）；以算法扩展训练数据。我们在早前的章节中就讨论过诸如此类的技巧，并且在本章中，对于那些最常用的思路都稍微做了讲解。

With that said, this really is a rather simple set of ideas. Simple, but powerful, when used in concert. Getting started with deep learning has turned out to be pretty easy!

如此说来，这真是一套简单的方法。简单，而有力，当你协调使用它们的时候。简单的深度网络的学习起点就这样呼之欲出！

How deep are these networks, anyway? Counting the convolutional-pooling layers as single layers, our final architecture has 4 hidden layers. Does such a network really deserve to be called a *deep* network? Of course, 4 hidden layers is many more than in the shallow networks we studied earlier. Most of those networks only had a single hidden layer, or occasionally 2 hidden layers. On the other hand, as of 2015 state-of-the-art deep networks sometimes have dozens of hidden layers. I've occasionally heard people adopt a deeper-than-thou attitude, holding that if you're not keeping-up-with-the-Joneses in terms of number of hidden layers, then you're not really doing deep learning. I'm not sympathetic to this attitude, in part because it makes the definition of deep learning into something which depends upon the result-of-the-moment. The real breakthrough in deep learning was to realize that it's practical to go beyond the shallow 1- and 2-hidden layer networks that dominated work until the mid-2000s. That really was a significant breakthrough, opening up the exploration of much more expressive models. But beyond that, the number of layers is not of primary fundamental interest. Rather, the use of deeper networks is a tool to use to help achieve other goals - like better classification accuracies.

这些网络有多深呢？ 将卷积池算作是一个单层的话，我们最终的网络有 4 个隐藏层。这样的网络够格叫做深度网络了吗？当然，4 个隐藏层对于我们早前研究的浅层网络来说已经很多了。大部分的那些网络只有一个隐藏层，偶尔会有 2 个隐藏层的。另一方面，截至 2015 年，最时髦的深度网络，有时会有几十个隐藏层。我偶尔听到，有人形成了一种就是要比你深的，在隐藏层的数量上执着于攀比隔壁老王的心态，那么你就不是在搞深度学习了。我不认同这样的态度，部分原因是，这使得深度学习的意义变成了争风吃醋的事情。在深度学习上的真正突破是，直至在二十世纪中叶实现了从 1 个浅层到 2 个隐藏层切实跨越。这个是一个巨大的突破，从而开启了众多意义深远的模型的探索。不过除此之外，层数不应该是主要的关心目标。相反，深层网络的用途是一个可以帮助我们实现目标的工具 - 去取得更好的分类目标。

A word on procedure: In this section, we've smoothly moved from single hidden-layer shallow networks to many-layer convolutional networks. It all seemed so easy! We make a change and, for the most part, we get an improvement. If you start experimenting, I can guarantee things won't always be so smooth. The reason is that I've presented a cleaned-up narrative, omitting many experiments - including many failed experiments. This cleaned-up narrative will hopefully help you get clear on the basic ideas. But it also runs the risk of conveying an incomplete impression. Getting a good, working network can involve a lot of trial and error, and occasional frustration. In practice, you should expect to engage in quite a bit of experimentation. To speed that process up you may find it helpful to revisit Chapter 3's discussion of how to choose a neural network's hyper-parameters, and perhaps also to look at some of the further reading suggested in that section.

实验过程的建言： 在这一段，我们平稳地从单层隐藏层的浅层网络过渡到多层卷积网络。所有的一切看起来是那么容易！我们作出改变，在大多数情况下，就取得了进展。如果你开始试验了，我保证事情应该不会那么顺利。理由是我讲述的是一个梳理清楚的故事，忽略了很多的试验 - 包括很多失败的实验。梳理清楚的讲述有助于你对基本思路取得清晰的认识。不过它也包含表述不完全的风险。得到一个良好，有效的网络会经历很多试验和错误，还有偶尔的挫折感。想加速这个过程，你会发现回顾第三章有关如何选择神经网络的超参数的讨论，并且进一步阅读那个段落中建议的相关内容非常有用。

The code for our convolutional networks

我们的卷积网络源代码

Alright, let's take a look at the code for our program, `network3.py`. Structurally, it's similar to `network2.py`, the program we developed in Chapter 3, although the details differ, due to the use of Theano. We'll start by looking at the `FullyConnectedLayer` class, which is similar to the layers studied earlier in the book. Here's the code (discussion below)*.

好了，让我们看看我们的程序代码，`network3.py` 。结构上，它类似 `network2.py` ，那个我们在第三章开发的程序，由于是使用 Theano，所以在细节上有差别。我们首先看 `FullConnectedLayer` 类，它类似于本书在早前研究过的那样。这里仅展示代码（讨论在后面展开）* 。

> Note added November 2016: several readers have noted that in the line initializing `self.w`, I set `scale=np.sqrt(1.0/n_out)`, when the arguments of Chapter 3 suggest a better initialization may be `scale=np.sqrt(1.0/n_in)`. This was simply a mistake on my part. In an ideal world I'd rerun all the examples in this chapter with the correct code. Still, I've moved on to other projects, so am going to let the error go.
>
> 注意，这些是 2016 年 11 月添加： 有些读者注意到在文件 `self.w` 中的初始化行，我设置了 `scale=np.sqrt(1.0/n_out)` ，这个自变量在第三章中建议初始化为 `scale=np.sqrt(1.0/n_in)` 更好。这是我一个简单的错误。在理想的世界中，我应该以正确的代码运行本章中的所有范例。不过我已经转移到了其他的项目，所以我打算让错误留下来了。

```python
class FullyConnectedLayer(object):

    def __init__(self, n_in, n_out, activation_fn=sigmoid, p_dropout=0.0):
        self.n_in = n_in
        self.n_out = n_out
        self.activation_fn = activation_fn
        self.p_dropout = p_dropout
        # Initialize weights and biases
        self.w = theano.shared(
            np.asarray(
                np.random.normal(
                    loc=0.0, scale=np.sqrt(1.0/n_out), size=(n_in, n_out)),
                dtype=theano.config.floatX),
            name='w', borrow=True)
        self.b = theano.shared(
            np.asarray(np.random.normal(loc=0.0, scale=1.0, size=(n_out,)),
                       dtype=theano.config.floatX),
            name='b', borrow=True)
        self.params = [self.w, self.b]

    def set_inpt(self, inpt, inpt_dropout, mini_batch_size):
        self.inpt = inpt.reshape((mini_batch_size, self.n_in))
        self.output = self.activation_fn(
            (1-self.p_dropout)*T.dot(self.inpt, self.w) + self.b)
        self.y_out = T.argmax(self.output, axis=1)
        self.inpt_dropout = dropout_layer(
            inpt_dropout.reshape((mini_batch_size, self.n_in)), self.p_dropout)
        self.output_dropout = self.activation_fn(
            T.dot(self.inpt_dropout, self.w) + self.b)

    def accuracy(self, y):
        "Return the accuracy for the mini-batch."
        return T.mean(T.eq(y, self.y_out))
```

Much of the `__init__` method is self-explanatory, but a few remarks may help clarify the code. As per usual, we randomly initialize the weights and biases as normal random variables with suitable standard deviations. The lines doing this look a little forbidding. However, most of the complication is just loading the weights and biases into what Theano calls shared variables. This ensures that these variables can be processed on the GPU, if one is available. We won't get too much into the details of this. If you're interested, you can dig into the Theano documentation. Note also that this weight and bias initialization is designed for the sigmoid activation function (as discussed earlier). Ideally, we'd initialize the weights and biases somewhat differently for activation functions such as the tanh and rectified linear function. This is discussed further in problems below. The `__init__` method finishes with `self.params = [self.w, self.b]`. This is a handy way to bundle up all the learnable parameters associated to the layer. Later on, the `Network.SGD` method will use `params` attributes to figure out what variables in a `Network` instance can learn.

大部分的 `__init__` 中的函数是不言而喻的，不过有点备注会对阐明代码有帮助。通常，我们会以限制在合适的标准差内的随机变量初始化权值和偏至。这个做法看起来有点鬼畜。不论如何，主要的难度就是将权值和偏至加载到 Theano 称为共享变量的地方。这样就可以保证有 GPU 来处理这些变量，要是系统中存在 GPU 的话。我们不打算涉及这个方面的太多细节。如果你有兴趣，可以参考 Theano 文档 。请注意，这里的权值与偏至的初始化，都是面向 sigmoid 激活函数来设计的（正如早前的讨论）。理想中，我们应该针对其他的一些激活函数来初始化权值和

偏至，譬如，tanh 和纠正线性函数。这将在后面进一步讨论。 `__init__` 函数以 `self.params = [selft.w, self.b]` 结尾。这是一个便捷的方法，它捆绑所有需要学习的参数，并将它们关联到层中。稍后， `Network.SGD` 函数将使用 `params` 属性去确定在一个 `Network` 实例中，那些变量需要学习。

The `set_inpt` method is used to set the input to the layer, and to compute the corresponding output. I use the name `inpt` rather than `input` because `input` is a built-in function in Python, and messing with built-ins tends to cause unpredictable behavior and difficult-to-diagnose bugs. Note that we actually set the input in two separate ways: as `self.inpt` and `self.inpt_dropout`. This is done because during training we may want to use dropout. If that's the case then we want to remove a fraction `self.p_dropout` of the neurons. That's what the function `dropout_layer` in the second-last line of the `set_inpt` method is doing. So `self.inpt_dropout` and `self.output_dropout` are used during training, while `self.inpt` and `self.output` are used for all other purposes, e.g., evaluating accuracy on the validation and test data.

`set_inpt` 函数用于将输入设置到层中，并且计算对应的输出。我宁愿用 `inpt` 而不是用 `input` 来命名，是因为 `input` 是 Python 的内建函数，搅混内建函数的名字会导致不可预测的行为以及难以诊断的缺陷。注意我们有两个分立的途径来设置输入：即 `self.inpt` 和 `self.inpt_dropout` 。这样做的目的是因为，我们可能在训练的过程中需要应用辍学。如果是这样，我们就会希望通过 `self.p_dropout` 移除部分神经元。这就是在函数 `set_inpt` 的倒数第二行中的 `dropout_layer` 函数所做的事情。所以， `self.inpt_dropout` 和 `self.output_dropout` 用于训练期间，而 `self.inpu` 和 `self.output` 则用于所有的其他目的，譬如，在验证数据与测试数据中评估精度。

The `ConvPoolLayer` and `SoftmaxLayer` class definitions are similar to `FullyConnectedLayer`. Indeed, they're so close that I won't excerpt the code here. If you're interested you can look at the full listing for `network3.py`, later in this section.

`ConvPoolLayer` 和 `SoftmaxLayer` 类的定义与 `FullyConnectedLayer` 类似。事实上，他们是如此接近，乃至我都不想在这里摘录它们的源码了。如果你有兴趣，你可以在本段后续部分看到它们完整的列举。

However, a couple of minor differences of detail are worth mentioning. Most obviously, in both `ConvPoolLayer` and `SoftmaxLayer` we compute the output activations in the way appropriate to that layer type. Fortunately, Theano makes that easy, providing built-in operations to compute convolutions, max-pooling, and the softmax function.

尽管如此，还是有些细节上的差异值得注意。非常明显，我们用 `ConvPoolLayer` 和 `SoftmaxLayer` 在合适的层中计算激活的输出值。幸运的是，Theano 提供的内建算子使我们非常容易计算卷积，极值池化，和 softmax 函数。

Less obviously, when we introduced the softmax layer, we never discussed how to initialize the weights and biases. Elsewhere we've argued that for sigmoid layers we should initialize the weights using suitably parameterized normal random variables. But that heuristic argument was specific to sigmoid neurons (and, with some amendment, to tanh neurons). However, there's no particular reason the argument should apply to softmax layers. So there's no *a priori* reason to apply that initialization again. Rather than do that, I shall initialize all the weights and biases to be 0. This is a rather *ad hoc* procedure, but works well enough in practice.

不太明显的差别是，当我们介绍 softmax 层时，我们从来没有讨论过如何初始化权值与偏至。在其他地方，我们辩明应该以恰当的随机变量去初始化 sigmoid 层的权值与偏至。不过这个试探性的参数是针对 sigmoid 神经元的（并且对于 tanh 神经元，需要有些修正）。无论如何，没有特别的理由表明这样的参数应该用到 softmax 层。没有什么先天的理由去再一次初始化。相比而言，我要将权值和偏至全部设置为 0 。这是一个特别的手法，但是在实际试验中效果良好。

Okay, we've looked at all the layer classes. What about the `Network` class? Let's start by looking at the `__init__` method:

OK，我们硬件看过所有的层类了。类 `Network` 又如何呢？让我们从查看 `__init__` 函数入手：

```
class Network(object):

    def __init__(self, layers, mini_batch_size):
        """Takes a list of `layers`, describing the network architecture, and
        a value for the `mini_batch_size` to be used during training
        by stochastic gradient descent.

        """
        self.layers = layers
        self.mini_batch_size = mini_batch_size
        self.params = [param for layer in self.layers for param in layer.params]
        self.x = T.matrix("x")
        self.y = T.ivector("y")
        init_layer = self.layers[0]
        init_layer.set_inpt(self.x, self.x, self.mini_batch_size)
        for j in xrange(1, len(self.layers)):
            prev_layer, layer  = self.layers[j-1], self.layers[j]
            layer.set_inpt(
                prev_layer.output, prev_layer.output_dropout, self.mini_batch_size)
        self.output = self.layers[-1].output
        self.output_dropout = self.layers[-1].output_dropout
```

Most of this is self-explanatory, or nearly so. The line `self.params = [param for layer in ...]` bundles up the parameters for each layer into a single list. As anticipated above, the `Network.SGD` method will use `self.params` to figure out what variables in the `Network` can learn. The lines `self.x = T.matrix("x")` and `self.y = T.ivector("y")` define Theano symbolic variables named `x` and `y`. These will be used to represent the input and desired output from the network.

大部分的内容几乎都是不言自明的。行 `self.params = [param for layer in ...]` 捆绑所有各个层的参数进入一个单独的链表。如上所述，函数 `Network.SGD` 将调用 `self.params` 来确定 `Network` 中的那些变量需要训练。行 `self.x = T.matrix("x")` 与 `self.y = T.ivector("y")` 定义 Theano 的符号变量 `x` 和 `y` ，它们将用来标注来自网络的输入与期望的输出。

Now, this isn't a Theano tutorial, and so we won't get too deeply into what it means that these are symbolic variables*.

