Image Processing with Keras in Python

Image Processing with Keras in Python

Black Raven (James Ng)
18 Mar 2021 · 31 min read

4 hours · 13 Videos · 45 Exercises · 21,137 Participants · 3,650 XP

This is a memo to share what I have learnt in Image Processing with Keras (in Python), capturing the learning objectives as well as my personal notes. The course is taught by Ariel Rokem from DataCamp, and it includes 4 chapters:

Chapter 1. Image Processing With Neural Networks
Chapter 2. Using Convolutions
Chapter 3. Going Deeper
Chapter 4. Understanding and Improving Deep Convolutional Networks

Deep learning methods use data to train neural network algorithms to do a variety of machine learning tasks, such as classification of different classes of objects. Convolutional neural networks are deep learning algorithms that are particularly powerful for analysis of images. This course will teach you how to construct, train and evaluate convolutional neural networks. You will also learn how to improve their ability to learn from data, and how to interpret the results of the training.

Chapter 1. Image Processing With Neural Networks

Convolutional neural networks use the data that is represented in images to learn. In this chapter, we will probe data in images, and we will learn how to use Keras to train a neural network to classify objects that appear in images.

Introducing convolutional neural networks

CNNs are powerful algorithms for processing images. In fact, these algorithms are currently the best algorithms we have for automated processing of images.
We will use Keras, which is a Python-based library that implements the building blocks you need to build your own CNNs.

```
import matplotlib.pyplot as plt
data = plt.imread('stop_sign.jpg')
plt.imshow(data)
plt.show()
```

```
data.shape
```

```
(2832, 4256, 3)
```

The computer doesn't see the image. All it sees is an array of numbers. Color images are stored in 3-dimensional arrays. The first two dimensions correspond to the height and width of the image (the number of pixels). The last dimension corresponds to the red, green and blue colors present in each pixel.

```
data[1000, 1500]
```

```
array([0.73333333, 0.07843137, 0.14509804])
```

🟥

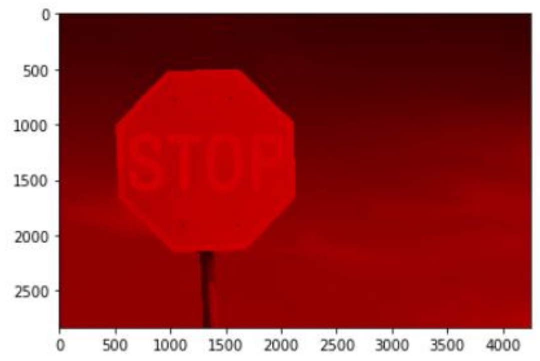
```
data[250, 3500]
```

```
array([0.25882353, 0.43921569, 0.77254902])
```

🟦

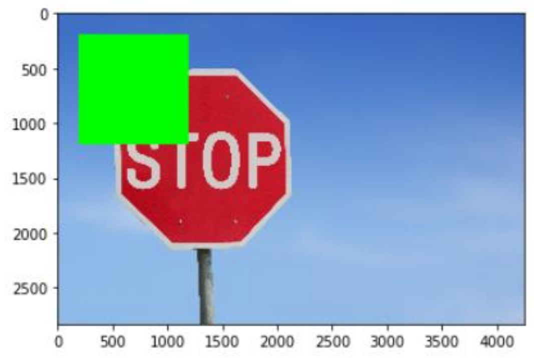
```
data[:, :, 1] = 0
data[:, :, 2] = 0
plt.imshow(data)
plt.show()
```

We can also change the image by changing the array data. For example, here we set the green and blue values of the pixels to zero. The result is an image that contains only the information in the red channel.

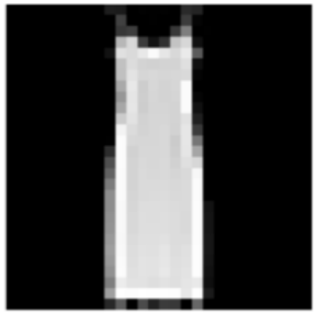


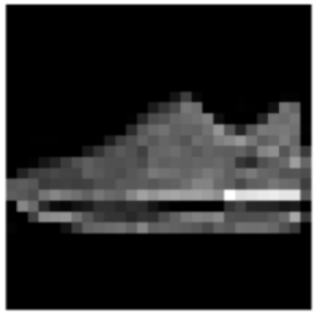
```
data[200:1200, 200:1200, :] = [0, 1, 0]
plt.imshow(data)
plt.show()
```

Alternatively, we could set all the pixels within some part of the image to have no red and no blue, but full intensity in the green channel. This results in an image with a green square in it.



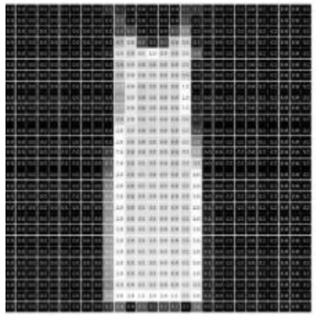
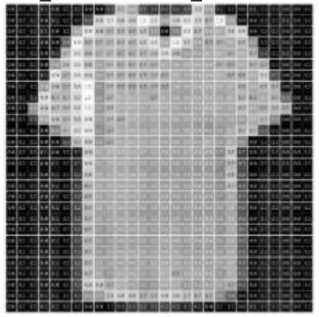
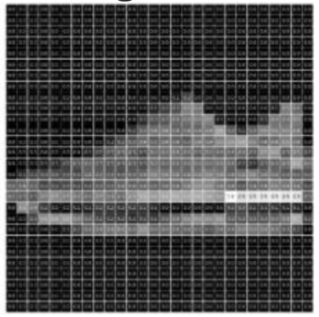
In this course, we will mostly look at black and white images. For example, consider these three images of three different items of clothing: a dress, a t-shirt and a shoe.





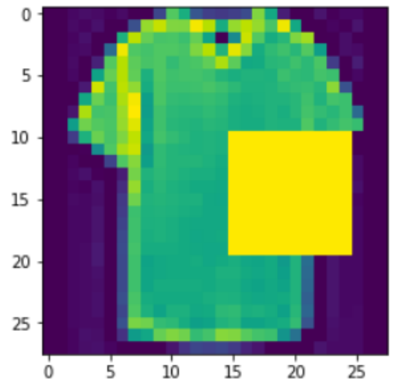
What the computer sees are the numbers that represent the intensity of the image in each pixel.

