SAIF

Shanghai Advanced Institute of Finance

上海高级金融学院

量化俱乐部-深度学习-CNN

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自我介绍

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Intro

Convolutional neural networks (CNNs) emerged from the study of the brain's visual cortex, and they have been used in image recognition since the 1980s. In the last few years, thanks to the increase in computational power, the amount of available training data, and the tricks presented in Chapter 11 for training deep nets, CNNs have managed to achieve superhuman performance on some complex visual tasks. They power image search services, self-driving cars, automatic video classification systems, and more. Moreover, CNNs are not restricted to visual perception: they are also successful at other tasks, such as *voice recognition* or *natural language processing* (NLP); however, we will focus on visual applications for now.

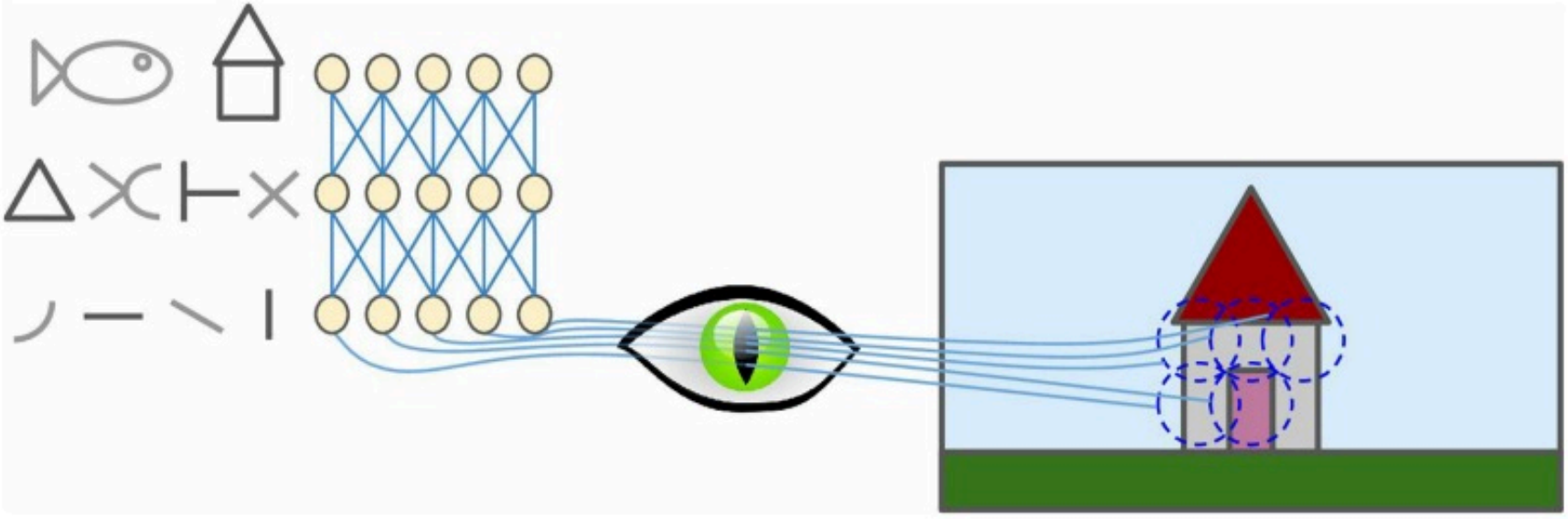
In this chapter we will present where CNNs came from, what their building blocks look like, and how to implement them using TensorFlow. Then we will present some of the best CNN architectures.

The Architecture of the Visual Cortex

Many neurons in the visual cortex have a small *local receptive field*, meaning they react only to visual stimuli located in a limited region of the visual field. The receptive fields of different neurons may overlap, and together they tile the whole visual field. Moreover, the authors showed that some neurons react only to images of horizontal lines, while others react only to lines with different orientations (two neurons may have the same receptive field but react to different line orientations). They also noticed that some neurons have larger receptive fields, and they react to more complex patterns that are combinations of the lower-level patterns. These observations led to the idea that the higher-level neurons are based on the outputs of neighboring lower-level neurons (in Figure 13-1, notice that each neuron is connected only to a few neurons from the previous layer). This powerful architecture is able to detect all sorts of complex patterns in any area of the visual field.

The Architecture of the Visual Cortex

These studies of the visual cortex inspired the neocognitron, introduced in 1980, which gradually evolved into what we now call *convolutional neural networks*. An important milestone was a 1998 paper[5] by Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner, which introduced the famous *LeNet-5* architecture, widely used to recognize handwritten check numbers. This architecture has some building blocks that you already know, such as fully connected layers and sigmoid activation functions, but it also introduces two new building blocks: *convolutional layers* and *pooling layers*. Let's look at them now.



Convolutional Layer

The most important building block of a CNN is the *convolutional layer:* Neurons in the first convolutional layer are not connected to every single pixel in the input image, but only to pixels in their receptive fields. In turn, each neuron in the second convolutional layer is connected only to neurons located within a small rectangle in the first layer. This architecture allows the network to concentrate on low-level features in the first hidden layer, then assemble them into higher-level features in the next hidden layer, and so on. This hierarchical structure is common in real-world images, which is one of the reasons why CNNs work so well for image recognition.