现在，这是一个 Theano 的教程，因而我们不打算对符号变量的含义涉及太深。

> The Theano documentation provides a good introduction to Theano. And if you get stuck, you may find it helpful to look at one of the other tutorials available online. For instance, this tutorial covers many basics.
>
> Theano 文档 提供了一个很好的介绍。如果你学习上卡壳了，你也会发现它能帮助你找到一个一个的在线教程。作为例子，这个教程覆盖了很多的基础知识。

But the rough idea is that these represent mathematical variables, *not* explicit values. We can do all the usual things one would do with such variables: add, subtract, and multiply them, apply functions, and so on. Indeed, Theano provides many ways of manipulating such symbolic variables, doing things like convolutions, max-pooling, and so on. But the big win is the ability to do fast symbolic differentiation, using a very general form of the backpropagation algorithm. This is extremely useful for applying stochastic gradient descent to a wide variety of network architectures. In particular, the next few lines of code define symbolic outputs from the network. We start by setting the input to the initial layer, with the line

不过粗略的印象是它们表示数学上的变量，而未进行赋值。我们通常可以对它们进行常规的操作：加法，减法，以及相乘与函数引用，如此等等。事实上，Theano 提供很多途径对符号变量进行操作，譬如，卷积，极值池化等等。Theano 的最大的优点还在于进行非常通用的反向传播算法计算时，能够进行快速的符号微分运算。这个特性对于在广泛类型的网络架构中，实行随机梯度下降计算非常有用。特别地，在下面几行源码中，定义网络的符号输出项。我们通过设置初始层的输入项来作为起点

```
        init_layer.set_inpt(self.x, self.x, self.mini_batch_size)
```

Note that the inputs are set one mini-batch at a time, which is why the mini-batch size is there. Note also that we pass the input `self.x` in twice: this is because we may use the network in two different ways (with or without dropout). The `for` loop then propagates the symbolic variable `self.x` forward through the layers of the `Network`. This allows us to define the final `output` and `output_dropout` attributes, which symbolically represent the output from the `Network`.

注意了，因为在输入集中设置过使用微批量（mini-batch）来训练，所以这里就要设置微批量尺寸。注意我们还两次设置了输入项 `self.x` ：这是因为我们可能会以两种不同的途径应用该网络（是否辍学）。`for` 循环通过符号变量 `self.x` 的步进来历遍整个网络。这里还可以定义最终的 `output` 和 `output_dropout` 属性，它是表示网络的符号下标标示的输出。

Now that we've understood how a `Network` is initialized, let's look at how it is trained, using the `SGD` method. The code looks lengthy, but its structure is actually rather simple. Explanatory comments after the code.

到现在，我们已经理解了网络是如何初始化的，让我们来看看他是如何用 `SGD` 函数训练的吧。

```python
def SGD(self, training_data, epochs, mini_batch_size, eta,
            validation_data, test_data, lmbda=0.0):
        """Train the network using mini-batch stochastic gradient descent."""
        training_x, training_y = training_data
        validation_x, validation_y = validation_data
        test_x, test_y = test_data

        # compute number of minibatches for training, validation and testing
        num_training_batches = size(training_data)/mini_batch_size
        num_validation_batches = size(validation_data)/mini_batch_size
        num_test_batches = size(test_data)/mini_batch_size

        # define the (regularized) cost function, symbolic gradients, and updates
        l2_norm_squared = sum([(layer.w**2).sum() for layer in self.layers])
        cost = self.layers[-1].cost(self)+\
               0.5*lmbda*l2_norm_squared/num_training_batches
        grads = T.grad(cost, self.params)
        updates = [(param, param-eta*grad)
                   for param, grad in zip(self.params, grads)]

        # define functions to train a mini-batch, and to compute the
        # accuracy in validation and test mini-batches.
        i = T.lscalar() # mini-batch index
        train_mb = theano.function(
            [i], cost, updates=updates,
            givens={
                self.x:
                training_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size],
                self.y:
                training_y[i*self.mini_batch_size: (i+1)*self.mini_batch_size]
            })
        validate_mb_accuracy = theano.function(
            [i], self.layers[-1].accuracy(self.y),
            givens={
                self.x:
                validation_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size],
                self.y:
                validation_y[i*self.mini_batch_size: (i+1)*self.mini_batch_size]
            })
        test_mb_accuracy = theano.function(
            [i], self.layers[-1].accuracy(self.y),
            givens={
                self.x:
                test_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size],
                self.y:
                test_y[i*self.mini_batch_size: (i+1)*self.mini_batch_size]
            })
        self.test_mb_predictions = theano.function(
            [i], self.layers[-1].y_out,
            givens={
                self.x:
                test_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size]

            })
        # Do the actual training
        best_validation_accuracy  = 0.0
        for epoch  in xrange(epochs):
            for minibatch_index  in xrange(num_training_batches ):
                iteration  = num_training_batches *epoch+minibatch_index
                if iteration
                    print("Training mini-batch number {0}" .format(iteration))
                cost_ij  = train_mb(minibatch_index )
                if (iteration+1)
                    validation_accuracy  = np.mean(
                        [ validate_mb_accuracy (j) for j in
xrange(num_validation_batches )])
                    print("Epoch {0}: validation accuracy {1:.2
                        epoch, validation_accuracy ))
                    if validation_accuracy  >= best_validation_accuracy :
                        print("This is the best validation accuracy to date."  )
                        best_validation_accuracy  = validation_accuracy
                        best_iteration  = iteration
                        if test_data:
                            test_accuracy  = np.mean(
                                [ test_mb_accuracy (j) for j in
xrange(num_test_batches )])
                            print('The corresponding test accuracy is {0:.2
                                test_accuracy ))
        print("Finished training network." )
        print("Best validation accuracy of {0:.2
            best_validation_accuracy , best_iteration ))
        print("Corresponding test accuracy of {0:.2
```

In these lines we symbolically set up the regularized log-likelihood cost function, compute the corresponding derivatives in the gradient function, as well as the corresponding parameter updates. Theano lets us achieve all of this in just these few lines. The only thing hidden is that computing the `cost` involves a call to the `cost` method for the output layer; that code is elsewhere in `network3.py`. But that code is short and simple, anyway. With all these things defined, the stage is set to define the `train_mb` function, a Theano symbolic function which uses the `updates` to update the `Network` parameters, given a mini-batch index. Similarly, `validate_mb_accuracy` and `test_mb_accuracy` compute the accuracy of the `Network` on any given mini-batch of validation or test data. By averaging over these functions, we will be able to compute accuracies on the entire validation and test data sets.

在这几行代码中，我们标志性地设置了正则化后的对数似然函数（log-likehood）作为代价函数，计算在梯度函数中对应的微分，同时刷新相关的参数。Theano 容许我们仅用几行代码就实现所有这些工作。唯一隐含的是在计算 `代价` 时对输出层调用了 `cost` 函数；那样的代码在 `network3.py` 的其他地方中也有出现，它们短而简单。万事具备，并且设定了微批量之后，就是定义 `train_mb` 函数的阶段，它通过 `updates` 属性去刷新网络的参数。类似地， `validate_mb_accuracy` 和 `test_mb_accuracy` 将计算在验证数据与测试数据中微批量的精度。平均这些函数的结果，我们就得到了在整个验证数据集和测试数据集上的精度。

The remainder of the `SGD` method is self-explanatory - we simply iterate over the epochs, repeatedly training the network on mini-batches of training data, and computing the validation and test accuracies.

`SGD` 函数剩余的部分就不言自明了 - 我们只要简单地迭代轮次，将训练数据的小批次反复训练网络，然后计算验证数据与测试数据的精度。

Okay, we've now understood the most important pieces of code in `network3.py`. Let's take a brief look at the entire program. You don't need to read through this in detail, but you may enjoy glancing over it, and perhaps diving down into any pieces that strike your fancy. The best way to really understand it is, of course, by modifying it, adding extra features, or refactoring anything you think could be done more elegantly. After the code, there are some problems which contain a few starter suggestions for things to do. Here's the code*.

Okay，我们现在已经理解了 `network3.py` 中大部分的重要代码片段。让我们简要回顾一下整个程序。你不必阅读细节，不过你可以从旁欣赏，或者沉浸到那些触动你的想象力的代码片段中。理解这份代码的最佳方法，当然就是修改它，加入些扩展的功能，又或者重构任何你认为可以做得更优雅的东西。有源码之后，会列举一些问题，它们包含对初学者要做的几件事情的建议。

> Using Theano on a GPU can be a little tricky. In particular, it's easy to make the mistake of pulling data off the GPU, which can slow things down a lot. I've tried to avoid this. With that said, this code can certainly be sped up quite a bit further with careful optimization of Theano's configuration. See the Theano documentation for more details.
>
> 在 GPU 上运行 Theano 可能会有点棘手。特别是，将数据从 GPU 中抽取时容易发生错误，会使运行非常缓慢。我曾经试图避免。话虽如此，这份代码一定可以通过仔细优化 Theano 的配置来进一步加速。请参考 Theano 的文档了解更多细节。

```python
"""network3.py
•~~~~~~~~~~~~~~

A Theano-based program for training and running simple neural
networks.

Supports several layer types (fully connected, convolutional, max
pooling, softmax), and activation functions (sigmoid, tanh, and
rectified linear units, with more easily added).

When run on a CPU, this program is much faster than network.py and
network2.py.  However, unlike network.py and network2.py it can also
be run on a GPU, which makes it faster still.

Because the code is based on Theano, the code is different in many
ways from network.py and network2.py.  However, where possible I have
tried to maintain consistency with the earlier programs.  In
particular, the API is similar to network2.py.  Note that I have
focused on making the code simple, easily readable, and easily
modifiable.  It is not optimized, and omits many desirable features.

This program incorporates ideas from the Theano documentation on
convolutional neural nets (notably,
http://deeplearning.net/tutorial/lenet.html ), from Misha Denil's
implementation of dropout (https://github.com/mdenil/dropout ), and
from Chris Olah (http://colah.github.io ).

Written for Theano 0.6 and 0.7, needs some changes for more recent
versions of Theano.

"""

#### Libraries
# Standard library
import cPickle
import gzip

# Third-party libraries
import numpy as np
import theano
import theano.tensor as T
from theano.tensor.nnet import conv
from theano.tensor.nnet import softmax
from theano.tensor import shared_randomstreams
from theano.tensor.signal import downsample

# Activation functions for neurons
def linear(z): return z
def ReLU(z): return T.maximum(0.0, z)
from theano.tensor.nnet import sigmoid
from theano.tensor import tanh
```

```
#### Constants
GPU = True
if GPU:
    print "Trying to run under a GPU.  If this is not desired, then modify " +\
        "network3.py\nto set the GPU flag to False."
    try: theano.config.device = 'gpu'
    except: pass # it's already set
    theano.config.floatX = 'float32'
else:
    print "Running with a CPU.  If this is not desired, then the modify " +\
        "network3.py to set\nthe GPU flag to True."

#### Load the MNIST data
def load_data_shared(filename="../data/mnist.pkl.gz"):
    f = gzip.open(filename, 'rb')
    training_data, validation_data, test_data = cPickle.load(f)
    f.close()
    def shared(data):
        """Place the data into shared variables.  This allows Theano to copy
        the data to the GPU, if one is available.

        """
        shared_x = theano.shared(
            np.asarray(data[0], dtype=theano.config.floatX), borrow=True)
        shared_y = theano.shared(
            np.asarray(data[1], dtype=theano.config.floatX), borrow=True)
        return shared_x, T.cast(shared_y, "int32")
    return [shared(training_data), shared(validation_data), shared(test_data)]

#### Main class used to construct and train networks
class Network(object):

    def __init__(self, layers, mini_batch_size):
        """Takes a list of `layers`, describing the network architecture, and
        a value for the `mini_batch_size` to be used during training
        by stochastic gradient descent.

        """
        self.layers = layers
        self.mini_batch_size = mini_batch_size
        self.params = [param for layer in self.layers for param in layer.params]
        self.x = T.matrix("x")
        self.y = T.ivector("y")
        init_layer = self.layers[0]
        init_layer.set_inpt(self.x, self.x, self.mini_batch_size)
        for j in xrange(1, len(self.layers)):
            prev_layer, layer  = self.layers[j-1], self.layers[j]
            layer.set_inpt(
                prev_layer.output, prev_layer.output_dropout, self.mini_batch_size)
        self.output = self.layers[-1].output
        self.output_dropout = self.layers[-1].output_dropout


    def SGD(self, training_data, epochs, mini_batch_size, eta,
            validation_data, test_data, lmbda=0.0):
        """Train the network using mini-batch stochastic gradient descent."""
        training_x, training_y = training_data
        validation_x, validation_y = validation_data
        test_x, test_y = test_data

        # compute number of minibatches for training, validation and testing
        num_training_batches = size(training_data)/mini_batch_size
        num_validation_batches = size(validation_data)/mini_batch_size
        num_test_batches = size(test_data)/mini_batch_size

        # define the (regularized) cost function, symbolic gradients, and updates
        l2_norm_squared = sum([(layer.w**2).sum() for layer in self.layers])
        cost = self.layers[-1].cost(self)+\
               0.5*lmbda*l2_norm_squared/num_training_batches
        grads = T.grad(cost, self.params)
        updates = [(param, param-eta*grad)
                   for param, grad in zip(self.params, grads)]

        # define functions to train a mini-batch, and to compute the
        # accuracy in validation and test mini-batches.
        i = T.lscalar() # mini-batch index
        train_mb = theano.function(
            [i], cost, updates=updates,
            givens={
                self.x:
                training_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size],
                self.y:
                training_y[i*self.mini_batch_size: (i+1)*self.mini_batch_size]
            })
        validate_mb_accuracy = theano.function(
            [i], self.layers[-1].accuracy(self.y),
            givens={
                self.x:
                validation_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size],
                self.y:
                validation_y[i*self.mini_batch_size: (i+1)*self.mini_batch_size]
            })
        test_mb_accuracy = theano.function(
            [i], self.layers[-1].accuracy(self.y),
            givens={
                self.x:
                test_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size],
                self.y:
                test_y[i*self.mini_batch_size: (i+1)*self.mini_batch_size]
            })
        self.test_mb_predictions = theano.function(
            [i], self.layers[-1].y_out,
            givens={
                self.x:
                test_x[i*self.mini_batch_size: (i+1)*self.mini_batch_size]
            })

        # Do the actual training
        best_validation_accuracy = 0.0
        for epoch in xrange(epochs):
            for minibatch_index in xrange(num_training_batches):
                iteration = num_training_batches*epoch+minibatch_index
                if iteration % 1000 == 0:
                    print("Training mini-batch number {0}".format(iteration))
                cost_ij = train_mb(minibatch_index)
                if (iteration+1) % num_training_batches == 0:
                    validation_accuracy = np.mean(
                        [validate_mb_accuracy(j) for j in
xrange(num_validation_batches)])
                    print("Epoch {0}: validation accuracy {1:.2%}".format(
                        epoch, validation_accuracy))
                    if validation_accuracy >= best_validation_accuracy:
                        print("This is the best validation accuracy to date.")
                        best_validation_accuracy = validation_accuracy
                        best_iteration = iteration
                        if test_data:
                            test_accuracy = np.mean(
                                [test_mb_accuracy(j) for j in
xrange(num_test_batches)])
                            print('The corresponding test accuracy is {0:.2%}'.format(
                                test_accuracy))
        print("Finished training network.")
        print("Best validation accuracy of {0:.2%} obtained at iteration {1}".format(
            best_validation_accuracy, best_iteration))
        print("Corresponding test accuracy of {0:.2%}".format(test_accuracy))

#### Define layer types

class ConvPoolLayer(object):
    """Used to create a combination of a convolutional and a max-pooling
    layer.  A more sophisticated implementation would separate the
    two, but for our purposes we'll always use them together, and it
    simplifies the code, so it makes sense to combine them.

    """

    def __init__(self, filter_shape, image_shape, poolsize=(2, 2),
                 activation_fn=sigmoid):
        """`filter_shape` is a tuple of length 4, whose entries are the number
        of filters, the number of input feature maps, the filter height, and the
        filter width.

        `image_shape` is a tuple of length 4, whose entries are the
        mini-batch size, the number of input feature maps, the image
        height, and the image width.

        `poolsize` is a tuple of length 2, whose entries are the y and
        x pooling sizes.

        """

        self.filter_shape = filter_shape
        self.image_shape = image_shape
        self.poolsize = poolsize
        self.activation_fn=activation_fn
        # initialize weights and biases
        n_out = (filter_shape[0]*np.prod(filter_shape[2:])/np.prod(poolsize))
        self.w = theano.shared(
            np.asarray(
                np.random.normal(loc=0, scale=np.sqrt(1.0/n_out), size=filter_shape),
                dtype=theano.config.floatX),
            borrow=True)
        self.b = theano.shared(
            np.asarray(
                np.random.normal(loc=0, scale=1.0, size=(filter_shape[0],)),
                dtype=theano.config.floatX),
            borrow=True)
        self.params = [self.w, self.b]

    def set_inpt(self, inpt, inpt_dropout, mini_batch_size):
        self.inpt = inpt.reshape(self.image_shape)
        conv_out = conv.conv2d(
            input=self.inpt, filters=self.w, filter_shape=self.filter_shape,
            image_shape=self.image_shape)
        pooled_out = downsample.max_pool_2d(
            input=conv_out, ds=self.poolsize, ignore_border=True)
        self.output = self.activation_fn(
            pooled_out + self.b.dimshuffle('x', 0, 'x', 'x'))
        self.output_dropout = self.output # no dropout in the convolutional layers

class FullyConnectedLayer(object):

    def __init__(self, n_in, n_out, activation_fn=sigmoid, p_dropout=0.0):
        self.n_in = n_in
        self.n_out = n_out
        self.activation_fn = activation_fn
        self.p_dropout = p_dropout
        # Initialize weights and biases
        self.w = theano.shared(
            np.asarray(
                np.random.normal(
                    loc=0.0, scale=np.sqrt(1.0/n_out), size=(n_in, n_out)),
                dtype=theano.config.floatX),
            name='w', borrow=True)
        self.b = theano.shared(
            np.asarray(np.random.normal(loc=0.0, scale=1.0, size=(n_out,)),
                       dtype=theano.config.floatX),
            name='b', borrow=True)
        self.params = [self.w, self.b]

    def set_inpt(self, inpt, inpt_dropout, mini_batch_size):
        self.inpt = inpt.reshape((mini_batch_size, self.n_in))
        self.output = self.activation_fn(
            (1-self.p_dropout)*T.dot(self.inpt, self.w) + self.b)

        self.y_out = T.argmax(self.output, axis=1)
        self.inpt_dropout = dropout_layer(
            inpt_dropout.reshape((mini_batch_size, self.n_in)), self.p_dropout)
        self.output_dropout = self.activation_fn(
            T.dot(self.inpt_dropout, self.w) + self.b)

    def accuracy(self, y):
        "Return the accuracy for the mini-batch."
        return T.mean(T.eq(y, self.y_out))

class SoftmaxLayer(object):

    def __init__(self, n_in, n_out, p_dropout=0.0):
        self.n_in = n_in
        self.n_out = n_out
        self.p_dropout = p_dropout
        # Initialize weights and biases
        self.w = theano.shared(
            np.zeros((n_in, n_out), dtype=theano.config.floatX),
            name='w', borrow=True)
        self.b = theano.shared(
            np.zeros((n_out,), dtype=theano.config.floatX),
            name='b', borrow=True)
        self.params = [self.w, self.b]

    def set_inpt(self, inpt, inpt_dropout, mini_batch_size):
        self.inpt = inpt.reshape((mini_batch_size, self.n_in))
        self.output = softmax((1-self.p_dropout)*T.dot(self.inpt, self.w) + self.b)
        self.y_out = T.argmax(self.output, axis=1)
        self.inpt_dropout = dropout_layer(
            inpt_dropout.reshape((mini_batch_size, self.n_in)), self.p_dropout)
        self.output_dropout = softmax(T.dot(self.inpt_dropout, self.w) + self.b)

    def cost(self, net):
        "Return the log-likelihood cost."
        return -T.mean(T.log(self.output_dropout)[T.arange(net.y.shape[0]), net.y])

    def accuracy(self, y):
        "Return the accuracy for the mini-batch."
        return T.mean(T.eq(y, self.y_out))


#### Miscellanea
def size(data):
    "Return the size of the dataset `data`."
    return data[0].get_value(borrow=True).shape[0]

def dropout_layer(layer, p_dropout):
    srng = shared_randomstreams.RandomStreams(
        np.random.RandomState(0).randint(999999))
    mask = srng.binomial(n=1, p=1-p_dropout, size=layer.shape)
    return layer*T.cast(mask, theano.config.floatX)
```