- High numbers represent parts of the image that are brighter
- Low numbers represent parts of the image that are darker

```python
tshirt[10:20, 15:25] = 1
plt.imshow(tshirt)
plt.show()
```

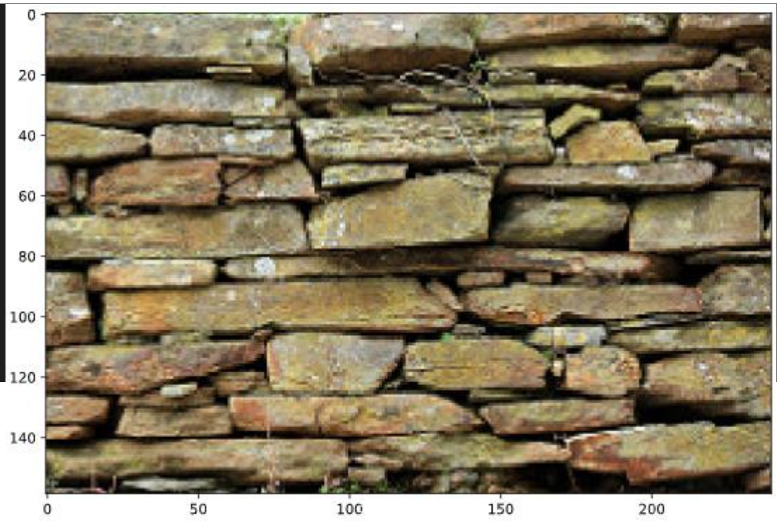
In these images as well, we can select a part of the image, using indexing on the rows and columns of the array and slicing, and change part of the array, using assignment.



Images as data: visualizations

To display image data, you will rely on Python's **Matplotlib** library, and specifically use matplotlib's `pyplot` sub-module, that contains many plotting commands. Some of these commands allow you to display the content of images stored in arrays.

```
# Import matplotlib
import matplotlib.pyplot as plt

# Load the image
data = plt.imread('bricks.png')

# Display the image
plt.imshow(data)
plt.show()
```



Visit [Matplotlib's website](#) to learn more about plotting commands you could use.

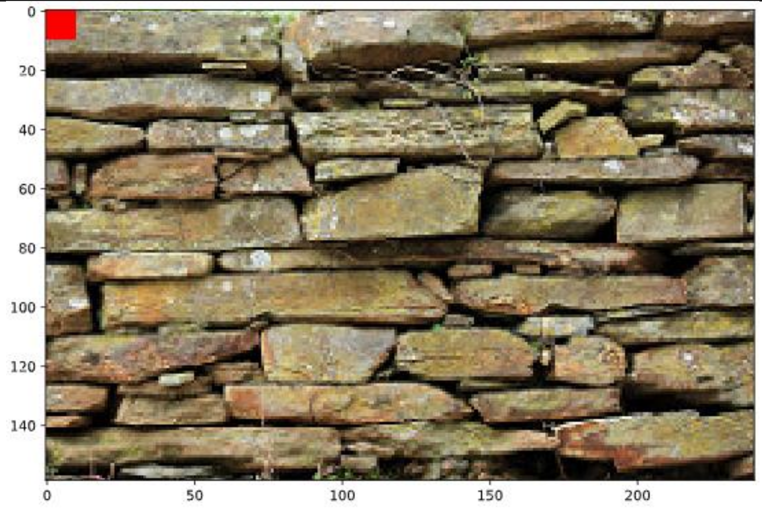
Images as data: changing images

To modify an image, you can modify the existing numbers in the array. In a color image, you can change the values in one of the color channels without affecting the other colors, by indexing on the last dimension of the array.

The image you imported in the previous exercise is available in `data`.

```
# Set the red channel in this part of the image to 1
data[:10, :10, 0] = 1

# Set the green channel in this part of the image to 0
data[:10, :10, 1] = 0

# Set the blue channel in this part of the image to 0
data[:10, :10, 2] = 0
```

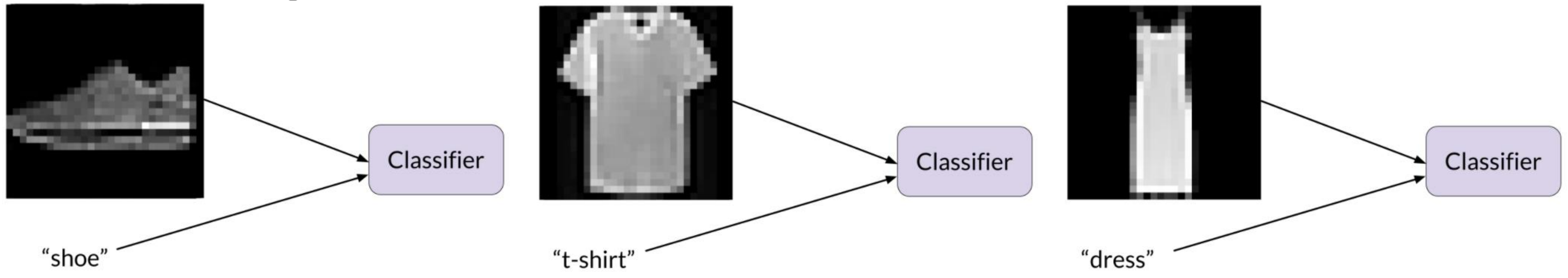
```
# Visualize the result
plt.imshow(data)
plt.show()
```



You now know how to manipulate images.
By the way, if you set both the green and red channels to 1, that part of the image would be yellow.

Classifying images

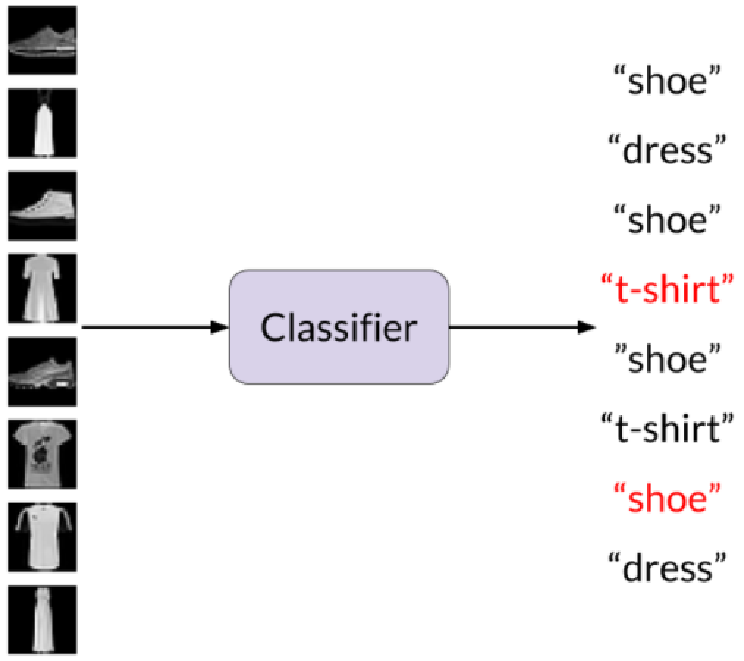
In the training phase, we present the algorithm with samples from these three classes, together with the class labels for each image.



Over the course of training, the algorithm adjusts its parameters to learn the patterns in the data that distinguish between the three different classes of clothing.

At the end of training, we would like to know how well our classifier does. To avoid an estimate that is overly optimistic because of overfitting, we evaluate it by testing it on a portion of the data that has been set aside in advance for this purpose.

In this case, the classifier is able to correctly classify some of the images, but incorrectly classifies an image of a dress as a t-shirt, and an image of a t-shirt as a shoe.