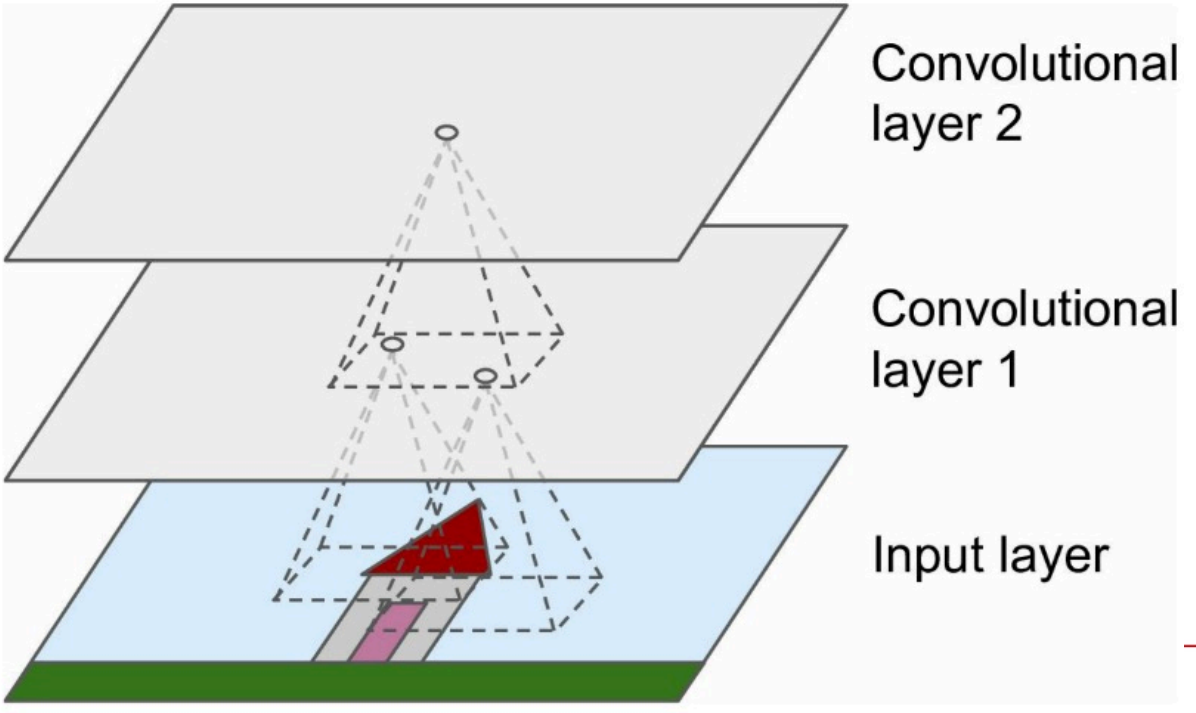
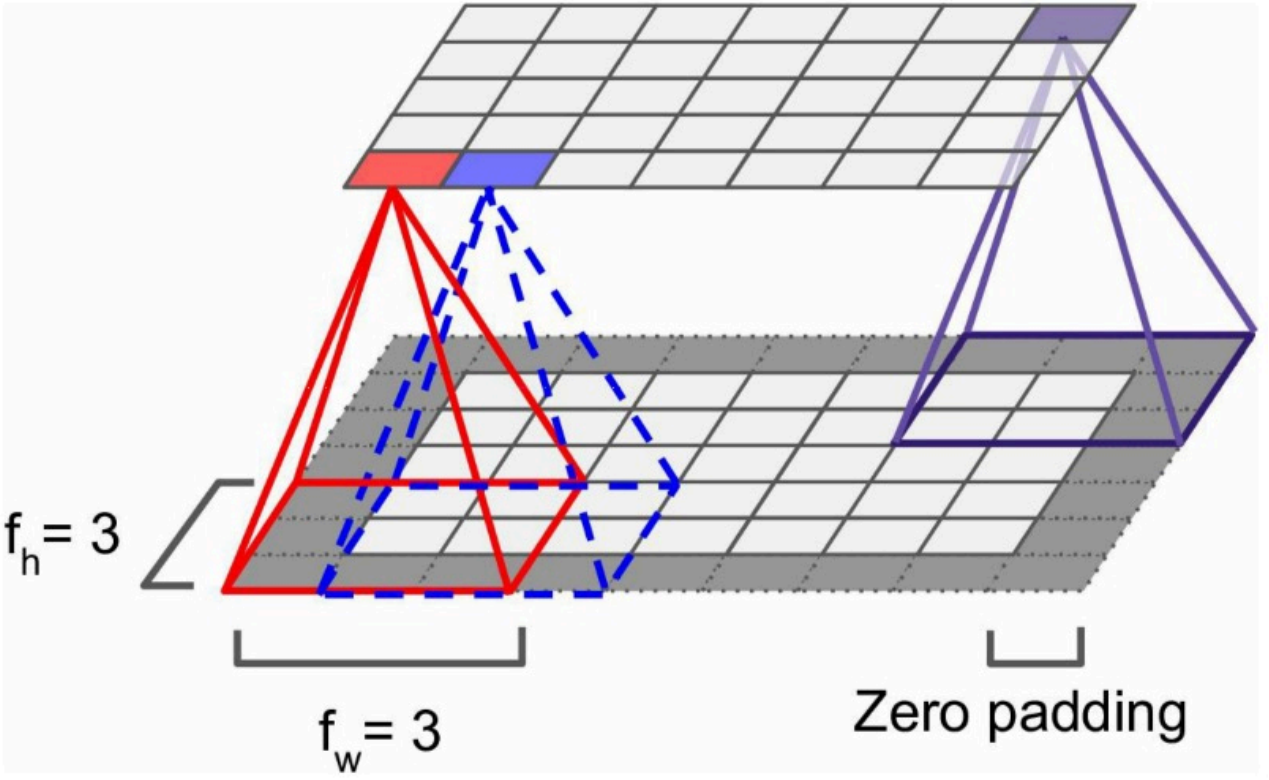