Problems

问题

- At present, the `SGD` method requires the user to manually choose the number of epochs to train for. Earlier in the book we discussed an automated way of selecting the number of epochs to train for, known as early stopping. Modify `network3.py` to implement early stopping.

  目前，`SGD` 函数需要用户手工选择训练轮次的数量。在本书早前的章节中，我们讨论过训练轮次的自动化选择的问题，称为早期停止。修改 `network3.py` 实现早期停止。

- Add a `Network` method to return the accuracy on an arbitrary data set.

  加入一个 `network` 函数，返回对任意数据集的分类精度。

- Modify the `SGD` method to allow the learning rate η to be a function of the epoch number. *Hint: After working on this problem for a while, you may find it useful to see the discussion at this link.*

  修改函数 `SGD` 容许学习步长 η 成为轮次数量的函数。*提示：在这个问题中工作过一段时间之后，你会发现它是非常有用的，参考这个链接*。

- Earlier in the chapter I described a technique for expanding the training data by applying (small) rotations, skewing, and translation. Modify `network3.py` to incorporate all these techniques. *Note: Unless you have a tremendous amount of memory, it is not practical to explicitly generate the entire expanded data set. So you should consider alternate approaches.*

  本章较早的时候，我描述过通过旋转，倾斜，和平移来扩展训练数据的技术。修改 `network3.py` 合并所有这些技术。注意：除非你有一个海量的内存，否则生成一整套扩展数据集是不现实的。所以，你应该考虑替代方案。

- Add the ability to load and save networks to `network3.py`.

  在 `network3.py` 中增加加载与保存网络的功能。

- A shortcoming of the current code is that it provides few diagnostic tools. Can you think of any diagnostics to add that would make it easier to understand to what extent a network is overfitting? Add them.

  当前源码的缺点是它只提供了有限的诊断工具。你能想到任何的诊断功能，使程序更容易了解过拟合的程度吗？添加他们。

- We've used the same initialization procedure for rectified linear units as for sigmoid (and tanh) neurons. Our argument for that initialization was specific to the sigmoid function. Consider a network made entirely of rectified linear units (including outputs). Show that rescaling all the weights in the network by a constant factor $c > 0$ simply rescales the outputs by a factor c^{L-1}, where L is the number of layers. How does this change if the final layer is a softmax? What do you think of using the sigmoid initialization procedure for the rectified linear units? Can you think of a better initialization procedure? *Note: This is a very open-ended problem, not something with a simple self-contained answer. Still, considering the problem will help you better understand networks containing rectified linear units.*

  我们已经用与初始化 sigmoid（与 tanh）神经元相同的初始化过程，来初始化纠正线性单元。考虑一个网络，它完全由纠正线性单元（包括输出）组成。展现一下以常数因子 $c > 0$ 来重整网络的所有权值，以因子 c^{L-1} 重整输出，这里 L 是层编号。如果最后一层是 softmax，应该如何变通？你认为有更好的初始化途径吗？*提示：这是一个无止境的问题，没有什么东西自带简单答案。不过，思考这个问题将帮助你更好地理解包含纠正线性单元的网络*。

- Our analysis of the unstable gradient problem was for sigmoid neurons. How does the analysis change for networks made up of rectified linear units? Can you think of a good way of modifying such a network so it doesn't suffer from the unstable gradient problem? *Note: The word good in the second part of this makes the problem a research problem. It's actually easy to think of ways of making such modifications. But I haven't investigated in enough depth to know of a really good technique.*

  我们对梯度失稳问题的分析是针对 sigmoid 神经元的。对于纠正线性单元组成的网络，分析会如何改变呢？你能想到什么好主意让网络免受梯度失稳的问题影响呢？提示：第二个问题的提法很好，它使得问题成为一个科研课题。想办法作出如此这般的修改，其实很容易。不过，我还没有对真正好的技术做过足够深入的调查。

Recent pr ogress in image r ecognition

图像识别的近期进展

In 1998, the year MNIST was introduced, it took weeks to train a state-of-the-art workstation to achieve accuracies substantially worse than those we can achieve using a GPU and less than an hour of training. Thus, MNIST is no longer a problem that pushes the limits of available technique; rather, the speed of training means that it is a problem good for teaching and learning purposes. Meanwhile, the focus of research has moved on, and modern work involves much more challenging image recognition problems. In this section, I briefly describe some recent work on image recognition using neural networks.

1998 年，MNIST 推出，它在一台当时最先进的工作站上经历了几周的训练，但是分类精度比我们在 GPU 上实现的差多了，而且我们仅用了个把小时来训练。因而，MNIST 在推进可用技术的发展上，已经不会有太多的贡献了；相反，训练的速度问题反而成为了很好的教学与学习的目的。同时，研究的重点也发生了改变，当前的工作，是挑战更多的涉及图像识别的问题。在本节中，我主要叙述目前应用神经网络进行图像识别的工作。

The section is different to most of the book. Through the book I've focused on ideas likely to be of lasting interest - ideas such as backpropagation, regularization, and convolutional networks. I've tried to avoid results which are fashionable as I write, but whose long-term value is unknown. In science, such results are more often than not ephemera which fade and have little lasting impact. Given this, a skeptic might say: "well, surely the recent progress in image recognition is an example of such ephemera? In another two or three years, things will have moved on. So surely these results are only of interest to a few specialists who want to compete at the absolute frontier? Why bother discussing it?"

本节与本书大部分其他段落不同。贯穿本书，我都聚焦于那些大家具有持久兴趣的想法上，譬如，反向传播，正则化，以及卷积网络。我已经试图避免将那些时髦的东西写进来，不过到底哪些东西最终具有长期价值，目前不得而知。从科学上看，我们的那些结果总比那些昙花一现的东西更具价值。对于这一点，怀疑论者会说："近期图像识别的进展是昙花一现吗？未来两三年，大家还是会往这方面走的。只有极少数的专家愿意向终极解决方案的方向发力的，为什么要自讨没趣讨论这个问题？"

Such a skeptic is right that some of the finer details of recent papers will gradually diminish in perceived importance. With that said, the past few years have seen extraordinary improvements using deep nets to attack extremely difficult image recognition tasks. Imagine a historian of science writing about computer vision in the year 2100. They will identify the years 2011 to 2015 (and probably a few years beyond) as a time of huge breakthroughs, driven by deep convolutional nets. That doesn't mean deep convolutional nets will still be used in 2100, much less detailed ideas such as dropout, rectified linear units, and so on. But it does mean that an important transition is taking place, right now, in the history of ideas. It's a bit like watching the discovery of the atom, or the invention of antibiotics: invention and discovery on a historic scale. And so while we won't dig down deep into details, it's worth getting some idea of the exciting discoveries currently being made.

有一点质疑是对的，近期的论文中，在认知关键性上的一些出色细节在逐步消失。就是说，在过去的几年中，应用深度网络去解决极其困难的图像识别的任务，取得了非凡的进步。想象一下，一个关于计算机视觉的科学史学家，在 2100 年，将会指出 2011 年至 2015 年（大约就是那几年吧）是图像识别由于深度卷积网络的推动，而取得重大突破的时刻。这并不意味着卷积网络将会使用到 2100 年，至少某些具体的思想是这样，譬如，辍学，纠正线性单元，如此等等。不过，从历史的角度来说，现在，它的确意味着一个重要的转变正在出现。它有点像原子的发现，或者是抗生素的发明：都是史诗式的发现与发明。即使我们不深入发掘细节，它已经可以给我们一个观念，一个激动人心的伟大发现正在实现。

The 2012 LRMD paper: Let me start with a 2012 paper* from a group of researchers from Stanford and Google. I'll refer to this paper as LRMD, after the last names of the first four authors. LRMD used a neural network to classify images from ImageNet, a very challenging image recognition problem. The 2011 ImageNet data that they used included 16 million full color images, in 20 thousand categories. The images were crawled from the open net, and classified by workers from Amazon's Mechanical Turk service. Here's a few ImageNet images*:

2012 LRMD 论文： 让我从 2012 年的一篇论文开始吧，它来自一个斯坦福大学与谷歌的研究者组成的小组。我将称其为 LRMD，这个简称是以论文前四位作者的姓氏的第一个字母组成的。LRMD 用一个神经网络从 ImageNet 进行图像分类，它是一个富有挑战性的图像识别问题。他们使用的 2011 年的 ImageNet 数据包含一千六百万个真彩图片，两万个分类。图片是从开放的网络中扒下来的，有来自 Amazon's Mechanical Turk 的工作者分类。下面是其中的几张图片。

> Building high-level features using large scale unsupervised learning, by Quoc Le, Marc'Aurelio Ranzato, Rajat Monga, Matthieu Devin, Kai Chen, Greg Corrado, Jeff Dean, and Andrew Ng (2012). Note that the detailed architecture of the network used in the paper differed in many details from the deep convolutional networks we've been studying. Broadly speaking, however, LRMD is based on many similar ideas.
>
> Building high-level features using large scale unsupervised learning, by Quoc Le, Marc'Aurelio Ranzato, Rajat Monga, Matthieu Devin, Kai Chen, Greg Corrado, Jeff Dean, and Andrew Ng (2012). 请注意，论文中所说的网络架构，与我们所研究的深度卷积网络细节上有不少差异。广义上说，无论如何，LRMD 是基于很多我们熟悉的思想的。

> These are from the 2014 dataset, which is somewhat changed from 2011. Qualitatively, however, the dataset is extremely similar. Details about ImageNet are available in the original ImageNet paper, ImageNet: a large-scale hierarchical image database, by Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei (2009).
>
> 这些图片来自 2014 年的数据集，较之 2011 年的版本有一些改动。品质上，数据集非常相似。ImageNet 的详情，请参考 ImageNet 的原创论文，ImageNet: a large-scale hierarchical image database，作者 Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, 与 Li Fei-Fei (2009)。

These are, respectively, in the categories for beading plane, brown root rot fungus, scalded milk, and the common roundworm. If you're looking for a challenge, I encourage you to visit ImageNet's list of hand tools, which distinguishes between beading planes, block planes, chamfer planes, and about a dozen other types of plane, amongst other categories. I don't know about you, but I cannot confidently distinguish between all these tool types. This is obviously a much more challenging image recognition task than MNIST! LRMD's network obtained a respectable 15.8 percent accuracy for correctly classifying ImageNet images. That may not sound impressive, but it was a huge improvement over the previous best result of 9.3 percent accuracy. That jump suggested that neural networks might offer a powerful approach to very challenging image recognition tasks, such as ImageNet.