Representing class data: one-hot encoding

```
labels = ["shoe", "dress", "shoe", "t-shirt",
          "shoe", "t-shirt", "shoe", "dress"]
```

```
array([[0., 0., 1.],     <= shoe
       [0., 1., 0.],     <= dress
       [0., 0., 1.],     <= shoe
       [1., 0., 0.],     <= t-shirt
       [0., 0., 1.],     <= shoe
       [1., 0., 0.],     <= t-shirt
       [0., 0., 1.],     <= shoe
       [0., 1., 0.]])    <= dress
```

```
categories = np.array(["t-shirt", "dress", "shoe"])
n_categories = 3
ohe_labels = np.zeros((len(labels), n_categories))
for ii in range(len(labels)):
    jj = np.where(categories == labels[ii])
    ohe_labels[ii, jj] = 1
```

```
test
```

```
array([[0., 0., 1.],
       [0., 1., 0.],
       [0., 0., 1.],
       [0., 1., 0.],
       [0., 0., 1.],
       [0., 0., 1.],
       [0., 0., 1.],
       [0., 1., 0.]])
```

```
prediction
```

```
array([[0., 0., 1.],
       [0., 1., 0.],
       [0., 0., 1.],
       [1., 0., 0.], <= incorrect
       [0., 0., 1.],
       [1., 0., 0.], <= incorrect
       [0., 0., 1.],
       [0., 1., 0.]])
```

```
(test * prediction).sum()
```

```
6.0
```

Using one-hot encoding to represent images

Neural networks expect the labels of classes in a dataset to be organized in a one-hot encoded manner: each row in the array contains zeros in all columns, except the column corresponding to a unique label, which is set to 1.

The fashion dataset contains three categories:

1. Shirts
2. Dresses
3. Shoes

In this exercise, you will create a one-hot encoding of a small sample of these labels.

```
# The number of image categories
n_categories = 3

# The unique values of categories in the data
```

```
categories = np.array(["shirt", "dress", "shoe"])

# Initialize ohe_labels as all zeros
ohe_labels = np.zeros((len(labels), n_categories))

# Loop over the labels
for ii in range(len(labels)):
    # Find the location of this label in the categories variable
    jj = np.where(categories == labels[ii])
    # Set the corresponding zero to one
    ohe_labels[ii, jj] = 1
```

```
labels: ['shoe', 'shirt', 'shoe', 'shirt', 'dress', 'dress', 'dress']
```

You can use this array to test classification performance.

Evaluating a classifier

To evaluate a classifier, we need to test it on images that were not used during training. This is called "cross-validation": a prediction of the class (e.g., t-shirt, dress or shoe) is made from each of the test images, and these predictions are compared with the true labels of these images.

The results of cross-validation are provided as one-hot encoded arrays: `test_labels` and `predictions`.

```
# Calculate the number of correct predictions
number_correct = (test_labels * predictions).sum()
print(number_correct)

# Calculate the proportion of correct predictions
proportion_correct = number_correct/len(predictions)
print(proportion_correct)
```

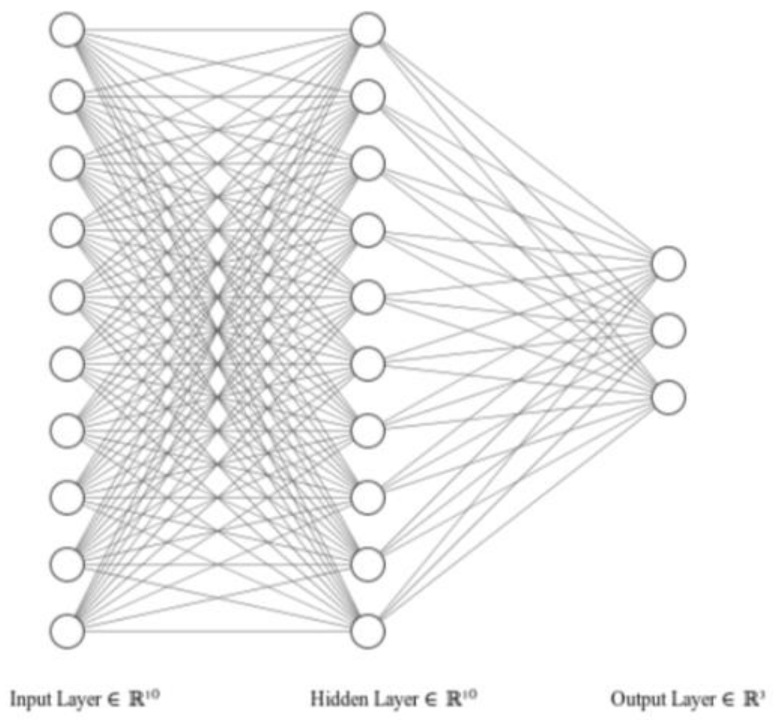
```
<script.py> output:
    6.0
    0.75
```

Let's talk about fitting classification models using Keras.

Classification with Keras

```python
from keras.models import Sequential
model = Sequential()
```

fully connected network



```python
from keras.layers import Dense
train_data.shape
```

```
(50, 28, 28, 1)
```

50 samples, each of 28 by 28 pixels (784), 1=images are black and white

```python
model.add(Dense(10, activation='relu',
          input_shape=(784,)))
model.add(Dense(10, activation='relu'))
model.add(Dense(3, activation='softmax'))
```

input, hidden, output

```python
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

The model expects samples to be rows in an array, and each column to represent a pixel in the image, so before we fit the model we need to convert the images into a two-dimensional table, using the "reshape" method.

```python
train_data = train_data.reshape((50, 784))
```

```python
model.fit(train_data, train_labels,
          validation_split=0.2,
          epochs=3)
```

Here, the model will run for 3 epochs,
meaning that it will go over all of the training data three times.
To avoid overfitting, we set aside 20% as a set of validation images.

```
Train on 40 samples, validate on 10 samples
Epoch 1/3
32/40 [=========>......] - ETA: 0s - loss: 1.0117 - acc: 0.4688
40/40 [================] - 0s 4ms/step - loss: 1.0438 - acc: 0.4250
                           - val_loss: 0.9668 - val_acc: 0.4000
Epoch 2/3
32/40 [=========>......] - ETA: 0s - loss: 0.9556 - acc: 0.5312
40/40 [================] - 0s 195us/step - loss: 0.9404 - acc: 0.5750
                         - val_loss: 0.9068 - val_acc: 0.4000
Epoch 3/3
32/40 [=========>......] - ETA: 0s - loss: 0.9143 - acc: 0.5938
40/40 [================] - 0s 189us/step - loss: 0.8726 - acc: 0.6750
                         - val_loss: 0.8452 - val_acc: 0.4000
```

```python
test_data = test_data.reshape((10, 784))
model.evaluate(test_data, test_labels)
```

```
10/10 [==============================] - 0s 335us/step
[1.0191701650619507, 0.4000000059604645]
```

Accuracy is still rather low, because we used a small amount of data, and we trained for only a few epochs. Final evaluation of the model should be done on a separate test set that was not used during training. This gives us a separate realistic evaluation of the model quality.

Build a neural network

We will use the `Keras` library to create neural networks and to train these neural networks to classify images. These models will all be of the `Sequential` type, meaning that the outputs of one layer are provided as inputs only to the next layer.

In this exercise, you will create a neural network with `Dense` layers, meaning that each unit in each layer is connected to all of the units in the previous layer. For example, each unit in the first layer is connected to all of the pixels in the input images. The `Dense` layer object receives as arguments the number of units in that layer, and the activation function for the units. For the first layer in the network, it also receives an `input_shape` keyword argument.

*This course touches on a lot of concepts you may have forgotten, so if you ever need a quick refresher, download the **Keras Cheat Sheet** and keep it handy!*

```
# Imports components from Keras
from keras.models import Sequential
from keras.layers import Dense

# Initializes a sequential model
model = Sequential()

# First layer
model.add(Dense(10, activation='relu', input_shape=(784,)))

# Second layer
model.add(Dense(10, activation='relu'))

# Output layer
model.add(Dense(3, activation='softmax'))
```

You've built a neural network!

Compile a neural network

Once you have constructed a model in `Keras`, the model needs to be compiled before you can fit it to data. This means that you need to specify the optimizer that will be used to fit the model and the loss function that will be used in optimization. Optionally, you can also specify a list of metrics that the model will keep track of. For example, if you want to know the classification accuracy, you will provide the list `['accuracy']` to the `metrics` keyword argument.