Figure 13-2. CNN layers with rectangular local receptive fields

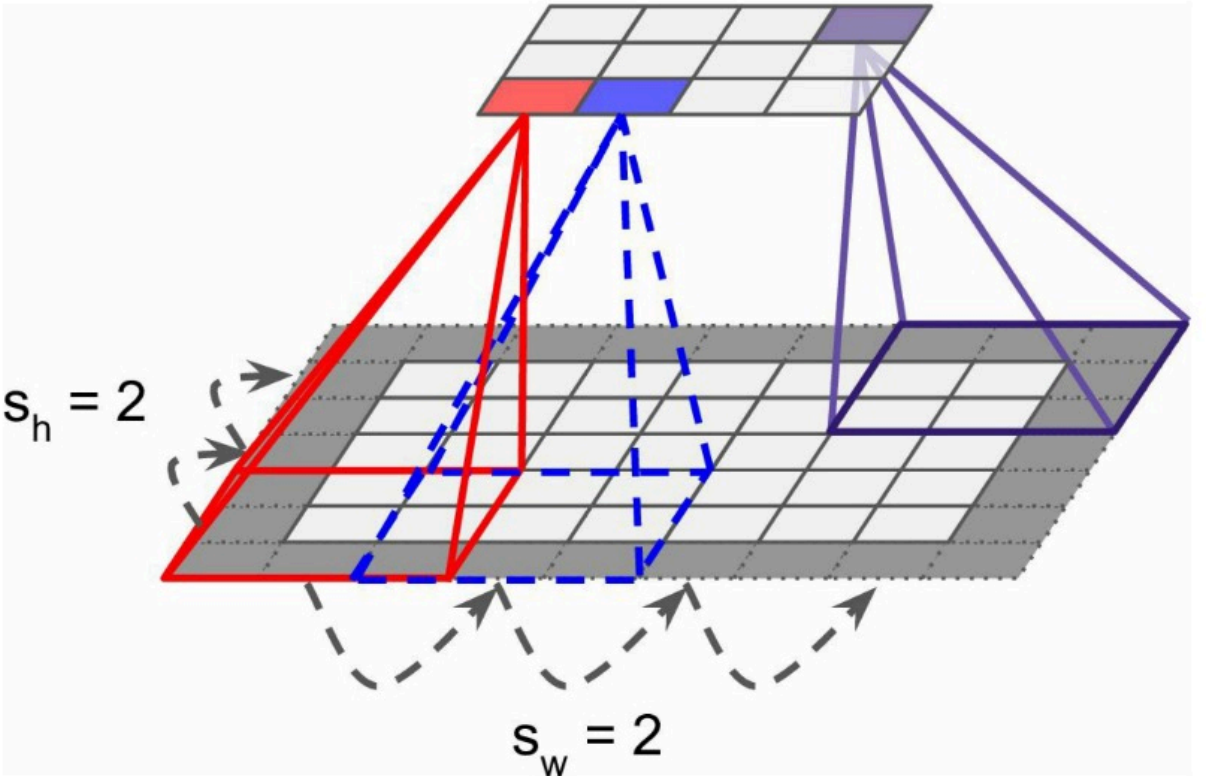
Convolutional Layer

A neuron located in row *i*, column *j* of a given layer is connected to the outputs of the neurons in the previous layer located in rows *i* to $i + f_h - 1$, columns *j* to $j + f_w - 1$, where f_h and f_w are the height and width of the receptive field. In order for a layer to have the same height and width as the previous layer, it is common to add zeros around the inputs, as shown in the diagram. This is called *zero padding*.