这几张图片分别是，圆线刨，葛根霉菌，煮沸的牛奶，以及常见的蛔虫。如果你想寻找挑战，我鼓励你访问 ImageNet 的手工工具列表，上面区分了圆角刨，平面刨，倒角刨，以及属于其他类别的大约十二种类型的刨。我不知道你会怎么样，反正我就没有信心区分所有这些工具的类型。这明显是一个比 MNIST 更具挑战性的图形识别问题！LRMD 的网络取得了不错的 15.8% 的分类准确率。听起来好像没有什么了不起，不过相比与之前的 9.3% 的准确率，它已经是巨大的进步了。这个飞跃标明，神经网络可以为极具挑战性的图像识别任务，例如，ImageNet，提供强有力的途径。

The 2012 KSH paper: The work of LRMD was followed by a 2012 paper of Krizhevsky, Sutskever and Hinton (KSH)*. KSH trained and tested a deep convolutional neural network using a restricted subset of the ImageNet data. The subset they used came from a popular machine learning competition - the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC). Using a competition dataset gave them a good way of comparing their approach to other leading techniques. The ILSVRC-2012 training set contained about 1.2 million ImageNet images, drawn from 1,000 categories. The validation and test sets contained 50,000 and 150,000 images, respectively, drawn from the same 1,000 categories.

2012 KSH 论文： LRMD 的工作由 Krizhevsky, Sutskever 和 Hinton (KSH)* 在 2012 年在一篇论文中接力。KSH 用一个有限的 ImageNet 数据集的子集，训练和测试了一个深度卷积神经网络。他们使用的子集来自一个非常流行的机器学习竞赛 - ImageNet Large-Scale Visual Recognition Challenge (ILSVRC)。使用竞赛数据集给了他们一个好的途径来比较他们的方法与其他的领先技术。ILSVRC-2012 训练集包含大约一百二十万张 ImageNet 图片，摘取自 1,000 个类别。验证与测试数据集包含 50,000 与 150,000 张图片，分别摘取自相同的 1,000 个类别。

> ImageNet classification with deep convolutional neural networks, by Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton (2012).

One difficulty in running the ILSVRC competition is that many ImageNet images contain multiple objects. Suppose an image shows a labrador retriever chasing a soccer ball. The so-called "correct" ImageNet classification of the image might be as a labrador retriever. Should an algorithm be penalized if it labels the image as a soccer ball? Because of this ambiguity, an algorithm was considered correct if the actual ImageNet classification was among the 5 classifications the algorithm considered most likely. By this top-5 criterion, KSH's deep convolutional network achieved an accuracy of 84.7 percent, vastly better than the next-best contest entry, which achieved an accuracy of 73.8 percent. Using the more restrictive metric of getting the label exactly right, KSH's network achieved an accuracy of 63.3 percent.

参与 ILSVRC 竞赛的一个难点是很多 ImageNet 图像包含多个实体。试想一下，图片显示一只拉布拉多猎犬在追逐一个橄榄球。所谓“正确的” ImageNet 图像分类可能就是拉布拉多猎犬。假如图片被标记为橄榄球，算法是否应该被判负呢？由于这种模糊性，如果实际的 ImageNet 分类属于算法计算出来的最可能的 5 个分类之一，算法就被认为是正确。借助这个 top-5 准则，KSH 的深度卷积网络取得了 84.7% 的准确率，远远优于比赛的第二名，他们取得了 73.8% 的准确率。在标签精确的更严格的标准下，KSH 网络取得了 63.3% 的准确率。

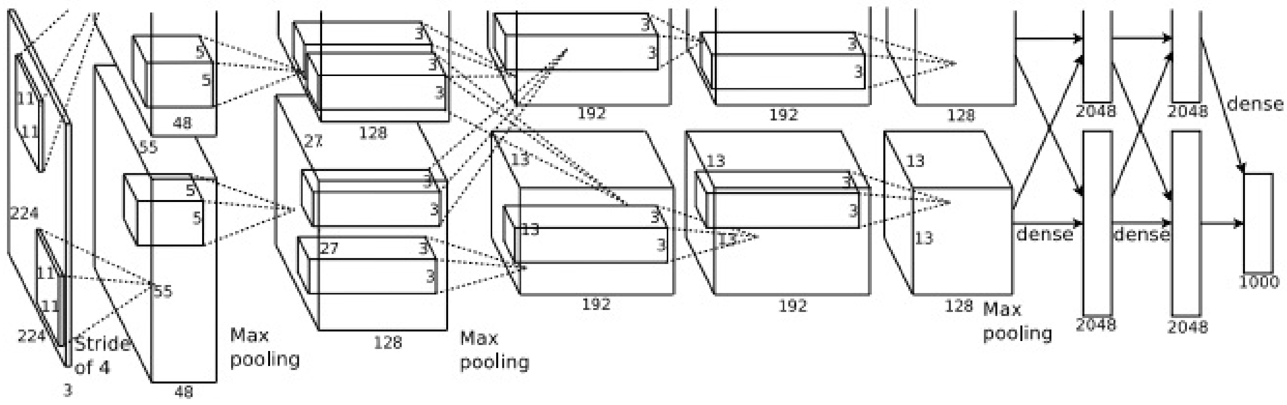
It's worth briefly describing KSH's network, since it has inspired much subsequent work. It's also, as we shall see, closely related to the networks we trained earlier in this chapter, albeit more elaborate. KSH used a deep convolutional neural network, trained on two GPUs. They used two GPUs because the particular type of GPU they were using (an NVIDIA GeForce GTX 580) didn't have enough on-chip memory to store their entire network. So they split the network into two parts, partitioned across the two GPUs.

简要描述一下 KSH 网络是值得的，因为它启发了很多后续的工作。正如我们看到的那样，它与我们在本章早前训练的网络密前相关，尽管复杂很多。KSH 使用一个深度网络，在两个 GPU 上训练。他们使用两个 GPU，是因为他们所使用的 GPU 型号（NVIDIA GeForce GTX 580）缺乏足够的片上内存来存放他们的整个网络。所以他们将网络分成两个部分，分隔在两个GPU 中。

The KSH network has 7 layers of hidden neurons. The first 5 hidden layers are convolutional layers (some with max-pooling), while the next 2 layers are fully-connected layers. The output layer is a 1,000-unit softmax layer, corresponding to the 1,000 image classes. Here's a sketch of the network, taken from the KSH paper*. The details are explained below. Note that many layers are split into 2 parts, corresponding to the 2 GPUs.

KSH 网络有 7 个隐藏神经元层。前面 5 个隐藏层是卷积层（有些带极值池化），后面是两个全连层。输出层是 1,000 单元的逻辑多分类层，对应 1,000 个图像分类。这里是网络的简图，摘取自 KSH 论文。详情将在下面解释。注意，许多层被分成两个部分，对应于两个 GPU。

> Thanks to Ilya Sutskever.



The input layer contains 3×224×224 neurons, representing the RGB values for a 224×224 image. Recall that, as mentioned earlier, ImageNet contains images of varying resolution. This poses a problem, since a neural network's input layer is usually of a fixed size. KSH dealt with this by rescaling each image so the shorter side had length 256. They then cropped out a 256×256 area in the center of the rescaled image. Finally, KSH extracted random 224×224 subimages (and horizontal reflections) from the 256×256 images. They did this random cropping as a way of expanding the training data, and thus reducing overfitting. This is particularly helpful in a large network such as KSH's. It was these 224×224 images which were used as inputs to the network. In most cases the cropped image still contains the main object from the uncropped image.

输入层包含 3x224x224 个神经元，表示在 224x224 图片中的 RGB 值。回忆一下，早前我们注意到，ImageNet 有不同解析度的图片。这就提出了一个问题，因为神经网络的输入层通常都是固定大小的。KSH 通过缩放每个图片来处理这个问题，使得每个图片的短边长度统一为 256。然后他们从缩放之后的图片的中心裁出 256x256 的区域。最后，KSH 从 256x256 的图像中，随机抽取 224x224 的子图（结合水平镜像）。他们通过这种随机剪裁的途径来扩展训练数据，避免过拟合。这个对于像 KSH 这样的大型网络来说，特别有帮助。这些 224x224 的图片就是用于网络输入的数据了。在大部分情况下，剪裁过的图片，依然包含在原图上的主要物体。

Moving on to the hidden layers in KSH's network, the first hidden layer is a convolutional layer, with a max-pooling step. It uses local receptive fields of size 11×11, and a stride length of 4 pixels. There are a total of 96 feature maps. The feature maps are split into two groups of 48 each, with the first 48 feature maps residing on one GPU, and the second 48 feature maps residing on the other GPU. The max-pooling in this and later layers is done in 3×3 regions, but the pooling regions are allowed to overlap, and are just 2 pixels apart.

深入 KSH 的隐藏层，第一个隐藏层是一个卷积层，带有一个极值池化步骤。它使用的局部接收域尺寸是 11x11，滑动步长 4 像素。有 96 个特征图。特征图以 48 个为一组，被分配到两组中，第一组 48 个特征图配置到一个 GPU 中，第二组 48 个特征图配置到另外一个 GPU 中。这一层以及后面的层的极值池化都是 3x3 的区域，池化区域被容许重叠，并且相距 2 个像素。

The second hidden layer is also a convolutional layer, with a max-pooling step. It uses 5×5 local receptive fields, and there's a total of 256 feature maps, split into 128 on each GPU. Note that the feature maps only use 48 input channels, not the full 96 output from the previous layer (as would usually be the case). This is because any single feature map only uses inputs from the same GPU. In this sense the network departs from the convolutional architecture we described earlier in the chapter, though obviously the basic idea is still the same.

第二个隐藏层也是卷积层，带一个极值池化。它使用 5x5 的局部接收域，总共有 256 个特征图，每个 GPU 分配 128 个。注意这里的特征图仅使用 48 个输入通道，而不是一一对应上一层的 96 个输出（正常情况下是这样）。这是因为任何一个单独的特征图，仅使用来自同一 GPU 的输入。从这个意义上说，网络已经离开了我们在本章早前讨论的卷积架构，然而，基本思想显然是一致的。

The third, fourth and fifth hidden layers are convolutional layers, but unlike the previous layers, they do not involve max-pooling. Their respectives parameters are: (3) 384 feature maps, with 3×3 local receptive fields, and 256 input channels; (4) 384 feature maps, with 3×3 local receptive fields, and 192 input channels; and (5) 256 feature maps, with 3×3 local receptive fields, and 192 input channels. Note that the third layer involves some inter-GPU communication (as depicted in the figure) in order that the feature maps use all 256 input channels.

第三，四和五个隐藏层是卷积层，不过与前面的层不同，它们不包括极值池化。它们的接收参数为：（3）384 个特征图，带 3x3 局部接收域，及 256 个输入通道；（4）384 个特征图，3x3 局部接收域，及 192 个输入通道；（5）256 个特征图，3x3 的局部接收域，192 个输入通道。注意，在第三层包括了某种 GPU 间的通讯机制（如图所示）以便特征图能用上所有 256 个输入通道。

The sixth and seventh hidden layers are fully-connected layers, with 4,096 neurons in each layer.

第六和第七个隐藏层是全连层，每层带有 4,096 个神经元。

The output layer is a 1,000-unit softmax layer.

输出层是 1,000 单元的 softmax 层。

The KSH network takes advantage of many techniques. Instead of using the sigmoid or tanh activation functions, KSH use rectified linear units, which sped up training significantly. KSH's network had roughly 60 million learned parameters, and was thus, even with the large training set, susceptible to overfitting. To overcome this, they expanded the training set using the random cropping strategy we discussed above. They also further addressed overfitting by using a variant of l2 regularization, and dropout. The network itself was trained using momentum-based mini-batch stochastic gradient descent.

KSH 取得了不少的技术进步。KSH 使用显著提高训练速度的纠正线性单元，替换掉 sigmoid 或者 tanh 激活函数。KSH 网络具有 6000 万个学习参数，有鉴于此，即使是使用巨大的训练集，也很容易导致过拟合。为了克服这个问题，他们使用我们在上面讨论过的随机裁切策略来扩展训练数据集。他们还使用了 l2 正则化的变体, 和辍学来进一步解决过拟合的问题。网络本身使用动量基小批量样本随机梯度下降来训练。

That's an overview of many of the core ideas in the KSH paper. I've omitted some details, for which you should look at the paper. You can also look at Alex Krizhevsky's cuda-convnet (and successors), which contains code implementing many of the ideas. A Theano-based implementation has also been developed*, with the code available here. The code is recognizably along similar lines to that developed in this chapter, although the use of multiple GPUs complicates things somewhat. The Caffe neural nets framework also includes a version of the KSH network, see their Model Zoo for details.

那些就是 KSH 的核心思想的概述。我忽略了一些细节，你应该去看看这篇论文。你也可以看看 Alex Krizhevsky 的 cuda-convnet（及后续）项目，那里包含了很多构思的实现代码。基于 Theano 的实现也在开发当中，源码可在这里找到。这份源码还是沿着本章所述的技术线路来开发的，尽管采用多 GPU 会是事情稍微变得复杂。Caffe 神经网络的框架同样包括一个 KSH 网络的版本，详情参考他们的 Model Zoo 。

> Theano-based large-scale visual recognition with multiple GPUs, by Weiguang Ding, Ruoyan Wang, Fei Mao, and Graham Taylor (2014).