```
# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

This neural network model is now ready to be fit to data.

Fitting a neural network model to clothing data

In this exercise, you will fit the fully connected neural network that you constructed in the previous exercise to image data. The training data is provided as two variables: `train_data` that contains the pixel data for 50 images of the three clothing classes and `train_labels`, which contains one-hot encoded representations of the labels for each one of these 50 images. Transform the data into the network's expected input and then fit the model on training data and training labels.

The `model` you compiled in the previous exercise, and `train_data` and `train_labels` are available in your workspace.

```
# Reshape the data to two-dimensional array
train_data = train_data.reshape(50, 784)

# Fit the model
model.fit(train_data, train_labels, validation_split=0.2, epochs=3)
```

```
<script.py> output:
    Train on 40 samples, validate on 10 samples
    Epoch 1/3

    32/40 [=======================>......] - ETA: 0s - loss: 1.0043 - acc: 0.5000
    40/40 [==============================] - 0s 7ms/step - loss: 1.0062 - acc: 0.5000 - val_loss: 0.9919 - val_acc: 0.4000
    Epoch 2/3
    32/40 [======================>......] - ETA: 0s - loss: 0.9582 - acc: 0.5625
    40/40 [==============================] - 0s 213us/step - loss: 0.9444 - acc: 0.6000 - val_loss: 0.9596 - val_acc: 0.4000
    Epoch 3/3

    32/40 [======================>......] - ETA: 0s - loss: 0.8760 - acc: 0.5625
    40/40 [==============================] - 0s 205us/step - loss: 0.8938 - acc: 0.5500 - val_loss: 0.9225 - val_acc: 0.4000
```

This model works well on the training data, but does it work well on test data?

Cross-validation for neural network evaluation

To evaluate the model, we use a separate test data-set. As in the train data, the images in the test data also need to be reshaped before they can be provided to the fully-connected network because the network expects one column per pixel in the input.

The `model` you fit in the previous exercise, and `test_data` and `test_labels` are available in your workspace.

```python
# Reshape test data
test_data = test_data.reshape(10, 784)

# Evaluate the model
model.evaluate(test_data, test_labels)
```

```
 <script.py> output:

    10/10 [==============================] - 0s 210us/step
```

The model cross-validates rather accurately.

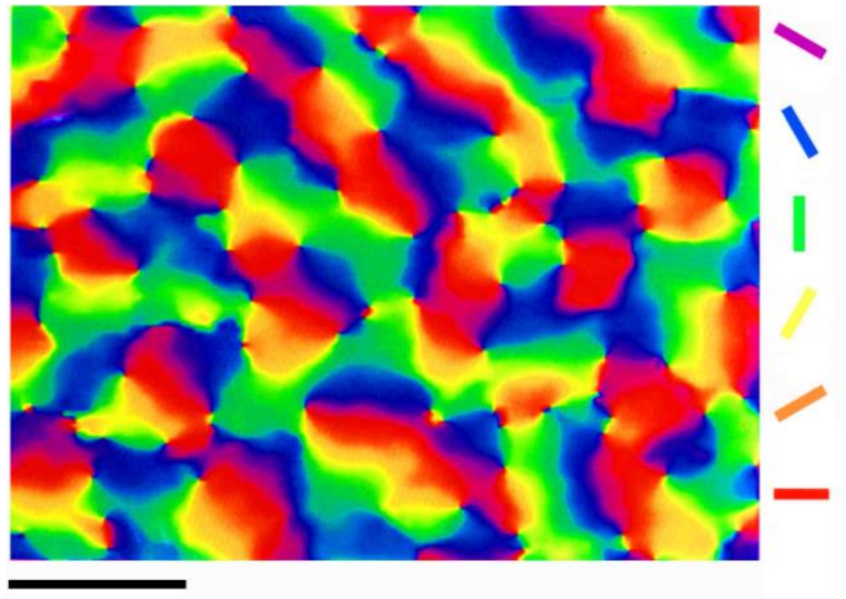
Chapter 2. Using Convolutions

Convolutions are the fundamental building blocks of convolutional neural networks. In this chapter, you will be introducted to convolutions and learn how they operate on image data. You will also see how you incorporate convolutions into Keras neural networks.

Convolutions

In the neural network that we previously constructed, each unit in the first layer had a weight connecting it separately with every pixel in the image.
Pixels in most images are not independent from their neighbors, ie, spatial correlations. For example, images of objects contain edges, and neighboring pixels along an edge tend to have similar patterns.
Our own visual system uses these correlations, and each nerve cell in the visual areas in our brain responds to oriented edges at a particular location in the visual field.

This image depicts a small part of the visual cortex (the scale bar is 1 millimeter in size). Each part of the image responds to some part of the visual field, and to the orientation depicted by the colors on the right. Looking for the same feature, such as a particular orientation, in every location in an image is like a mathematical operation called a convolution. This is the fundamental operation that convolutional neural networks use to process images.



Let's start with a simple version: a convolution in one dimension. We create here an array that contains 5 zeros followed by 5 ones. This array contains an "edge" in the middle, where the values go from zero to one.

```
array = np.array([0, 0, 0, 0, 0, 1, 1, 1, 1, 1])
kernel = np.array([-1, 1])
```

The kernel defines the feature that we are looking for. In this case, we are looking for a change from small values on the left to large values on the right. We start the result as all zeros. Then, we slide the kernel along the array. In each location we multiply the values in the array with the values in the Kernel and sum them up.

```
conv = np.array([0, 0, 0, 0, 0, 0, 0, 0, 0])
conv[0] = (kernel * array[0:2]).sum()
conv[1] = (kernel * array[1:3]).sum()
conv[2] = (kernel * array[2:4]).sum()
...
for ii in range(8):
    conv[ii] = (kernel * array[ii:ii+2]).sum()
```

This is the result for that location:

```
conv
```

```
array([0, 0, 0, 0, 1, 0, 0, 0, 0])
```