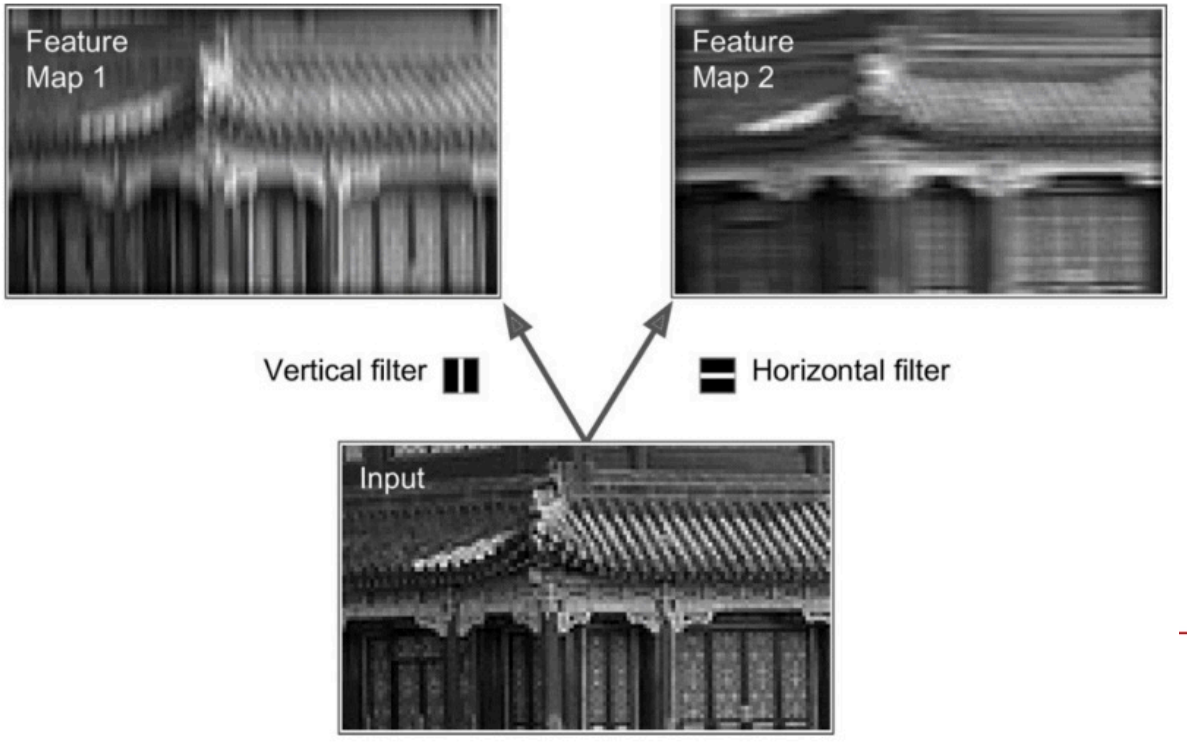
Convolutional Layer

It is also possible to connect a large input layer to a much smaller layer by spacing out the receptive fields as shown below. The distance between two consecutive receptive fields is called the *stride*. In the diagram, a 5 × 7 input layer (plus zero padding) is connected to a 3 × 4 layer, using 3 ×3 receptive fields and a stride of 2 (in this example the stride is the same in both directions, but it does not have to be so). A neuron located in row i, column j in the upper layer is connected to the outputs of the neurons in the previous layer located in rows $i \times s_h$ to $i \times s_h + f_h - 1$, columns $j \times s_w + f_w - 1$, where s_h and s_w are the vertical and horizontal strides.



Convolutional Layer – Filters

A neuron’s weights can be represented as a small image the size of the receptive field. For example, below shows two possible sets of weights, called *filters* (or *convolution kernels*). The first one is represented as a black square with a vertical white line in the middle (it is a 7 × 7 matrix full of 0s except for the central column, which is full of 1s); neurons using these weights will ignore everything in their receptive field except for the central vertical line (since all inputs will get multiplied by 0, except for the ones located in the central vertical line). The second filter is a black square with a horizontal white line in the middle. Once again, neurons using these weights will ignore everything in their receptive field except for the central horizontal line.



Convolutional- Stacking Multiple Feature Maps

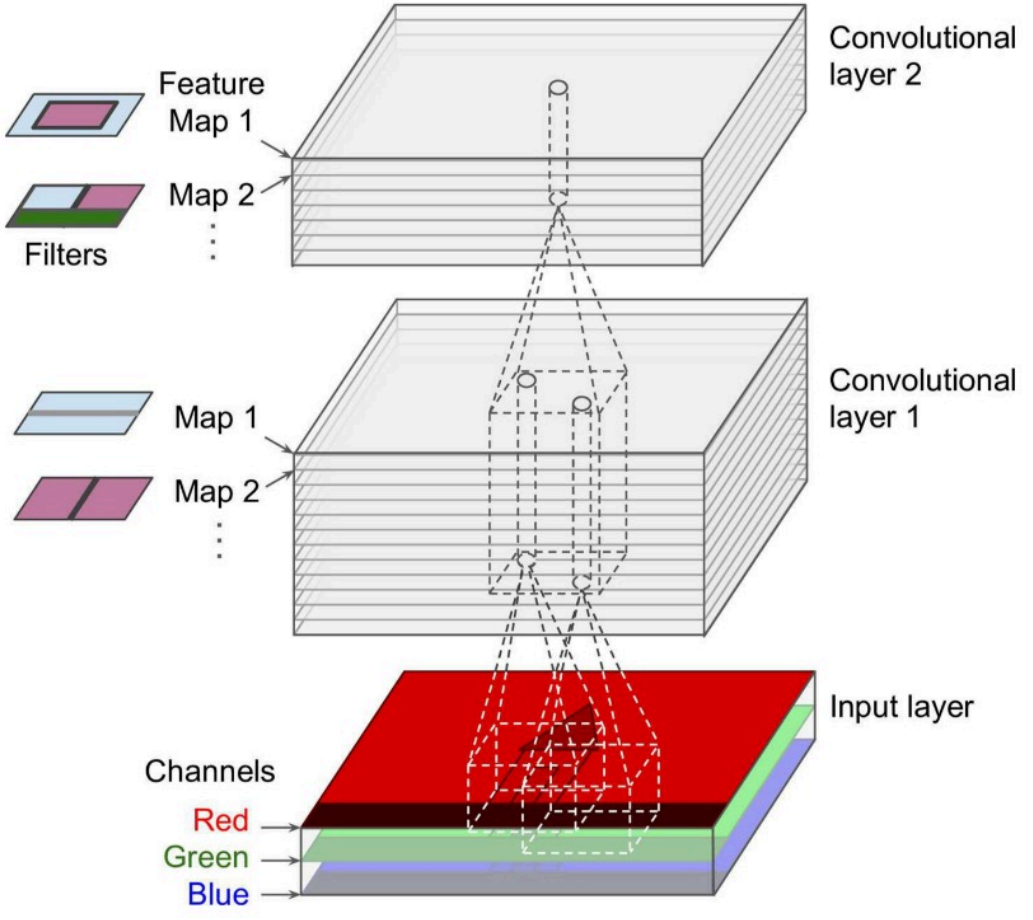
Up to now, for simplicity, we have represented each convolutional layer as a thin 2D layer, but in reality it is composed of several feature maps of equal sizes, so it is more accurately represented in 3D. Within one feature map, all neurons share the same parameters (weights and bias term), but different feature maps may have different parameters. A neuron’ s receptive field is the same as described earlier, but it extends across all the previous layers’ feature maps. In short, a convolutional layer simultaneously applies multiple filters to its inputs, making it capable of detecting multiple features anywhere in its inputs.