The 2014 ILSVRC competition: Since 2012, rapid progress continues to be made. Consider the 2014 ILSVRC competition. As in 2012, it involved a training set of 1.2 million images, in 1,000 categories, and the figure of merit was whether the top 5 predictions included the correct category. The winning team, based primarily at Google*, used a deep convolutional network with 22 layers of neurons. They called their network GoogLeNet, as a homage to LeNet-5. GoogLeNet achieved a top-5 accuracy of 93.33 percent, a giant improvement over the 2013 winner (Clarifai, with 88.3 percent), and the 2012 winner (KSH, with 84.7 percent).

2014 ILSVRC 竞赛： 自 2012 年起，继续快速发展。察看 2014 年的比赛。与 2012 年一样，它包括一套一百二十万张图片的训练集，1,000 个类别，评分标准是预测的前 5 项是否包含正确的类型。获胜的队伍，成员主要来自 Google*，他们使用一个 20 层的深度卷积网络。他们称其为 GoogLeNet，作为对 LeNet-5 的致敬。GoogLeNet 取得 top-5 评分的 93.33% 的准确率，是个了不起的进步，远胜 2013 年的优胜者（Clarifar, 88.3%），以及 2012 年的优胜者（KSH, 84.7%）。

> Going deeper with convolutions, by Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich (2014).

Just how good is GoogLeNet's 93.33 percent accuracy? In 2014 a team of researchers wrote a survey paper about the ILSVRC competition*. One of the questions they address is how well humans perform on ILSVRC. To do this, they built a system which lets humans classify ILSVRC images. As one of the authors, Andrej Karpathy, explains in an informative blog post, it was a lot of trouble to get the humans up to GoogLeNet's performance:

GoogLeNet 的 93.33% 的准确度到底好到什么程度呢？在 2014 年，有一队研究人员写了一篇关于 ILSVRC 竞赛的调查论文。其中一个他们关注的问题是，人类在 ILSVRC 比赛中的表现会如何。为了做到这点，他们建设了一个系统，让人类来分辨 ILSVRC 图片。正如论文的作者之一 Andrej Karpathy，在他的博客上说明的那样，要想让人类的表现胜过 GoogLeNet，那是将超级麻烦：

> > ...the task of labeling images with 5 out of 1000 categories quickly turned out to be extremely challenging, even for some friends in the lab who have been working on ILSVRC and its classes for a while. First we thought we would put it up on [Amazon Mechanical Turk]. Then we thought we could recruit paid undergrads. Then I organized a labeling party of intense labeling effort only among the (expert labelers) in our lab. Then I developed a modified interface that used GoogLeNet predictions to prune the number of categories from 1000 to only about 100. It was still too hard - people kept missing categories and getting up to ranges of 13-15% error rates. In the end I realized that to get anywhere competitively close to GoogLeNet, it was most efficient if I sat down and went through the painfully long training process and the subsequent careful annotation process myself... The labeling happened at a rate of about 1 per minute, but this decreased over time... Some images are easily recognized, while some images (such as those of fine-grained breeds of dogs, birds, or monkeys) can require multiple minutes of concentrated effort. I became very good at identifying breeds of

> > dogs... Based on the sample of images I worked on, the GoogLeNet classification error turned out to be 6.8%... My own error in the end turned out to be 5.1%, approximately 1.7% better.
> >
> > 为图片在 1000 个类别中标出 5 个标签，这样的任务很快被证实是极具挑战性的，即使是对于那些在实验室里面专门为 ILSVRC 或者同类任务工作过一段时间的朋友来说，都是这样。我们首先想到的是，将图片上传到 Amazon Mechanical Turk。我们认为我们可以招募受薪的本科生。之后，我就可以在我们的实验室组织一个可以进行紧张的专家级定标工作的定标团体。然后，我开发了一个修改后的界面，它使用 GoogLeNet 预测功能将 1000 个类别剪裁到 100 个类别。这仍然很困难 - 人们维持着 13-15% 的分类错误率。最终，我实现了在许多图片的识别比拼中，都有接近 GoogLeNet 的水准，当我安静坐下，经历痛苦漫长的训练过程，并且将这些过程认真做好后续笔记的时候，打标签的效率最高 ... 定标频率大约为 1 分钟，不过随着时间的推移而降低。有些图片容易识别，有些图片（譬如，那些狗，鸟，或者是猴子的细分品种）就需要花费几分钟的注意力。我变得非常擅长分辨狗的品种 ... 对于我工作的那些图片样本，GoogLeNet 的分辨错误率为 6.8% ... 我的最终分辨错误率为 5.1%，大约好 1.7% 。
>
> ImageNet large scale visual recognition challenge, by Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei (2014).

In other words, an expert human, working painstakingly, was with great effort able to narrowly beat the deep neural network. In fact, Karpathy reports that a second human expert, trained on a smaller sample of images, was only able to attain a 12.0 percent top-5 error rate, significantly below GoogLeNet's performance. About half the errors were due to the expert "failing to spot and consider the ground truth label as an option".

换言之，一个人类专家，经过刻苦工作，付出巨大努力之后，以微弱的优势击败了深度网络。事实上，Karpathy 报告说，一个二流的人类专家，经过一个小样品量的图片训练之后，仅可达到 12.0% 的错误率，明显落后于 GoogLeNet 的表现。大约有一半的错误是由于人类专家“没有发现和考虑到背景上的标志物也是一个选项”。

These are astonishing results. Indeed, since this work, several teams have reported systems whose top-5 error rate is actually *better* than 5.1%. This has sometimes been reported in the media as the systems having better-than-human vision. While the results are genuinely exciting, there are many caveats that make it misleading to think of the systems as having better-than-human vision. The ILSVRC challenge is in many ways a rather limited problem - a crawl of the open web is not necessarily representative of images found in applications! And, of course, the top-5 criterion is quite artificial. We are still a long way from solving the problem of image recognition or, more broadly, computer vision. Still, it's extremely encouraging to see so much progress made on such a challenging problem, over just a few years.

有些令人惊讶的结果。事实上，对于这个工作，有些团队报告说他们的系统，在 top-5 评分规则下，取得了错误率低于 5.1% 的成绩。这些消息有时是出现在媒体上的关于计算机视觉系统优于人类的报道之中。虽然结果令人兴奋，然而也有很多忠告指出，计算机系统的视觉分辨能力优于人类是种误解。ILSVRC 挑战赛在形式上就有很多局限性 - 开放的网页爬行的比赛形式，图片的分辨表现未必就是计算机程序作出的！况且，top-5 是完全人为的评判规则。我们在解决图像识别，更广义地说是计算机视觉问题上，我们还有很长的路要走。纵观这几年，我们在一个如此具有挑战性的问题上取得的巨大进步，仍然令人十分鼓舞。

Other activity: I've focused on ImageNet, but there's a considerable amount of other activity using neural nets to do image recognition. Let me briefly describe a few interesting recent results, just to give the flavour of some current work.

其他的动向： 我已经集中讨论过 ImageNet，不过还有大量活跃的用神经网络进行图像识别的项目。让我简要地介绍一些当前有意思的进展，权当是为目前的工作带来点趣味吧。

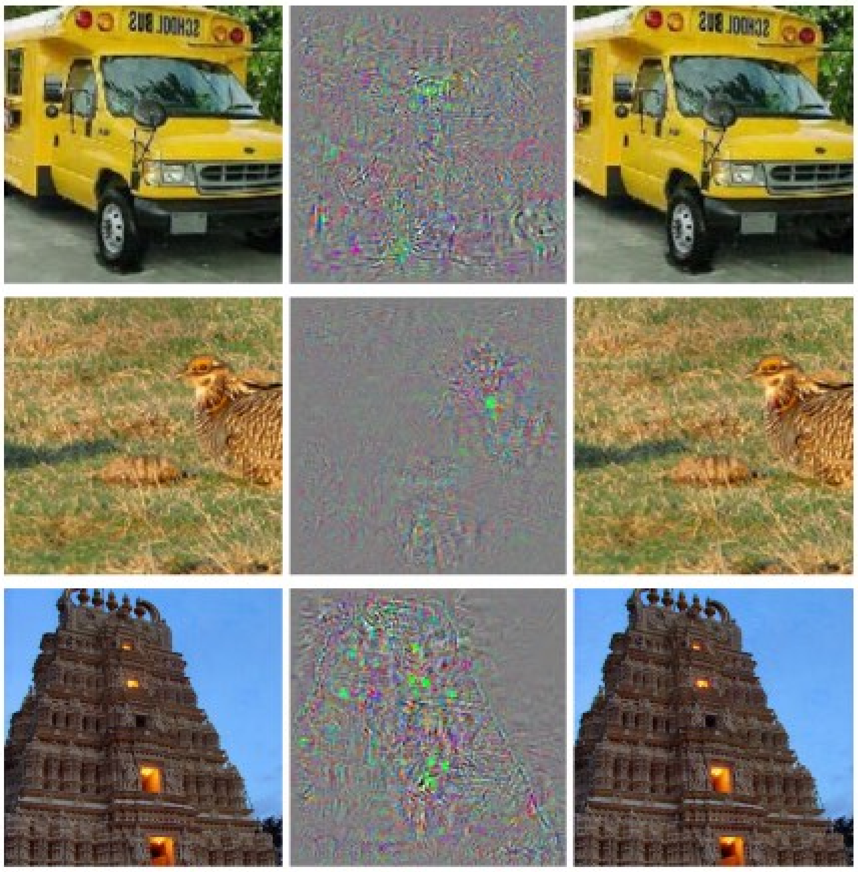
One encouraging practical set of results comes from a team at Google, who applied deep convolutional networks to the problem of recognizing street numbers in Google's Street View imagery*. In their paper, they report detecting and automatically transcribing nearly 100 million street numbers at an accuracy similar to that of a human operator. The system is fast: their system transcribed all of Street View's images of street numbers in France in less than an hour! They say: "Having this new dataset significantly increased the geocoding quality of Google Maps in several countries especially the ones that did not already have other sources of good geocoding." And they go on to make the broader claim: "We believe with this model we have solved [optical character recognition] for short sequences [of characters] for many applications."

成果中的一个令人振奋的实践来自谷歌的团队，他们使用深度卷积网络解决谷歌街景项目中的门牌识别问题*。在他们的论文当中报道，侦测和自动转换近一亿个门牌号码的准确度，非常接近人类作业者。系统很快：他们的系统转换法国的所有街景的门牌号码，只用了不到一个小时的时间！他们说：“拥有这个新的数据库，显著地提高了在一系列国家的谷歌地图的质量，尤其是谷歌那些没有足够的地理信息的国家。”并且他们在迈向更广阔的目标：“我们相信通过这个我们已经实现了的模型，不但能够为许多应用识别字符，也可以识别短语。”

> Multi-digit Number Recognition from Street View Imagery using Deep Convolutional Neural Networks, by Ian J. Goodfellow, Yaroslav Bulatov, Julian Ibarz, Sacha Arnoud, and Vinay Shet (2013).

I've perhaps given the impression that it's all a parade of encouraging results. Of course, some of the most interesting work reports on fundamental things we don't yet understand. For instance, a 2013 paper* showed that deep networks may suffer from what are effectively blind spots. Consider the lines of images below. On the left is an ImageNet image classified correctly by their network. On the right is a slightly perturbed image (the perturbation is in the middle) which is classified *incorrectly* by the network. The authors found that there are such "adversarial" images for every sample image, not just a few special ones.

我可能给大家一个印象，就是过分吹嘘那些令人鼓舞的结果了。的确，很多有趣的工作报告说，对于一些底层的问题，我们仍然未能搞懂。例如，一篇 2013 年的论文*指出，深度网络可能会因为盲点而变糟。考虑下面的图片线索。左边的是被他们的网络正确分类的 ImageNet 图片。右边是一张经过轻度扰动的图片（扰动部位在中间），网络那就*不能正确*分类了。作者还发现每个样品图片都存在这样的“敌对”图片，而不是个别现象。



> Intriguing properties of neural networks, by Christian Szegedy, Wojciech Zaremba, Ilya Sutskever, Joan Bruna, Dumitru Erhan, Ian Goodfellow, and Rob Fergus (2013)

This is a disturbing result. The paper used a network based on the same code as KSH's network - that is, just the type of network that is being increasingly widely used. While such neural networks compute functions which are, in principle, continuous, results like this suggest that in practice they're likely to compute functions which are very nearly discontinuous. Worse, they'll be discontinuous in ways that violate our intuition about what is reasonable behavior. That's concerning. Furthermore, it's not yet well understood what's causing the discontinuity: is it something about the loss function? The activation functions used? The architecture of the network? Something else? We don't yet know.

这是一个令人不安的结果。论文所使用的网络是基于 KSH 网络相同的代码的 - 那意味着，这是应用范围正在不断扩大的网络类型。这样的神经网络的计算功能，原理上应该是连续的，而他们的实验结果表明，其计算功能非常可能不连续。更糟糕的是，它们的不连续的方式，违反了我们对计算功能的合理表现的直觉。此外，环环相扣的是，造成不连续的原因目前还不清楚：是与损失函数有关？还是激活函数的使用？架构的问题？还是其他什么东西？我们不得而知。

Now, these results are not quite as bad as they sound. Although such adversarial images are common, they're also unlikely in practice. As the paper notes:

目前，结果完全不像他们说的那样糟糕。尽管那些敌对图片很普遍，不过它们在实践中并非太常见。正如论文中指出的那样：

> > The existence of the adversarial negatives appears to be in contradiction with the network's ability to achieve high generalization performance. Indeed, if the network can generalize well, how can it be confused by these adversarial negatives, which are indistinguishable from the regular examples? The explanation is that the set of adversarial negatives is of extremely low probability, and thus is

> > never (or rarely) observed in the test set, yet it is dense (much like the rational numbers), and so it is found near virtually every test case.
> >
> > 敌对负面问题的出现与网络实现的高度泛化的能力相矛盾。的确，如果网络泛化得好，它又是如何被那些敌对数据所扰乱的，而那些现象又无法从常规的案例中区分？解释是，敌对数据出现在测试数据集中的概率极低，以至于无法（或者很少）在测试数据集中被观察到，而以它的密度（非常类似于有理数），又足以在全部实际测试案例中发现。

Nonetheless, it is distressing that we understand neural nets so poorly that this kind of result should be a recent discovery. Of course, a major benefit of the results is that they have stimulated much followup work. For example, one recent paper* shows that given a trained network it's possible to generate images which look to a human like white noise, but which the network classifies as being in a known category with a very high degree of confidence. This is another demonstration that we have a long way to go in understanding neural networks and their use in image recognition.