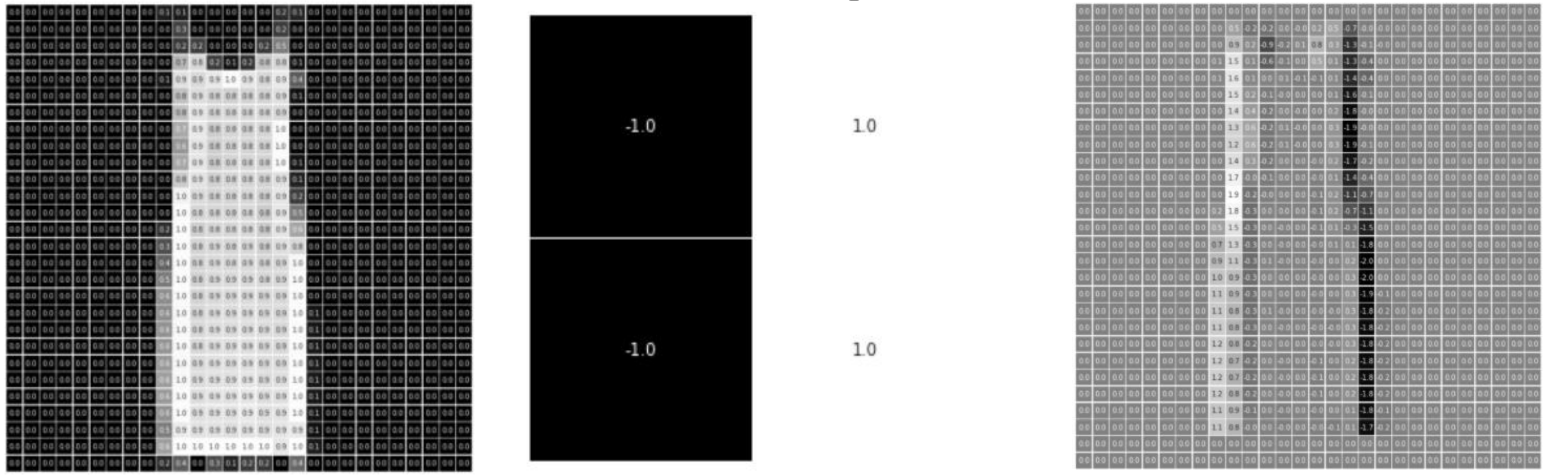
In this example, the array goes between 0 and 1 twice. In this case, the edges that go from zero to one match the kernel, but the edges from 1 to 0 are the opposite of the kernel. In these locations, the convolution becomes negative.

```
array = np.array([0, 0, 1, 1, 0, 0, 1, 1, 0, 0])
kernel = np.array([-1, 1])
```

```
conv = np.array([0, 0, 0, 0, 0, 0, 0, 0, 0])
for ii in range(8):
    conv[ii] = (kernel * array[ii:ii+2]).sum()
conv
```

```
array([ 0,  1,  0, -1,  0,  1,  0, -1,  0])
```

Convolutions of images do the same operation, but in two dimensions. In this case, we convolve the image of a dress with a kernel that matches vertical edges on the left.

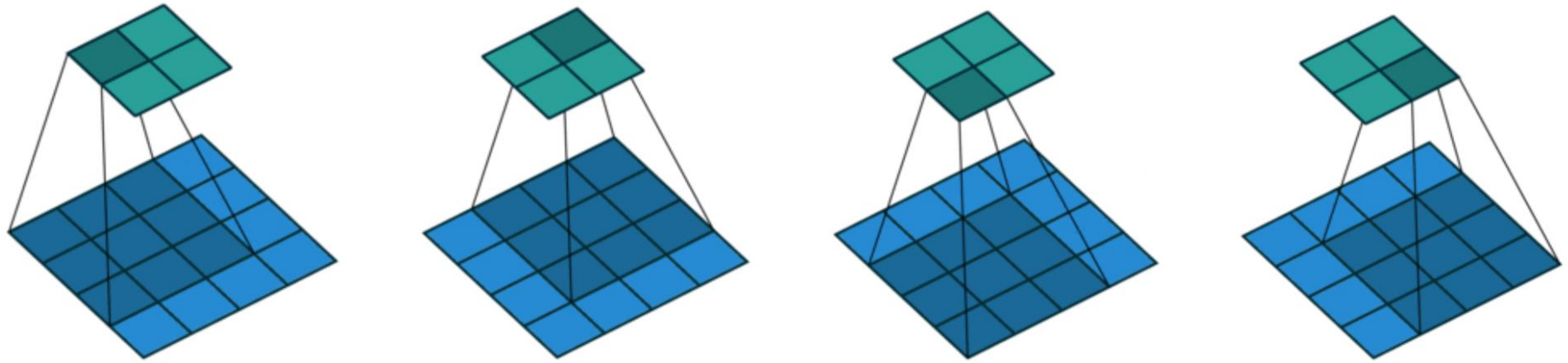


This means that when we convolve the image with this kernel, the left edge is emphasized. The right side of the dress is the opposite of this kernel, and the convolution is negative there.

```
kernel = np.array([[-1, 1],
                   [-1, 1]])


conv = np.zeros((27, 27)
for ii in range(27):
    for jj in range(27):
        window = image[ii:ii+2, jj:jj+2]
        conv[ii, jj] = np.sum(window * kernel)
```

First, we create the kernel. Then, we create the array that will store the results of the convolution. We iterate over all the locations in the image. In each location, we select a window that is the size of the kernel, we multiply that window with the kernel, and then sum it up. This sum is then entered as the value of the convolved image in that location. At the end of the loop, the array will contain the results of the convolution.

Here is a graphic that demonstrates the convolution operation. The kernel is the gray 3-by-3 box that slides over the blue input image at the bottom.



In each location, the window is multiplied with the values in the kernel and added up to create the value of one of the pixels in the resulting green array at the top. In neural networks, we call this resulting array a "feature map", because it contains a map of the locations in the image that match the feature represented by this kernel.

One dimensional convolutions

A convolution of an one-dimensional array with a kernel comprises of taking the kernel, sliding it along the array, multiplying it with the items in the array that overlap with the kernel in that location and summing this product.

```
array = np.array([1, 0, 1, 0, 1, 0, 1, 0, 1, 0])
kernel = np.array([1, -1, 0])
conv = np.array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0])

# Output array
for ii in range(8):
    conv[ii] = (kernel * array[ii:ii+3]).sum()

# Print conv
print(conv)
```

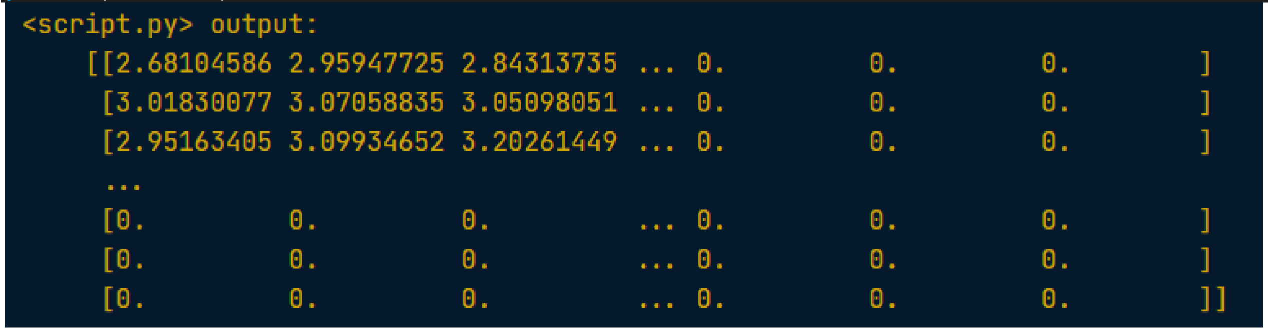
```
<script.py> output:
    [ 1 -1  1 -1  1 -1  1 -1  0  0]
```