NOTE

The fact that all neurons in a feature map share the same parameters dramatically reduces the number of parameters in the model, but most importantly it means that once the CNN has learned to recognize a pattern in one location, it can recognize it in any other location.

Convolutional- Stacking Multiple Feature Maps

Moreover, input images are also composed of multiple sublayers: one per *color channel*. There are typically three: red, green, and blue (RGB). Grayscale images have just one channel, but some images may have much more — for example, satellite images that capture extra light frequencies (such as infrared).



Convolutional- Stacking Multiple Feature Maps

Specifically, a neuron located in row i, column j of the feature map k in a given convolutional layer l is connected to the outputs of the neurons in the previous layer $l-1$, located in rows $i \times s_w$ to $i \times s_w + f_w - 1$ and columns $j \times s_h$ to $j \times s_h + f_h - 1$, across all feature maps (in layer $l-1$). Note that all neurons located in the same row i and column j but in different feature maps are connected to the outputs of the exact same neurons in the previous layer.

Convolutional- Stacking Multiple Feature Maps

Equation 13-1 summarizes the preceding explanations in one big mathematical equation: it shows how to compute the output of a given neuronin a convolutional layer. It is a bit ugly due to all the different indices, but all it does is calculate the weighted sum of all the inputs, plus the bias term.

$$z_{i,j,k} = b_k + \sum_{u=1}^{f_h} \sum_{v=1}^{f_w} \sum_{k'=1}^{f_{n'}} x_{i',j',k'} \cdot w_{u,v,k',k} \quad \text{with} \begin{cases} i' = u.s_h + f_h - 1 \\ j' = v.s_w + f_w - 1 \end{cases}$$

- *zi, j, k* is the output of the neuron located in row *i*, column *j* in feature map *k* of the convolutional layer (layer *l*).
- As explained earlier, *sh* and *sw* are the vertical and horizontal strides, *fh* and *fw* are the height and width of the receptive field, and *fn'* is the number of feature maps in the previous layer (layer *l* – 1).
- *xi', j', k'* is the output of the neuron located in layer *l* – 1, row *i'*, column *j'*, feature map *k'* (or channel *k'* if the previous layer is the input layer).
- *bk* is the bias term for feature map *k* (in layer *l*). You can think of it as a knob that tweaks the overall brightness of the feature map *k*.
- *wu, v, k' ,k* is the connection weight between any neuron in feature map *k* of the layer *l* and its input located at row *u*, column *v* (relative to the neuron' s receptive field), and feature map *k'*.

Convolutional- TensorFlow Implementation

In TensorFlow, each input image is typically represented as a 3D tensor of shape [height, width, channels]. A mini-batch is represented as a 4D tensor of shape [mini-batch size, height, width, channels]. The weights of a convolutional layer are represented as a 4D tensor of shape [f_h, f_w, f_n, $f_{n'}$]. The bias terms of a convolutional layer are simply represented as a 1D tensor of shape [f_n].

In [11]:
```
import numpy as np
from sklearn.datasets import load_sample_images

# Load sample images
china = load_sample_image("china.jpg")
flower = load_sample_image("flower.jpg")
dataset = np.array([china, flower], dtype=np.float32)
batch_size, height, width, channels = dataset.shape

# Create 2 filters
filters = np.zeros(shape=(7, 7, channels, 2), dtype=np.float32)
filters[:, 3, :, 0] = 1  # vertical line
filters[3, :, :, 1] = 1  # horizontal line

# Create a graph with input X plus a convolutional layer applying the 2 filters
X = tf.placeholder(tf.float32, shape=(None, height, width, channels))
convolution = tf.nn.conv2d(X, filters, strides=[1,2,2,1], padding="SAME")

with tf.Session() as sess:
    output = sess.run(convolution, feed_dict={X: dataset})

plt.imshow(output[0, :, :, 1], cmap="gray") # plot 1st image's 2nd feature map
plt.show()
```