尽管如此，令人郁闷的是，我们对神经网络的了解是如此贫乏，这类问题是最近才发现的。当然，这个结果的主要好处是，将会激发很多的后续工作。例如，最近一篇论文*指出，给一个训练好的神经网络产生一些图片，这些图片人类看起来就像是白噪声，然而网络会以非常高的自信度将它归类为某个它学习过的类型。这是另外一个事例，说明我们在理解神经网络并将其用在图像识别上，还有很长的路要走。

> Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images, by Anh Nguyen, Jason Yosinski, and Jeff Clune (2014).
>
> 译注： 这篇论文的试验结果表明，深度神经网络甚至可以将人类看起来是白噪声的一张图片，以 99.99% 的确信度判定为是一只狮子！

Despite results like this, the overall picture is encouraging. We're seeing rapid progress on extremely difficult benchmarks, like ImageNet. We're also seeing rapid progress in the solution of real-world problems, like recognizing street numbers in StreetView. But while this is encouraging it's not enough just to see improvements on benchmarks, or even real-world applications. There are fundamental phenomena which we still understand poorly, such as the existence of adversarial images. When such fundamental problems are still being discovered (never mind solved), it is premature to say that we're near solving the problem of image recognition. At the same time such problems are an exciting stimulus to further work.

尽管有诸如此类的问题，总体上还是令人鼓舞的。即使在有如 ImageNet 那样极端困难的基准下，我们也能看到快速的进展。我们同样看到对真实世界问题的解决方案上的快速发展，譬如，在街景中的门牌号码识别。尽管令人鼓舞，但在基准的发展，或者在现实世界的应用上，进步还不足够。还有一些根本的问题，我们仍然了解得很少，譬如，敌对图片的现象。当这类的根本问题仍然不断被发现（从来未专心去解决），那么要说我们已经接近解决图像识别的问题，为时尚早。同时，这样的问题也是对未来工作的一个让人兴奋的激励。

Other appr oaches to deep neur al nets

其他深度神经网络的实现

Through this book, we've concentrated on a single problem: classifying the MNIST digits. It's a juicy problem which forced us to understand many powerful ideas: stochastic gradient descent, backpropagation, convolutional nets, regularization, and more. But it's also a narrow problem. If you read the neural networks literature, you'll run into many ideas we haven't discussed: recurrent neural networks, Boltzmann machines, generative models, transfer learning, reinforcement learning, and so on, on and on ... and on! Neural networks is a vast field. However, many important ideas are variations on ideas we've already discussed, and can be understood with a little effort. In this section I provide a glimpse of these as yet unseen vistas. The discussion isn't detailed, nor comprehensive - that would greatly expand the book. Rather, it's impressionistic, an attempt to evoke the conceptual richness of the field, and to relate some of those riches to what we've already seen. Through the section, I'll provide a few links to other sources, as entrees to learn more. Of course, many of these links will soon be superseded, and you may wish to search out more recent literature. That point notwithstanding, I expect many of the underlying ideas to be of lasting interest.

贯穿此书，我们都专注于一个单一问题： MNIST 数字的分类。它是一个内容丰富的问题，迫使我们去了解很多强有力的思想： 随机梯度下降，反向传播，卷积网络，正则化等等。不过，它仍然是个狭窄的问题。如果你去阅读神经网络的文献，你会遇到很多的思想是我们仍未涉足的： 循环神经网络，波尔兹曼机，生成模型，迁移学习，强化学习，等等，等等！神经网络是一个巨大的领域。然而，很多重要的思想是我们已经讨论过的思想的变种，并且付出一点努力就可以理解。在本节中，我给大家瞄一眼这些内容，作为以前仍未触及的东西的展望。讨论不会很详尽，也不会很全面 - 然而会极大地扩展本书。反而，它是印象主义的，它尝试令你对该领域的印象丰满起来，并且与我们已经了解过的那些财富关联起来。贯穿这一节，我会提供一些链接到其他的资源，作为学习的入口。当然，许多的这些链接会很快被替换掉，你也许可以搜索更多的文献来学习。尽管如此，我希望这些潜在的思想会被持续关注。

Recurrent neural networks (RNNs): In the feedforward nets we've been using there is a single input which completely determines the activations of all the neurons through the remaining layers. It's a very static picture: everything in the network is fixed, with a frozen, crystalline quality to it. But suppose we allow the elements in the network to keep changing in a dynamic way. For instance, the behaviour of hidden neurons might not just be determined by the activations in previous hidden layers, but also by the activations at earlier times. Indeed, a neuron's activation might be determined in part by its own activation at an earlier time. That's certainly not what happens in a feedforward network. Or perhaps the activations of hidden and output neurons won't be determined just by the current input to the network, but also by earlier inputs.

循环神经网络（**RNNs**） ： 在我们前边使用过的前馈网络中，只有一个输入，它决定了剩下的层的所有神经元的激活。这是一幅静态的图画：网络中的所有东西都是固定的，它伴随着冻结和晶莹的质感。设想一下，我们容许网络中的每个元素，保持持续改变的动态方式。例如，隐藏神经元的行为，并不一定是由前面隐藏层的激活值来支配，而是有之前的时间的激活值来支配。那样的事情是绝不会发生在前馈网络之中的。或者可能隐藏神经元的激活和输出神经元不由当前作用于网络的输入来赋值，而是由之前的输入赋值。

Neural networks with this kind of time-varying behaviour are known as *recurrent neural networks* or *RNNs*. There are many different ways of mathematically formalizing the informal description of recurrent nets given in the last paragraph. You can get the flavour of some of these mathematical models by glancing at the Wikipedia article on RNNs. As I write, that page lists no fewer than 13 different models. But mathematical details aside, the broad idea is that RNNs are neural networks in which there is some notion of dynamic change over time. And, not surprisingly, they're particularly useful in analysing data or processes that change over time. Such data and processes arise naturally in problems such as speech or natural language, for example.

这种行为随时间而改变的神经网络类型，被成为*循环神经网络*或 *RNNs* 。在上一段中，有许多不同的方法从数学上规范对循环网络的各种非正式的描述。你可以浏览维基百科关于 RNNs 的文章，选择你喜欢的那些数学模型。正如我所写的，网页上列举了不少于 13 种不同的模型。不过除了数学的细节之外，广义的思想是，RNNs 是一种神经网络的类型，它具有随时间而动态改变的概念。请不必惊讶，他们在分析那些数据或过程随时间改变的问题时，特别有用。例如，这类数据和过程出现在语音或者自然语言这类问题上。

One way RNNs are currently being used is to connect neural networks more closely to traditional ways of thinking about algorithms, ways of thinking based on concepts such as Turing machines and (conventional) programming languages. A 2014 paper developed an RNN which could take as input a character-by-character description of a (very, very simple!) Python program, and use that description to predict the output. Informally, the network is learning to "understand" certain Python programs. A second paper, also from 2014, used RNNs as a starting point to develop what they called a neural Turing machine (NTM). This is a universal computer whose entire structure can be trained using gradient descent. They trained their NTM to infer algorithms for several simple problems, such as sorting and copying.

RNNs 的其中一种应用是将一些传统算法的思维方式与神经网络联系起来，诸如图灵机与传统的编程语言的基本思维方法。一篇 2014 年的论文，开发了一个 RNN，它可以一个一个字符地输入（非常，非常简单的） Python 程序的脚本，并通过脚本来预测程序的输出。非正式地，网络正在学习去“理解”某些 Python 程序。第二篇论文，同样来自 2014 年，使用 RNN 作为起点，开发一个他们称之为神经图灵机（NTM）的东西。那是一个通用计算机，整个结构可以用梯度下降来训练。他们训练他们的 NTM 去推导一些简单问题的算法，譬如排序和复制。

As it stands, these are extremely simple toy models. Learning to execute the Python program `print(398345+42598)` doesn't make a network into a full-fledged Python interpreter! It's not clear how much further it will be possible to push the ideas. Still, the results are intriguing. Historically, neural networks have done well at pattern recognition problems where conventional algorithmic approaches have trouble. Vice versa, conventional algorithmic approaches are good at solving problems that neural nets aren't so good at. No-one today implements a web server or a database program using a neural network! It'd be great to develop unified models that integrate the strengths of both neural networks and more traditional approaches to algorithms. RNNs and ideas inspired by RNNs may help us do that.

正如它的样子那样，这些是极其简单的玩具模型。学习执行 Python 程序 `print(398345+42598)` 不会导致网络成为完整的 Python 解释器！现在还不清楚，它可以带着这个想法走多远。不过，结果挺奇妙。历史上，神经网络在模式识别问题上做得很好，而对于这些问题传统算法有麻烦。反之亦然，传统算法很好地解决了的问题，神经网络就未必好使。今天，没有一个网页服务或者是数据库程序是用什么网络去做到！开发一个统一的模型会很了不起，它应该整合神经网络和传统算法的力量。RNNs 和由 RNNs 启发而来的想法将帮助我们实现这一点。

RNNs have also been used in recent years to attack many other problems. They've been particularly useful in speech recognition. Approaches based on RNNs have, for example, set records for the accuracy of phoneme recognition. They've also been used to develop improved models of the language people use while speaking. Better language models help disambiguate utterances that otherwise sound alike. A good language model will, for example, tell us that "to infinity and beyond" is much more likely than "two infinity and beyond", despite the fact that the phrases sound identical. RNNs have been used to set new records for certain language benchmarks.

RNNs 在最近几年同样用来解决很多其他的问题。它们在语音识别方面尤其有用。例如，基于 RNNs 的方法设置音素识别的准确记录。它们还用于开发发言过程中的语言处理改进模型。更好的语言处理模型有助于消除发音相似的发言中的歧义，例如，跟我们说：“to infinity and beyond” 非常像 “two infinity and beyond”，事实上两个短语的发音一样。RNNs 已经被用来设置某些语言处理的新基准。

This work is, incidentally, part of a broader use of deep neural nets of all types, not just RNNs, in speech recognition. For example, an approach based on deep nets has achieved outstanding results on large vocabulary continuous speech recognition. And another system based on deep nets has been deployed in Google's Android operating system (for related technical work, see Vincent Vanhoucke's 2012-2015 papers).

顺便说明一下，对于语音识别这个工作，只是各种类型的深度神经网络的广泛应用的一个部分，不限于 RNNs。例如，基于深度神经网络在大词汇连续语音识别上，已经取得出类拔萃的成果。另外一些基于深度神经网络的系统，已经被配置到谷歌安卓操作系统之中（相关的技术工作，详见 Vincent Vanhoucke 的 2012-2015 年的论文）。

I've said a little about what RNNs can do, but not so much about how they work. It perhaps won't surprise you to learn that many of the ideas used in feedforward networks can also be used in RNNs. In particular, we can train RNNs using straightforward modifications to gradient descent and backpropagation. Many other ideas used in feedforward nets, ranging from regularization techniques to convolutions to the activation and cost functions used, are also useful in recurrent nets. And so many of the techniques we've developed in the book can be adapted for use with RNNs.

我谈论了一点关于 RNNs 能干什么的话题，不过没有涉及太多关于它们如何工作的内容。它可能不会让你学习起来感到太惊奇，许多用在前馈网络中的思想同样可以用在 RNNs 当中。特别是，我们可以直接使用梯度下降和反向传播来训练 RNNs 。很多其他的前馈网络的思想，从正则化技术到卷积到激活函数和代价函数的使用，对于循环网络来说都同样有用。所以，几乎本书中我们所开发的各项技术，同样适用于 RNNs 。

Long short-term memory units (LSTMs): One challenge affecting RNNs is that early models turned out to be very difficult to train, harder even than deep feedforward networks. The reason is the unstable gradient problem discussed in Chapter 5. Recall that the usual manifestation of this problem is that the gradient gets smaller and smaller as it is propagated back through layers. This makes learning in early layers extremely slow. The problem actually gets worse in RNNs, since gradients aren't just propagated backward through layers, they're propagated backward through time. If the network runs for a long time that can make the gradient extremely unstable and hard to learn from. Fortunately, it's possible to incorporate an idea known as long short-term memory units (LSTMs) into RNNs. The units were introduced by Hochreiter and Schmidhuber in 1997 with the explicit purpose of helping address the unstable gradient problem. LSTMs make it much easier to get good results when training RNNs, and many recent papers (including many that I linked above) make use of LSTMs or related ideas.

长短期记忆单元（**LSTMs**）： 一个影响 RNNs 的挑战是早期的模型训练非常困难，艰难程度甚于深度前馈网络。原因是在第五章讨论过的梯度失稳的问题。回想一下这个问题的通常表现，就是当梯度反向穿越各个层时，变得越来越小。这使得比较靠前的层的训练极其缓慢。这个问题在 RNNs 下面变得更糟，因为梯度不光是要反向穿越层，它还反向穿越时间。如果网络运行了一段长的时间，那就会造成梯度极端不稳并且难以训练。幸运的是，可以将称为长短期记忆单元引入 RNNs 。这个单元是 Hochreiter 和 Schmidhuber 在 1997 年 推出的，主要的目的就是帮助解决梯度失稳的问题。LSTMs 使得训练 RNNs 时很容易取得好成绩，并且近期的论文（包括许多我上面给出链接的那些）都在应用 LSTMs 或者相关的思想。

Deep belief nets, generative models, and Boltzmann machines: Modern interest in deep learning began in 2006, with papers explaining how to train a type of neural network known as a *deep belief network* (DBN)*. DBNs were influential for several years, but have since lessened in popularity, while models such as feedforward networks and recurrent neural nets have become fashionable. Despite this, DBNs have several properties that make them interesting.

深度置信网络，生成模型，与波尔兹曼机： 对深度学习的关注兴起自 2006 年，它是随着介绍如何训练一种被称为*深度置信网络*（DBN）*的神经网络类型而兴起的。DBNs 火过几年，不过现在人气逐渐消散，因为前馈网络和循环神经网络已经流行起来。尽管如此，DBNs 还是有些让人感兴趣的特性。

> See A fast learning algorithm for deep belief nets, by Geoffrey Hinton, Simon Osindero, and Yee-Whye Teh (2006), as well as the related work in Reducing the dimensionality of data with neural networks, by Geoffrey Hinton and Ruslan Salakhutdinov (2006).

One reason DBNs are interesting is that they're an example of what's called a *generative model*. In a feedforward network, we specify the input activations, and they determine the activations of the feature neurons later in the network. A generative model like a DBN can be used in a similar way, but it's also possible to specify the values of some of the feature neurons and then "run the network backward", generating values for the input activations. More concretely, a DBN trained on images of handwritten digits can (potentially, and with some care) also be used to generate images that look like handwritten digits. In other words, the DBN would in some sense be learning to write. In this, a generative model is much like the human brain: not only can it read digits, it can also write them. In Geoffrey Hinton's memorable phrase, to recognize shapes, first learn to generate images.