Notice that we've only multiplied the kernel with eight different positions

Image convolutions

The convolution of an image with a kernel summarizes a part of the image as the sum of the multiplication of that part of the image with the kernel. In this exercise, you will write the code that executes a convolution of an image with a kernel using Numpy. Given a black and white image that is stored in the variable `im`, write the operations inside the loop that would execute the convolution with the provided kernel.

```python
kernel = np.array([[0, 1, 0], [1, 1, 1], [0, 1, 0]])
result = np.zeros(im.shape)

# Output array
for ii in range(im.shape[0] - 3):
    for jj in range(im.shape[1] - 3):
        result[ii, jj] = (im[ii:ii+3, jj:jj+3] * kernel).sum()

# Print result
print(result)
```



```
 <script.py> output:
    [[2.68104586 2.95947725 2.84313735 ... 0.         0.         0.        ]
     [3.01830077 3.07058835 3.05098051 ... 0.         0.         0.        ]
     [2.95163405 3.09934652 3.20261449 ... 0.         0.         0.        ]
     ...
     [0.         0.         0.         ... 0.         0.         0.        ]
     [0.         0.         0.         ... 0.         0.         0.        ]
     [0.         0.         0.         ... 0.         0.         0.        ]]
```

In a future exercise, you will see how to use Keras to implement a convolution like this one.

Defining image convolution kernels

In the previous exercise, you wrote code that performs a convolution given an image and a kernel. This code is now stored in a function called `convolution()` that takes two inputs: `image` and `kernel` and produces the convolved image. In this exercise, you will be asked to define the kernel that finds a particular feature in the image.

For example, the following kernel finds a vertical line in images:

```
np.array([[-1, 1, -1],
          [-1, 1, -1],
          [-1, 1, -1]])
```

Define a kernel that finds horizontal lines in images.

```
kernel = np.array([[-1, -1, -1],
                   [1, 1, 1],
                   [-1, -1, -1]])
```

Define a kernel that finds a light spot surrounded by dark pixels.

```
kernel = np.array([[-1, -1, -1],
                   [-1, 1, -1],
                   [-1, -1, -1]])
```

Define a kernel that finds a dark spot surrounded by bright pixels.

```
kernel = np.array([[1, 1, 1],
                   [1, -1, 1],
                   [1, 1, 1]])
```

Implementing image convolutions in Keras

Keras has objects to represent convolution layers.

```
from keras.layers import Conv2D
Conv2D(10, kernel_size=3, activation='relu')
```

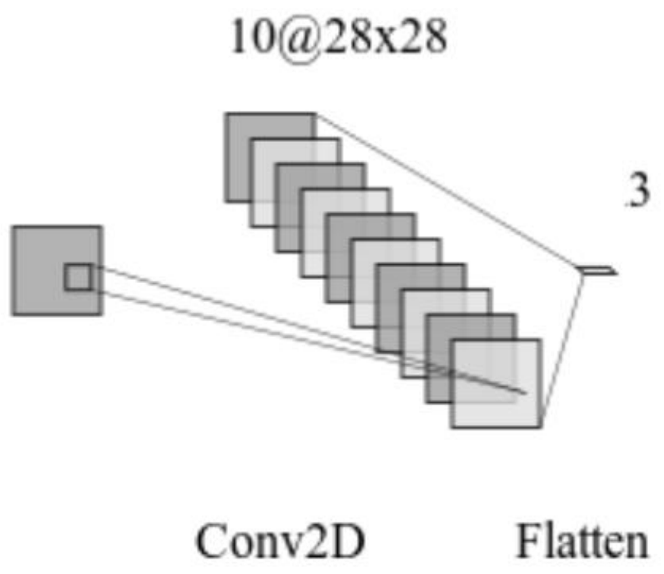
The two-dimensional convolution connects to the previous layer through a convolution kernel. This means that the output of each unit in this layer is a convolution of a kernel over the image input. Here, we have ten convolution units.

During training of a neural network that has convolutional layers, the kernels in each unit would be adjusted using back-propagation. The principle is the same as learning in the Dense, but with fewer weights. A dense layer has one weight for each *pixel* in the image, but a convolution layer has only one weight for each pixel in the *kernel*. For example, if we set the kernel_size argument to 3, that means that the kernel of each unit has 9 pixels. If the layer has 10 units, it would have 90 parameters for these kernels.

```
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten
model = Sequential()
model.add(Conv2D(10, kernel_size=3, activation='relu',
          input_shape=(img_rows, img_cols, 1)))
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
train_data.shape
```

```
(50, 28, 28, 1)
```

```
model.fit(train_data, train_labels, validation_split=0.2,
          epochs=3)

model.evaluate(test_data, test_labels, epochs=3)
```



Convolutional network for image classification

Convolutional networks for classification are constructed from a sequence of convolutional layers (for image processing) and fully connected (`Dense`) layers (for readout). In this exercise, you will construct a small convolutional network for classification of the data from the fashion dataset.

```
# Import the necessary components from Keras
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten
```

```
# Initialize the model object
model = Sequential()

# Add a convolutional layer
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)))

# Flatten the output of the convolutional layer
model.add(Flatten())
# Add an output layer for the 3 categories
model.add(Dense(3, activation='softmax'))
```

Training a CNN to classify clothing types

Before training a neural network it needs to be compiled with the right cost function, using the right optimizer. During compilation, you can also define metrics that the network calculates and reports in every epoch. Model fitting requires a training data set, together with the training labels to the network. The Conv2D `model` you built in the previous exercise is available in your workspace.

```
# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Fit the model on a training set
model.fit(train_data, train_labels,
          validation_split=0.2,
          epochs=3, batch_size=10)
```

```
<script.py> output:
    Train on 40 samples, validate on 10 samples
    Epoch 1/3

    10/40 [======>.......................] - ETA: 0s - loss: 1.1084 - acc: 0.3000
    40/40 [==============================] - 0s 7ms/step - loss: 0.9589 - acc: 0.4750 - val_loss: 0.6300 - val_acc: 0.9000
    Epoch 2/3
    10/40 [======>.......................] - ETA: 0s - loss: 0.7656 - acc: 0.9000
    40/40 [==============================] - 0s 477us/step - loss: 0.6722 - acc: 0.8500 - val_loss: 0.4497 - val_acc: 1.0000
    Epoch 3/3

    10/40 [======>.......................] - ETA: 0s - loss: 0.5367 - acc: 1.0000
    40/40 [==============================] - 0s 473us/step - loss: 0.4332 - acc: 0.9750 - val_loss: 0.3750 - val_acc: 1.0000
```

Validation accuracy converges to 100%!