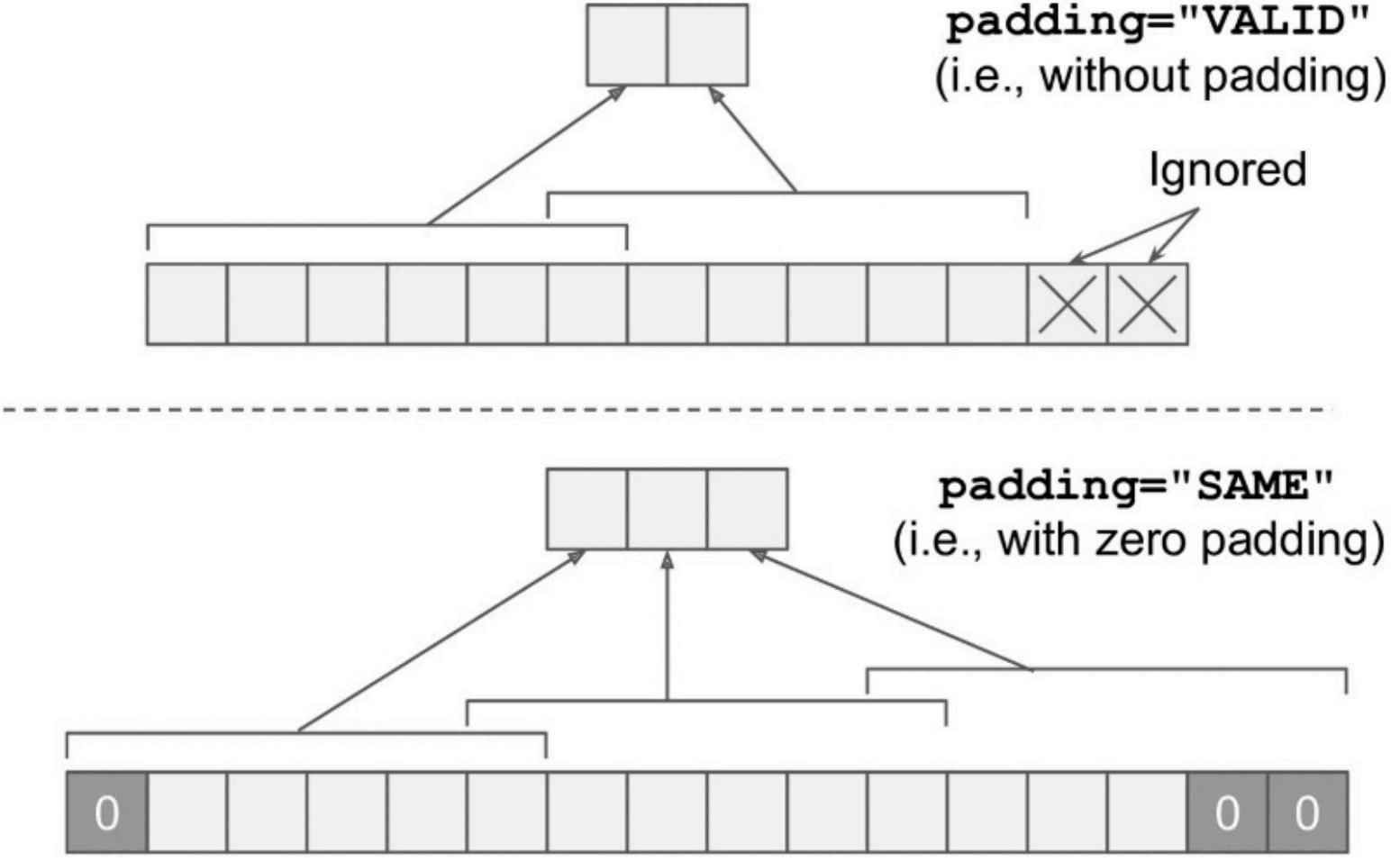
Convolutional- TensorFlow Implementation

Most of this code is self-explanatory, but the conv2d() line deserves a bit of explanation:

- X is the input mini-batch (a 4D tensor, as explained earlier).
- filters is the set of filters to apply (also a 4D tensor, as explained earlier).
- strides is a four-element 1D array, where the two central elements are the vertical and horizontal strides (*sh* and *sw*). The first and last elements must currently be equal to 1. They may one day be used to specify a batch stride (to skip some instances) and a channel stride (to skip some of the previous layer's feature maps or channels).
- padding must be either "VALID" or "SAME":

1. If set to "VALID", the convolutional layer does *not* use zero padding, and may ignore some rows and columns at the bottom and right of the input image, depending on the stride, as shown in Figure 13-7 (for simplicity, only the horizontal dimension is shown here, but of course the same logic applies to the vertical dimension).
2. If set to "SAME", the convolutional layer uses zero padding if necessary. In this case, the number of output neurons is equal to the number of input neurons divided by the stride, rounded up (in this example, ceil (13 / 5) = 3). Then zeros are added as evenly as possible around the inputs.

Convolutional- TensorFlow Implementation



Convolutional- Memory Requirements

Another problem with CNNs is that the convolutional layers require a huge amount of RAM, especially during training, because the reverse pass of backpropagation requires all the intermediate values computed during the forward pass. For example, consider a convolutional layer with 5 × 5 filters, outputting 200 feature maps of size 150 × 100, with stride 1 and SAME padding. If the input is a 150 × 100 RGB image (three channels), then the number of parameters is (5 × 5 × 3 + 1) × 200 = 15,200 (the +1 corresponds to the bias terms), which is fairly small compared to a fully connected layer. However, each of the 200 feature maps contains 150 × 100 neurons, and each of these neurons needs to compute a weighted sum of its 5 × 5 × 3 = 75 inputs: that's a total of 225 million float multiplications. Not as bad as a fully connected layer, but still quite computationally intensive. Moreover, if the feature maps are represented using 32-bit floats, then the convolutional layer's output will occupy 200 × 150 × 100 × 32 = 96 million bits (about 11.4 MB) of RAM. And that's just for one instance! If a training batch contains 100 instances, then this layer will use up over 1 GB of RAM!

***If training crashes because of an out-of-memory error, you can try reducing the mini-batch size. Alternatively, you can try reducing dimensionality using a stride, or removing a few layers. Or you can try using 16-bit floats instead of 32-bit floats. Or you could distribute the CNN across multiple devices.*

Pooling Layer

Pooling layers are quite easy to grasp. Their goal is to *subsample* (i.e., shrink) the input image in order to reduce the computational load, the memory usage, and the number of Parameters. Reducing the input image size also makes the neural network tolerate a little bit of image shift.
Below shows a *max pooling layer*, which is the most common type of pooling layer. In this example, we use a 2 × 2 *pooling kernel*, a stride of 2, and no padding. Note that only the max input value in each kernel makes it to the next layer. The other inputs are dropped.