DBNs 的一个诱人的理由是，它们是被称为*生成模型*的一个实例。在前馈网络中，有我们输入确定的激活值，并且它们支配着网络中后续特征神经元的激活值。一个像 DBN 那样的生成模型可以使用类似的方法，不过它容许指定某些特征神经元的值，并且“向后运行网络”，给输入单元生成数值。更具体地说，一个由手写数字图片训练的 DBN，也可以同样用于生成类似手写数字的图片。换言之，DBN 在某种意义上是在学习书写。一个生成模型非常像人脑：不但可以阅读数字，还可以书写它们。借用 Geoffrey Hinton 的名言，to recognize shapes, first learn to generate images 。

A second reason DBNs are interesting is that they can do unsupervised and semi-supervised learning. For instance, when trained with image data, DBNs can learn useful features for understanding other images, even if the training images are unlabelled. And the ability to do unsupervised learning is extremely interesting both for fundamental scientific reasons, and - if it can be made to work well enough - for practical applications.

DBN 的第二个诱人的理由是，它们可以做无监督和半监督训练。例如，使用一组图像进行训练时，DBNs 可以从当前图像中学习到有用的特征用于理解其他的图像，即使训练的图像没有被打过标签。无监督训练的能力极具科学基础意义，如果它能够在实践应用中做得足够好的话。

Given these attractive features, why have DBNs lessened in popularity as models for deep learning? Part of the reason is that models such as feedforward and recurrent nets have achieved many spectacular results, such as their breakthroughs on image and speech recognition benchmarks. It's not surprising and quite right that there's now lots of attention being paid to these models. There's an unfortunate corollary, however. The marketplace of ideas often functions in a winner-take-all fashion, with nearly all attention going to the current fashion-of-the-moment in any given area. It can become extremely difficult for people to work on momentarily unfashionable ideas, even when those ideas are obviously of real long-term interest. My personal opinion is that DBNs and other generative models likely deserve more attention than they are currently receiving. And I won't be surprised if DBNs or a related model one day surpass the currently fashionable models. For an introduction to DBNs, see this overview. I've also found this article helpful. It isn't primarily about deep belief nets, *per se*, but does contain much useful information about restricted Boltzmann machines, which are a key component of DBNs.

有这么引人入胜的功能，为什么 DBNs 的人气逐步衰弱呢？部分的原因是前馈和循环网络已经取得了很多辉煌的成果，尤其是它们在图像与语音识别上的根本性突破。大家已经没有太多的注意力放到那些模型上，这一点都不奇怪。有个不幸的推论，技术思想的市场，经常形成赢者通杀的风气，在特定的领域，大家都几乎将所有注意力都放到现时的主流风气之中。这使得人们很难为那些短暂的非主流的想法去付出努力，即使那些想法明显具有长期的意义。我个人的观点是，DBNs 以及其他的生成模型，它们值得受到比现在更多的关注。如果 DBNs 或者关联模型，有一天超越当前的流行模型，我不会感到吃惊。DBNs 的介绍请看这个概述。我还发现这篇著作很有用。它主要涉及的并不是深度置信网络本身，不过的确包含很多有关受限波尔兹曼机的有用信息，它是 DBNs 的关键组件。

Other ideas: What else is going on in neural networks and deep learning? Well, there's a huge amount of other fascinating work. Active areas of research include using neural networks to do natural language processing (see also this informative review paper), machine translation, as well as perhaps more surprising applications such as music informatics. There are, of course, many other areas too. In many cases, having read this book you should be able to begin following recent work, although (of course) you'll need to fill in gaps in presumed background knowledge.

其他的想法： 神经网络和深度学习上，还有什么动向呢？有，有数量庞大的引人入胜的工作。活跃的研究领域包括用神经网络去做自然语言处理（请查看消息回顾网页），机器翻译，也有更令人奇怪的应用，譬如音学信息学。当然还有其他许多的领域。在阅读本书之后，你应该可以开始跟踪这些最近的工作了，尽管（当然）你需要补习一下空缺的背景知识。

Let me finish this section by mentioning a particularly fun paper. It combines deep convolutional networks with a technique known as reinforcement learning in order to learn to play video games well (see also this followup). The idea is to use the convolutional network to simplify the pixel data from the game screen, turning it into a simpler set of features, which can be used to decide which action to take: "go left", "go down", "fire", and so on. What is particularly interesting is that a single network learned to play seven different classic video games pretty well, outperforming human experts on three of the games. Now, this all sounds like a stunt, and there's no doubt the paper was well marketed, with the title "Playing Atari with reinforcement learning". But looking past the surface gloss, consider that this system is taking raw pixel data - it doesn't even know the game rules! - and from that data learning to do high-quality decision-making in several very different and very adversarial environments, each with its own complex set of rules. That's pretty neat.

让我介绍一篇特别有趣的论文来结束本节吧。它整合了一个叫强化学习的技术到深度卷积网络之中，以便学习将视频游戏玩得更好（再参看后续工作）。它的想法是运用卷积网络简化游戏屏幕的像素数据，再转化为更简练的特征集，根据这个特征集来决定采取那个动作："向左"，"向下"，"开火"等等。特别有趣的是，一个单一网络，学会了玩七种不同类型的视频游戏，在其中三种中，击败人类专家级玩家。现在，这听起来像是特技，毫无疑问，这篇题为"用强化学习玩 Atari"的论文大有市场。不过，在它过往风光的表面之下，考虑到系统仅是截取原始的像素数据 - 它甚至都不知道游戏规则 - 仅从这样的数据中学习，面对不同的游戏以及不同的对抗环境，而每个都有着自身复杂的规则，就能做出高质量的决策。干的真漂亮。

On the futur e of neur al networks

神经网络的未来

Intention-driven user interfaces: There's an old joke in which an impatient professor tells a confused student: "don't listen to what I say; listen to what I *mean*". Historically, computers have often been, like the confused student, in the dark about what their users mean. But this is changing. I still remember my surprise the first time I misspelled a Google search query, only to have Google say "Did you mean [corrected query]?" and to offer the corresponding search results. Google CEO Larry Page once described the perfect search engine as understanding exactly what (your queries) mean and giving you back exactly what you want.

意念驱动的用户界面： 有个老笑话，说得是一个不耐烦的教授对一个已经蒙逼的学生说："不要听我说的话，要听我的*意思*"。有史以来，计算机对用户意向的理解，就像那个蒙逼的学生，都是一抹黑的。不过这正在改变。我仍然记得第一被 Google 搜索吓到的情形，我拼写出错时，只听得 Google 说"你的意思是搜索xxx吗？"，并且给出了相关搜索的结果。Google 的 CEO Larry Page 有一次这样描述，完美的搜索引擎应该是准确地理解你查询什么，并且准确地给出你想要的东西。

This is a vision of an *intention-driven user interface*. In this vision, instead of responding to users' literal queries, search will use machine learning to take vague user input, discern precisely what was meant, and take action on the basis of those insights.

这个就是*意念驱动用户界面*的景愿。在这个景愿中，取代对用户的文本查询而作出响应的是，搜索引擎将以机器学习去取得用户的模糊输入，准确领会用户的意图，并且基于理解而采取行动。

The idea of intention-driven interfaces can be applied far more broadly than search. Over the next few decades, thousands of companies will build products which use machine learning to make user interfaces that can tolerate imprecision, while discerning and acting on the user's true intent. We're already seeing early examples of such intention-driven interfaces: Apple's Siri; Wolfram Alpha; IBM's Watson; systems which can annotate photos and videos; and much more.

意念驱动界面可以应用到比搜索引擎更广阔的领域。今后几十年，成千上万的公司将建立使用机器学习的用户界面，它可以容忍欠准确的输入，领会用户的真实意图并采取行动。我们已经可以看到早期的意念驱动界面的例子：苹果公司的 Siri；Wolfram Alpha；IBM 公司的 Watson；可以给图片和视频写评语的系统；还有很多很多。

Most of these products will fail. Inspired user interface design is hard, and I expect many companies will take powerful machine learning technology and use it to build insipid user interfaces. The best machine learning in the world won't help if your user interface concept stinks. But there will be a residue of products which succeed. Over time that will cause a profound change in how we relate to computers. Not so long ago - let's say, 2005 - users took it for granted that they needed precision in most interactions with computers. Indeed, computer literacy to a great extent meant internalizing the idea that computers are extremely literal; a single misplaced semi-colon may completely change the nature of an interaction with a computer. But over the next few decades I expect we'll develop many successful intention-driven user interfaces, and that will dramatically change what we expect when interacting with computers.

大部分这些产品都将死掉。有创意的用户界面是很难设计的，我预计很多公司将采用强大的机器学习技术并用它来建设平庸的用户界面。如果你的用户界面理念很烂，世上最好的机器学习都无济于事。不过总有成功者幸存。久而久之，将会造成我们与计算机的关系的深刻改变。不久之前，就说是 2005 年吧，用户都会认为与计算机的大部分互动都需要精确的操作。事实上，计算机的读写能力很大程度上意味着我们有一种内在的观念，就是计算机是个刻板的东西。现在一个放错地方的分号就足以改变我们与计算机交互的本意。不过接下来的几十年，我期待我们可以开发出很多成功的意念驱动的用户界面，并且将戏剧性地改变我们与计算机互动时的预期。

Machine learning, data science, and the virtuous circle of innovation: Of course, machine learning isn't just being used to build intention-driven interfaces. Another notable application is in data science, where machine learning is used to find the "known unknowns" hidden in data. This is already a fashionable area, and much has been written about it, so I won't say much. But I do want to mention one consequence of this fashion that is not so often remarked: over the long run it's possible the biggest breakthrough in machine learning won't be any single conceptual breakthrough. Rather, the biggest breakthrough will be that machine learning research becomes profitable, through applications to data science and other areas. If a company can invest 1 dollar in machine learning research and get 1 dollar and 10 cents back reasonably rapidly, then a lot of money will end up in machine learning research. Put another way, machine learning is an engine driving the creation of several major new markets and areas of growth in technology. The result will be large teams of people with deep subject expertise, and with access to extraordinary resources. That will propel machine learning further forward, creating more markets and opportunities, a virtuous circle of innovation.

机器学习，数据科学，与创新的良性循环： 当然，机器学习不仅仅用在建立意念驱动界面上。另一个值得关注的应用是在数据科学，在这里，机器学习用于发掘数据背后“已知的未知”。这已经是一个热门的领域，并且有很多相关的著作，所以我不想说太多。不过，我的确想提示一下这个流行领域的结局，它不常被谈论：从长远来看，可能机器学习最大的突破，不会是任何单一概念的突破了。相反，通过将机器学习应用到数据科学和其他领域，最大的突破就是机器学习的研究变得有利可图了。如果公司往机器学习研究中投入 1 美元，并且能快速取得 1.1 美元的回报，那么就有很多资金投入到机器学习的研究当中。换个角度去看，机器学习是推动几个主要新兴业务与技术增长领域的动力。其结果是产生具有深厚专业素养的大型团队，以及获取非凡的资源。那将推动机器学习继续向前，创造更多的市场和机遇，形成创新的良性循环。

The role of neural networks and deep learning: I've been talking broadly about machine learning as a creator of new opportunities for technology. What will be the specific role of neural networks and deep learning in all this?

神经网络与深度学习的角色： 我已经广泛谈及关于机器学习是新的技术机遇的缔造者。那么神经网络和深度学习在这里扮演什么特殊的角色呢？

To answer the question, it helps to look at history. Back in the 1980s there was a great deal of excitement and optimism about neural networks, especially after backpropagation became widely known. That excitement faded, and in the 1990s the machine learning baton passed to other techniques, such as support vector machines. Today, neural networks are again riding high, setting all sorts of records, defeating all comers on many problems. But who is to say that tomorrow some new approach won't be developed that sweeps neural networks away again? Or perhaps progress with neural networks will stagnate, and nothing will immediately arise to take their place?

回答这个问题，需要回顾一下历史。在 20 世纪 80 年代，大家对神经网络曾经有过巨大的热情和乐观，特别是反向传播被广泛认识之后。热情的冷却是在 20 世纪 90 年代，机器学习的接力棒传给了其他的技术，譬如，支持向量机。今天，神经网络再次攀上高位，搅乱了所有的江湖地位，在很多问题上击败了所有参与者。谁敢说明天没有新的技术再次绊倒神经网络呢？或者神经网络的进步就此停滞不前，以及无法迅速上位呢？

For this reason, it's much easier to think broadly about the future of machine learning than about neural networks specifically. Part of the problem is that we understand neural networks so poorly. Why is it that neural networks can generalize so well? How is it that they avoid overfitting as well as they do, given the very large number of parameters they learn? Why is it that stochastic gradient descent works as well as it does? How well will neural networks perform as data sets are scaled? For instance, if ImageNet was expanded by a factor of 10, would neural networks' performance improve more or less than other machine learning techniques? These are all simple, fundamental questions. And, at present, we understand the answers to these questions very poorly. While that's the case, it's difficult to say what role neural networks will play in the future of machine learning.

基于这样的理由，以开阔的思路去考虑机器学习的未来，比单纯考虑神经网络更容易。部分的理由是，我们对神经网络的了解是那么贫乏。为什么神经网络可以泛化得那么好？它们被设定了数量庞大的参数需要学习，它们是如何避免过拟合的？为什么随机梯度下降运作起来那么有效？神经网络的表现如何伴随数据集的扩展而对应发展呢？例如，如果 ImageNet 扩大了 10 倍，神经网络的表现提高得比其他机器学习的技术更大还是更小呢？这些是简单而根本的问题。现在，我们对这些问题的答案了解得非常贫乏。在这样的情况下，很难说神经网络在未来的机器学习中扮演什么角色。

I will make one prediction: I believe deep learning is here to stay. The ability to learn hierarchies of concepts, building up multiple layers of abstraction, seems to be fundamental to making sense of the world. This doesn't mean tomorrow's deep learners won't be radically different than today's. We could see major changes in the constituent units used, in the architectures, or in the learning algorithms. Those changes may be dramatic enough that we no longer think of the resulting systems as neural networks. But they'd still be doing deep learning.