Evaluating a CNN with test data

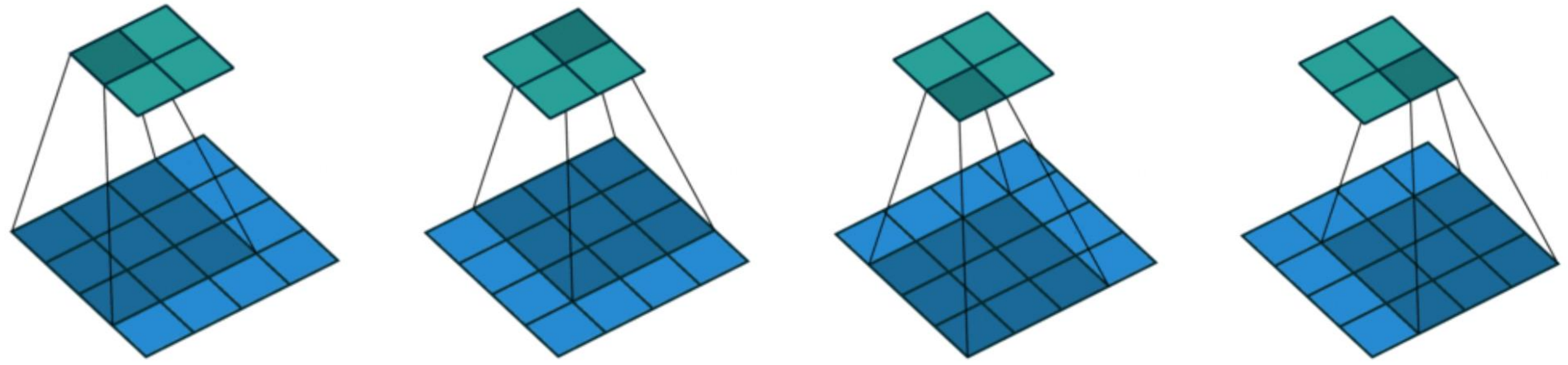
To evaluate a trained neural network, you should provide a separate testing data set of labeled images. The `model` you fit in the previous exercise is available in your workspace.

```
# Evaluate the model on separate test data
model.evaluate(test_data, test_labels, batch_size=10)
```

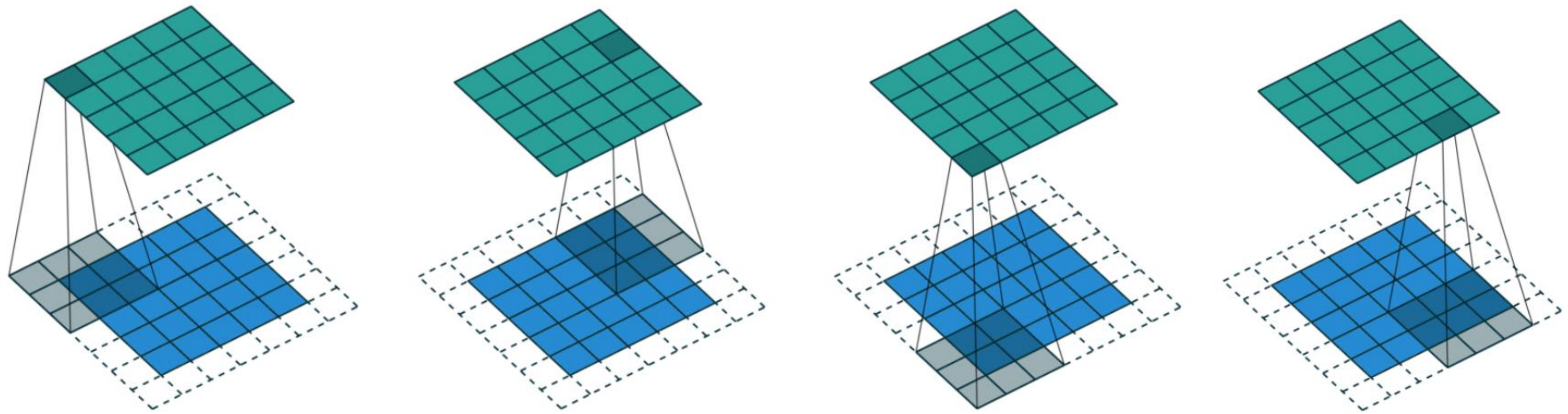
```
<script.py> output:

    10/10 [==============================] - 0s 295us/step
```

The first number in the output is the value of the cross-entropy loss, the second is the value of the accuracy. For this model, it's 100%!

Tweaking your convolutions



The blue input image is larger than the green output image. This is because the convolution kernel has the size of three-by-three pixels. In this case, it converts a three-by-three window into one pixel in the output image. One way to deal with this issue is to zero-pad the input image.



When the input image is **zero padded**, the output feature map has the same size as the input. This can be useful if you want to build a network that has many layers. Otherwise, you might lose a pixel off the edge of the image in each subsequent layer.

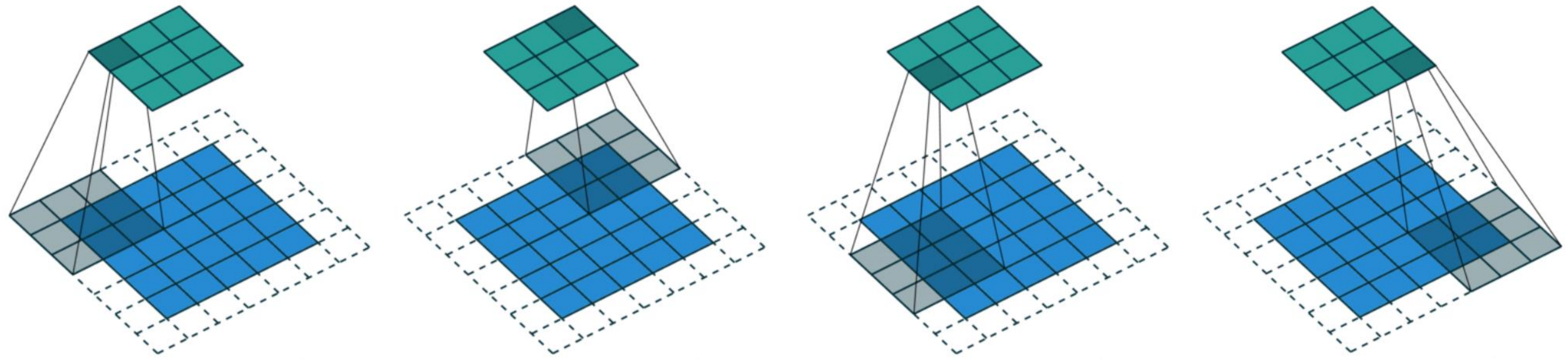
```
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)),
                 padding='valid')
```

If we provide the value "valid", no zero padding is added (default).

```
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)),
                 padding='same')
```

If we provide the value "same", zero padding will be applied to the input to this layer, so that the output of the convolution has the same size as the input into the convolution.

Another factor that affects the size of the output of a convolution is the size of the step that we take with the kernel between input pixels. This is called the **size of the stride**. For example, in this animation the kernel is strided by two pixels in each step. This means again that the output size is smaller than the input size.



```
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)),
          strides=1)
```

```
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)),
          strides=2)
```

Calculating the size of the output

$$O = ((I - K + 2P)/S) + 1$$

where

- I = size of the input
- K = size of the kernel
- P = size of the zero padding
- S = strides

For example, if the input image is five by five and there is both zero padding and strides set to 2, the output will have a size of three by three.