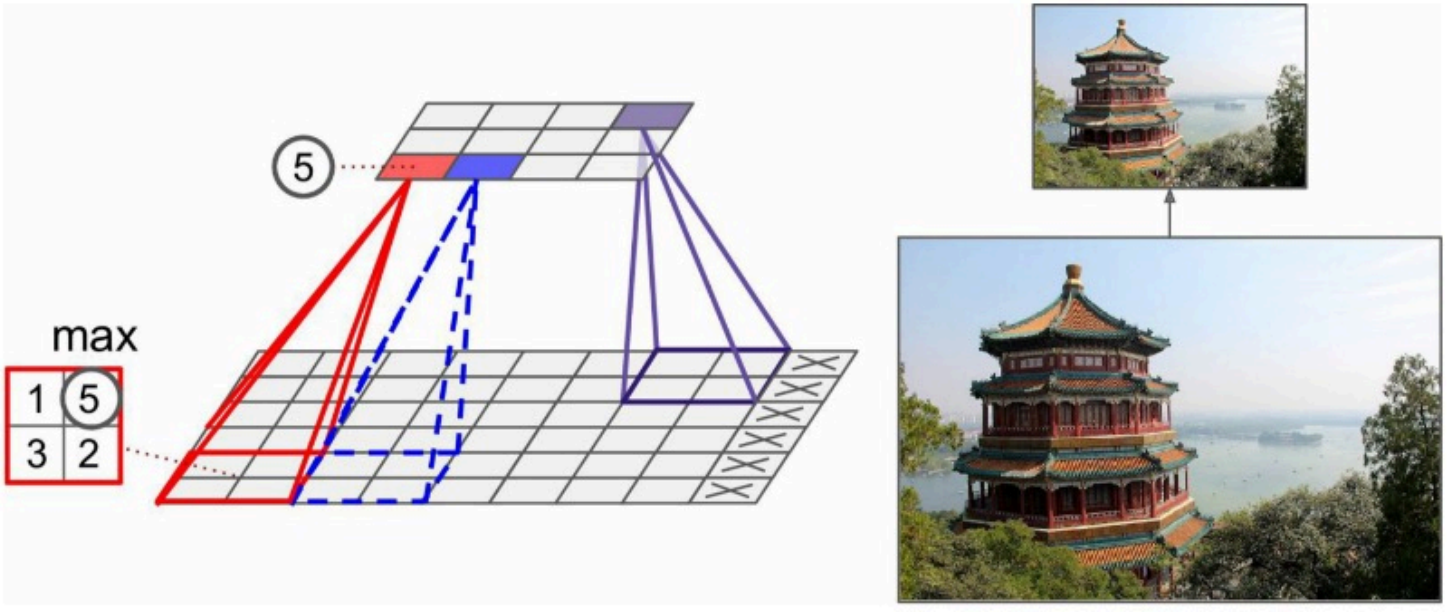


Figure 13-8. Max pooling layer (2 × 2 pooling kernel, stride 2, no padding)

Pooling Layer

The following code creates a max pooling layer using a 2 × 2 kernel, stride 2, and no padding, then applies it to all the images in the dataset. The ksize argument contains the kernel shape along all four dimensions of the input tensor: [batch size, height, width, channels]. TensorFlow currently does not support pooling over multiple instances, so the first element of ksize must be equal to 1. Moreover, it does not support pooling over both the spatial dimensions (height and width) and the depth dimension, so either ksize[1] and ksize[2] must both be equal to 1, or ksize[3] must be equal to 1. To create an *average pooling layer*, just use the avg_pool() function instead of max_pool().

In [19]:
```
X = tf.placeholder(tf.float32, shape=(None, height, width, channels))
max_pool = tf.nn.max_pool(X, ksize=[1,2,2,1], strides=[1,2,2,1],padding="VALID")

with tf.Session() as sess:
    output = sess.run(max_pool, feed_dict={X: dataset})

plt.imshow(output[0].astype(np.uint8))  # plot the output for the 1st image
plt.show()
```

CNN Architectures

Typical CNN architectures stack a few convolutional layers (each one generally followed by a ReLU layer), then a pooling layer, then another few convolutional layers (+ReLU), then another pooling layer, and so on. The image gets smaller and smaller as it progresses through the network, but it also typically gets deeper and deeper (i.e., with more feature maps) thanks to the convolutional layers. At the top of the stack, a regular feedforward neural network is added, composed of a few fully connected layers (+ReLUs), and the final layer outputs the prediction (e.g., a softmax layer that outputs estimated class probabilities).