我来做个预测：我相信深度学习是会留存下来的。对概念的分层学习的能力，构筑多层的抽象，似乎是理解世界的基本原理。这并不意味着明天的深度学习，相比于今天的不可以有根本的差别。我们可以看到主要的改变会发生在结构单元的使用，架构，或者是训练算法上。这些的戏剧性的变化，足以让我们不再将系统视为神经网络。不过，它们做的仍然是深度学习。

Will neural networks and deep learning soon lead to artificial intelligence? In this book we've focused on using neural nets to do specific tasks, such as classifying images. Let's broaden our ambitions, and ask: what about general-purpose thinking computers? Can neural networks and deep learning help us solve the problem of (general) artificial intelligence (AI)? And, if so, given the rapid recent progress of deep learning, can we expect general AI any time soon?

神经网络和深度学习会很快导致人工智能吗？ 在本书中，我们聚焦在应用神经网络去解决专门的任务，例如，图像分类。让我们拓宽一下我们的雄心，再追问：拥有通用目的思维的计算机情况如何呢？神经网络和深度学习能够帮助我们解决（通用）人工智能（AI）的问题吗？以现在深度学习的快速发展，我们能够期待通用 AI 很快出现吗？

Addressing these questions comprehensively would take a separate book. Instead, let me offer one observation. It's based on an idea known as Conway's law:

全面地对付这堆问题应该写本单独的书。不过，我可以提供一种观点。它基于 Conway 定律的观点：

> Any organization that designs a system... will inevitably produce a design whose structure is a copy of the organization's communication structure.
>
> 任何系统设计的组织 ... 将不可避免地产生一个设计，它的结构是组织者的通讯结构的副本。

So, for example, Conway's law suggests that the design of a Boeing 747 aircraft will mirror the extended organizational structure of Boeing and its contractors at the time the 747 was designed. Or for a simple, specific example, consider a company building a complex software application. If the application's dashboard is supposed to be integrated with some machine learning algorithm, the person building the dashboard better be talking to the company's machine learning expert. Conway's law is merely that observation, writ large.

举个例子，Conway 定律建议在波音 747 的设计阶段，在波音 747 的设计中反映波音公司与协作厂商的组织结构关系。或者举个简单具体的例子吧，考虑一个公司开发一套复杂的应用程序。如果应用程序模块组态中设想整合某些机器学习的算法，设计模块组态的人最好还是跟机器学习的专家交流一下。夸张点说，Conway 定律就是这样一种观点。

What about the other objection, that Conway's law is banal and obvious? This may perhaps be true, but I don't think so, for organizations too often act with disregard for Conway's law. Teams building new products are often bloated with legacy hires or, contrariwise, lack a person with some crucial expertise. Think of all the products which have useless complicating features. Or think of all the products which have obvious major deficiencies - e.g., a terrible user interface. Problems in both classes are often caused by a mismatch between the team that was needed to produce a good product, and the team that was actually assembled. Conway's law may be obvious, but that doesn't mean people don't routinely ignore it.

那些反对的意见呢，Conway 定律是那么平淡无奇吗？这可能是对的，不过我不是这样认为，许多组织经常不尊重 Conway 定律而行事。新产品的开发经常充斥着老旧员工，或者因循守旧，缺乏有关键专业知识的人。回想一下各种产品所包含的无用而复杂的属性，或者是主要功能的缺陷 - 例如，可怕的用户界面。这两个类型的问题，经常是由于现实和理想的不匹配造成的，好的产品需要好的团队，而团队的集结又只能与现实条件妥协。Conway 定律也许平凡，但是并不意味着人们不会经常性地忽视它。

Conway's law applies to the design and engineering of systems where we start out with a pretty good understanding of the likely constituent parts, and how to build them. It can't be applied directly to the development of artificial intelligence, because AI isn't (yet) such a problem: we don't know what the constituent parts are. Indeed, we're not even sure what basic questions to be asking. In others words, at this point AI is more a problem of science than of engineering. Imagine beginning the design of the 747 without knowing about jet engines or the principles of aerodynamics. You wouldn't know what kinds of experts to hire into your organization. As Wernher von Braun put it, "basic research is what I'm doing when I don't know what I'm doing". Is there a version of Conway's law that applies to problems which are more science than engineering?

Conway 定律往往被应用到系统的设计以及工程实施的阶段，此时我们已经充分了解其构成部件，以及如何制作它们。然而，它并不能在人工智能的开发中直接应用，因为 AI（仍然）不是那样的问题：我们还不知道它的组成部分是什么。事实上，我们甚至连该问什么基本的问题都还没搞清楚。换言之，在目前，AI 在科学性上的问题比工程性的问题多。设想一下，开始设计波音 747 时，你并不了解飞机的发动机或者空气动力学的原理，你就不会知道招聘些什么人进你的组织机构当中。正如 Wernher von Braun 所说，“基础研究就是我不知道我在做什么的时候所做的事情”。

To gain insight into this question, consider the history of medicine. In the early days, medicine was the domain of practitioners like Galen and Hippocrates, who studied the entire body. But as our knowledge grew, people were forced to specialize. We discovered many deep new ideas*: think of things like the germ theory of disease, for instance, or the understanding of how antibodies work, or the understanding that the heart, lungs, veins and arteries form a complete cardiovascular system. Such deep insights formed the basis for subfields such as epidemiology, immunology, and the cluster of inter-linked fields around the cardiovascular system. And so the structure of our knowledge has shaped the social structure of medicine. This is particularly striking in the case of immunology: realizing the immune system exists and is a system worthy of study is an extremely non-trivial insight. So we have an entire field of medicine - with specialists, conferences, even prizes, and so on - organized around something which is not just invisible, it's arguably not a distinct thing at all.

要取得这个问题的深刻理解，请考虑医学的历史。在早期，医学是像 Galen 和 Hippocrates 这样的从业者的领域，他们研究整体的人体。不过随着知识的增长，人们被迫走向细分专业。我们发现许多深层的新思想*：思考细菌的疾病理论，例如，或者是理解抗体如何工作，或者是理解心，肺，静脉和动脉形成一个完整的心血管系统。这些深刻的见解形成了细分专业的基础，譬如流行病学，免疫学，以及围绕心血管系统的内部关联领域的组学。并且我们的知识结构已经塑造了医学的学科结构。这在免疫学方面尤其突出：证实免疫系统的存在，以及揭示对系统整体研究的价值，本身就见地非凡。所以，我们拥有了医学的各个方面 - 包括专家，会议，甚至是各种奖项，等等 - 这些东西在我们身边比比皆是，我们并不会感到新鲜。

> My apologies for overloading "deep". I won't define "deep ideas" precisely, but loosely I mean the kind of idea which is the basis for a rich field of enquiry. The backpropagation algorithm and the germ theory of disease are both good examples.
>
> 抱歉我过度使用“深度”。我无法准确地定义“深度思想”，不过我的意思是指那些现在还充满疑问的领域。反向传播算法和细菌疾病理论都是很好的例子。

This is a common pattern that has been repeated in many well-established sciences: not just medicine, but physics, mathematics, chemistry, and others. The fields start out monolithic, with just a few deep ideas. Early experts can master all those ideas. But as time passes that monolithic character changes. We discover many deep new ideas, too many for any one person to really master. As a result, the social structure of the field re-organizes and divides around those ideas. Instead of a monolith, we have fields within fields within fields, a complex, recursive, self-referential social structure, whose organization mirrors the connections between our deepest insights. *And so the structure of our knowledge shapes the social organization of science. But that social shape in turn constrains and helps determine what we can discover.* This is the scientific analogue of Conway's law.

这是一个不断被重复的模式，在那些成熟的学科之中：不但是医学，还有物理，数学，化学等等。这些领域开始时只是个别单薄深刻的思想。早期的专家们就可以掌握全部的知识。随着时间的推移，单一性性质就会改变。我们会发现很多新的深刻的想法，要由一个人去切实掌握它们，就实在是太多了。结果是，围绕这些思想的社群结构就会重新划分和整合。取代单一学科状态的是，我们的领域中又有领域，形成复杂的，递归的，自引用的社会结构，这些组织反映了我们那些最深刻的见解的联系。*我们的知识结构，塑造了我们的学科社会组织形式。*然而，学科形态又约束和限定了我们可以去发现的内容。这个是 Conway 定律的科学的类比。

So what's this got to do with deep learning or AI?

那么这些与深度学习和 AI 有什么关系呢？

Well, since the early days of AI there have been arguments about it that go, on one side, "Hey, it's not going to be so hard, we've got [super-special weapon] on our side", countered by "[super-special weapon] won't be enough". Deep learning is the latest super-special weapon I've heard used in such arguments*; earlier versions of the argument used logic, or Prolog, or expert systems, or whatever the most powerful technique of the day was. The problem with such arguments is that they don't give you any good way of saying just how powerful any given candidate super-special weapon is. Of course, we've just spent a chapter reviewing evidence that deep learning can solve extremely challenging problems. It certainly looks very exciting and promising. But that was also true of systems like Prolog or Eurisko or expert systems in their day. And so the mere fact that a set of ideas looks very promising doesn't mean much. How can we tell if deep learning is truly different from these earlier ideas? Is there some way of measuring how powerful and promising a set of ideas is? Conway's law suggests that as a rough and heuristic proxy metric we can evaluate the complexity of the social structure associated to those ideas.

在 AI 的早期阶段，就已经有各种争论在进行，一边说，“嘿，它没有那么难的，我们找到了超级专杀武器了”，反对的声音说“超级专杀武器还不靠谱”。在我听到的这些争论之中，深度学习是最新在使用的超级专杀武器*；早期版本的争论，针对的是逻辑学，或者 Prolog 语言，或者专家系统，又或者是随便什么当时最强有力的技术。这些争论的问题是它们无法给你一个说法，说明那些超级专杀武器到底有多强大。尽管我们已经花费了一章的篇幅来回顾深度学习可以解决极具挑战性的问题的证据。它的确让人兴奋和充满期待。不过类似的系统，譬如，Prolog 或者 Eurisko 或者专家系统，在它们风光的日子里，看起来也很靠谱。然而，这堆技术的现实表现并不如人们期待的那样。我们如何能确定深度学习确实比之前的各种技术更有力呢？Conway 定律指出，我们可以用这些技术的关联复杂度来作为一个粗略的，启发性的替代指标。

> Interestingly, often not by leading experts in deep learning, who have been quite restrained. See, for example, this thoughtful post by Yann LeCun. This is a difference from many earlier incarnations of the argument.
>
> 有趣的是，争论一般不会由深度学习的专家挑起，他们是比较矜持的。请看个例子，这个是 Yann LeCun 写的深思熟虑的帖子。它与那些早期的肉搏式的争论明显不同。

So, there are two questions to ask. First, how powerful a set of ideas are associated to deep learning, according to this metric of social complexity? Second, how powerful a theory will we need, in order to be able to build a general artificial intelligence?

所以，有两个问题要问。第一，根据这个社会复杂度指标，与深度学习相关的思想集群到底有多强大？第二，要达致建设通用人工智能的能力，我们需要多强的理论动力？

As to the first question: when we look at deep learning today, it's an exciting and fast-paced but also relatively monolithic field. There are a few deep ideas, and a few main conferences, with substantial overlap between several of the conferences. And there is paper after paper leveraging the same basic set of ideas: using stochastic gradient descent (or a close variation) to optimize a cost function. It's fantastic those ideas are so successful. But what we don't yet see is lots of well-developed subfields, each exploring their own sets of deep ideas, pushing deep learning in many directions. And so, according to the metric of social complexity, deep learning is, if you'll forgive the play on words, still a rather shallow field. It's still possible for one person to master most of the deepest ideas in the field.

对于第一个问题：当我们注视深度学习的今天，它是一个激动人心和快节奏，但仍然是一个单一的领域。有几个深刻的思想，以及几个主要的研讨会，研讨会之间的议题严重重叠。并且一篇接一篇的论文撬动着相同的基本概念：使用随机梯度下降（或者是近似的变体）去优化代价函数。这些思想如此成功，真是奇妙。不过，还没有看到发展得很好的分支领域，每个人都在探索一套属于自己的想法，推出了很多深度学习的发展方向。所以，根据深度学习的社会复杂度指标，如果你忽略那些文字游戏，它还是一个浅度的领域。在这个领域中，它仍然有可能由一个人来掌握主要的最深层思想。

On the second question: how complex and powerful a set of ideas will be needed to obtain AI? Of course, the answer to this question is: no-one knows for sure. But in the appendix I examine some of the existing evidence on this question. I conclude that, even rather optimistically, it's going to take many, many deep ideas to build an AI. And so Conway's law suggests that to get to such a point we will necessarily see the emergence of many interrelating disciplines, with a complex and surprising structure mirroring the structure in our deepest insights. We don't yet see this rich social structure in the use of neural networks and deep learning. And so, I believe that we are several decades (at least) from using deep learning to develop general AI.

对于第二个问题：实现 AI 需要多么复杂和强大的思想集群呢？可以肯定，这个问题的答案是：没有人知道。不过在附录中，我检验过这个问题的一些证据。我的结论是，即使在最乐观的情况下，也需要很多很多深刻的思想去实现 AI 。并且，Conway 定律指出，要达到这一点，我们需要看到许多交叉学科的融合，并且伴随着反映我们深刻见解的复杂而神奇的结构。我们还没有见到如此丰满的社群结构在使用神经网络和深度学习。我相信我们在未来几十年（至少）都会通过使用深度学习来开发通用 AI 。

I've gone to a lot of trouble to construct an argument which is tentative, perhaps seems rather obvious, and which has an indefinite conclusion. This will no doubt frustrate people who crave certainty. Reading around online, I see many people who loudly assert very definite, very strongly held opinions about AI, often on the basis of flimsy reasoning and non-existent evidence. My frank opinion is this: it's too early to say. As the old joke goes, if you ask a scientist how far away some discovery is and they say "10 years" (or more), what they mean is "I've got no idea". AI, like controlled fusion and a few other technologies, has been 10 years away for 60 plus years. On the flipside, what we definitely do have in deep learning is a powerful technique whose limits have not yet been found, and many wide-open fundamental problems. That's an exciting creative opportunity.

我经历过很多的困难想去构筑某个论点，哪怕它只是暂时性，或许看起来比较清晰的也好，然而最终只有不明确的结论。这毫无疑问会挫伤那些渴望得到明确答案的人。在线浏览时，我看到很多人在大声断言，非常明确，非常强烈地坚持关于 AI 的种种观点，而且经常是基于薄弱的理由和无中生有的证据。我坦诚的观点是：现在说什么都为时尚早，正如老笑话所说，如果你问一个科学家离获得发现还有多远，他们说“10 年”（或者更久），其实他们的意思是“我不知道”。AI，就像受控核聚变和其他某些技术那样，60 多年前就说用 10 年时间可以解决了。从反面来看，我们在深度学习中所从事的，肯定是一种强大的技术，它的局限性还没有被发现，并且仍然存在许多根本性的问题需要解决。这是一个激动人心，充满创造性的机遇。