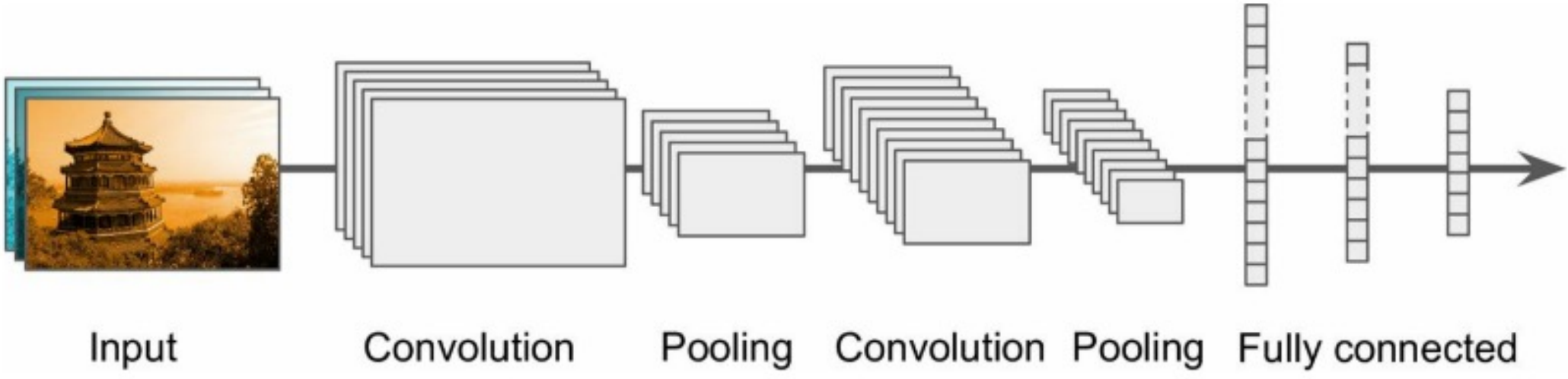


Figure 13-9. Typical CNN architecture

CNN Architectures - LeNet-5

The LeNet-5 architecture is perhaps the most widely known CNN architecture. As mentioned earlier, it was created by Yann LeCun in 1998 and widely used for handwritten digit recognition (MNIST). It is composed of the layers shown:

Table 13-1. LeNet-5 architecture

Layer	Type	Maps	Size	Kernel size	Stride	Activation
Out	Fully Connected	–	10	–	–	RBF
F6	Fully Connected	–	84	–	–	tanh
C5	Convolution	120	1 × 1	5 × 5	1	tanh
S4	Avg Pooling	16	5 × 5	2 × 2	2	tanh
C3	Convolution	16	10 × 10	5 × 5	1	tanh
S2	Avg Pooling	6	14 × 14	2 × 2	2	tanh
C1	Convolution	6	28 × 28	5 × 5	1	tanh
In	Input	1	32 × 32	–	–	–

CNN Architectures - LeNet-5

There are a few extra details to be noted:

- MNIST images are 28 × 28 pixels, but they are zero-padded to 32 × 32 pixels and normalized before being fed to the network. The rest of the network does not use any padding, which is why the size keeps shrinking as the image progresses through the network.
- The average pooling layers are slightly more complex than usual: each neuron computes the mean of its inputs, then multiplies the result by a learnable coefficient (one per map) and adds a learnable bias term (again, one per map), then finally applies the activation function.
- Most neurons in C3 maps are connected to neurons in only three or four S2 maps (instead of all six S2 maps).
- The output layer is a bit special: instead of computing the dot product of the inputs and the weight vector, each neuron outputs the square of the Euclidian distance between its input vector and its weight vector. Each output measures how much the image belongs to a particular digit class. The cross entropy cost function is now preferred, as it penalizes bad predictions much more, producing larger gradients and thus converging faster.

CNN Architectures – AlexNet

The *AlexNet* CNN architecture won the 2012 ImageNet ILSVRC challenge by a large margin: it achieved 17% top-5 error rate while the second best achieved only 26%! It was developed by Alex Krizhevsky (hence the name), Ilya Sutskever, and Geoffrey Hinton. It is quite similar to LeNet-5, only much larger and deeper, and it was the first to stack convolutional layers directly on top of each other, instead of stacking a pooling layer on top of each convolutional layer.

Table 13-2. AlexNet architecture

Layer	Type	Maps	Size	Kernel size	Stride	Padding	Activation
Out	Fully Connected	–	1,000	–	–	–	Softmax
F9	Fully Connected	–	4,096	–	–	–	ReLU
F8	Fully Connected	–	4,096	–	–	–	ReLU
C7	Convolution	256	13 × 13	3 × 3	1	SAME	ReLU
C6	Convolution	384	13 × 13	3 × 3	1	SAME	ReLU
C5	Convolution	384	13 × 13	3 × 3	1	SAME	ReLU
S4	Max Pooling	256	13 × 13	3 × 3	2	VALID	–
C3	Convolution	256	27 × 27	5 × 5	1	SAME	ReLU
S2	Max Pooling	96	27 × 27	3 × 3	2	VALID	–
C1	Convolution	96	55 × 55	11 × 11	4	SAME	ReLU
In	Input	3 (RGB)	224 × 224	–	–	–	–

CNN Architectures – Others

The GoogLeNet architecture was developed by Christian Szegedy et al. from Google Research, and it won the ILSVRC 2014 challenge by pushing the top-5 error rate below 7%. This great performance came in large part from the fact that the network was much deeper than previous CNNs. This was made possible by sub-networks called *inception modules*, which allow GoogLeNet to use parameters much more efficiently than previous architectures: GoogLeNet actually has 10 times fewer parameters than AlexNet (roughly 6 million instead of 60 million).

Last but not least, the winner of the ILSVRC 2015 challenge was the *Residual Network* (or *ResNet*), developed by Kaiming He et al., which delivered an astounding top-5 error rate under 3.6%, using an extremely deep CNN composed of 152 layers. The key to being able to train such a deep network is to use *skip connections* (also called *shortcut connections*): the signal feeding into a layer is also added to the output of a layer located a bit higher up the stack.

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