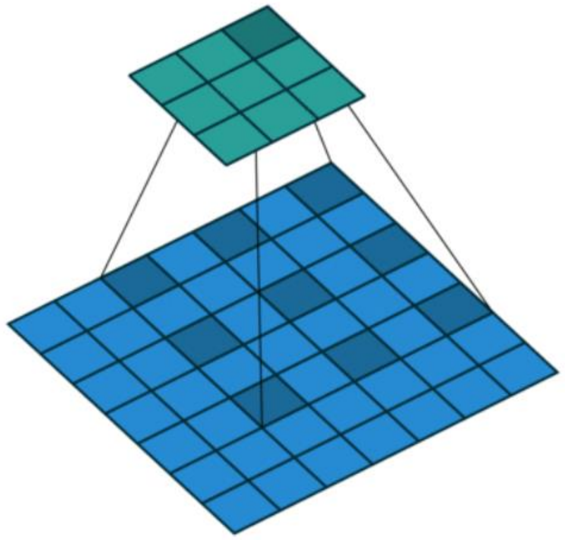
Generally, we can calculate the size of the output using a simple formula: (I - K + 2P) / (S + 1) Where I is the size of the input, K is the size of the kernel, P is the size of the zero padding, and S is the stride.

$$28 = ((28 - 3 + 2)/1) + 1$$

$$10 = ((28 - 3 + 2)/3) + 1$$

For example, if the input is 28 pixels, the kernel is 3 by 3, the padding is of 1 and the stride is 1, this number will be: (28 - 3 + 2) / 1 + 1 = 28. If instead the stride is 3 the output size would be 10 by 10.

You can also tweak the spacing between the pixels affected by the kernel. This is called a dilated convolution. In this case, the convolution kernel has only 9 parameters, but it has the same field of view as a kernel that would have the size 5 by 5. This is useful in cases where you need to aggregate information across multiple scales.



This too is controlled through a keyword argument, "dilation_rate", that sets the distance between subsequent pixels.

```
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)),
          dilation_rate=2)
```

Add padding to a CNN

Padding allows a convolutional layer to retain the resolution of the input into this layer. This is done by adding zeros around the edges of the input image, so that the convolution kernel can overlap with the pixels on the edge of the image.

```
# Initialize the model
model = Sequential()

# Add the convolutional layer
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1),
                 padding='same'))

# Feed into output layer
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

With padding set to 'same', the output layer will have the same size as the input layer!

Add strides to a convolutional network

The size of the strides of the convolution kernel determines whether the kernel will skip over some of the pixels as it slides along the image. This affects the size of the output because when strides are larger than one, the kernel will be centered on only some of the pixels.

```
# Initialize the model
model = Sequential()

# Add a convolutional layer
model.add(Conv2D(10, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1),
                 strides=2))

# Feed into output layer
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

With strides set to 2, the network skips every other pixel.

Calculate the size of convolutional layer output

Zero padding and strides affect the size of the output of a convolution.

What is the size of the output for an input of size 256 by 256, with a kernel of size 4 by 4, padding of 1 and strides of 2?

- 127
- 255
- [✓ 128]
- 256

Answer: 128

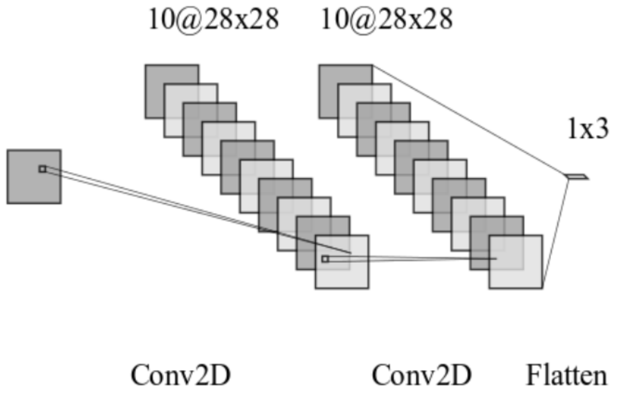
Chapter 3. Going Deeper

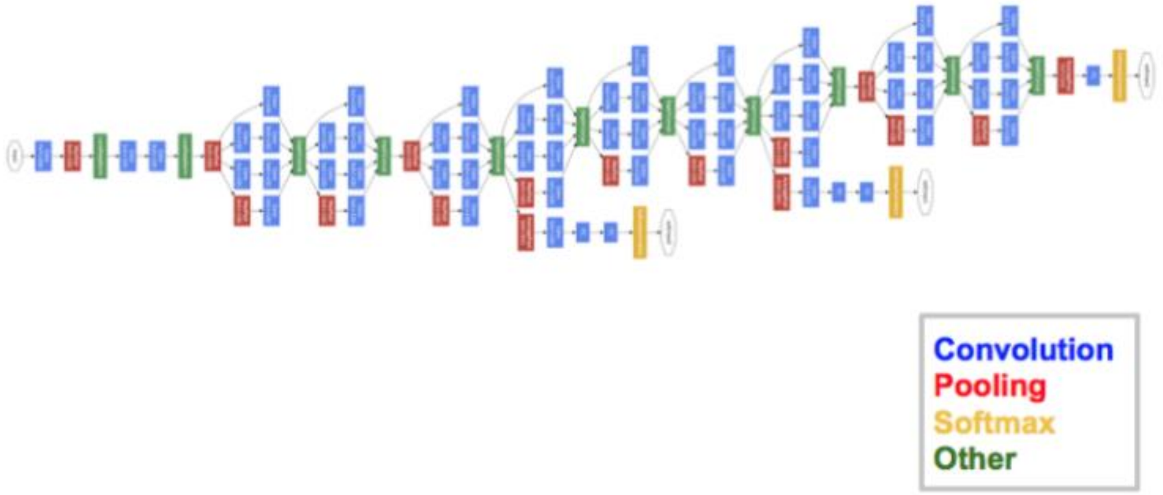
Convolutional neural networks gain a lot of power when they are constructed with multiple layers (deep networks). In this chapter, you will learn how to stack multiple convolutional layers into a deep network. You will also learn how to keep track of the number of parameters, as the network grows, and how to control this number.

Going deeper

One of the major strengths of convolutional neural networks comes from building networks with multiple layers of convolutional filters.

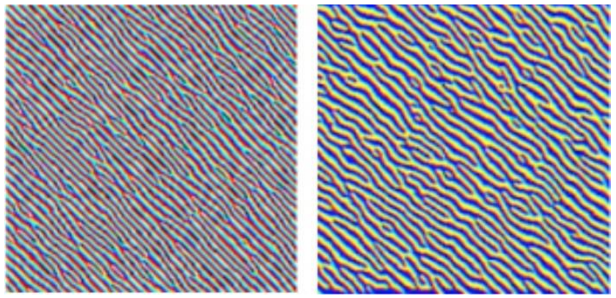
```
model = Sequential()
model.add(Conv2D(10, kernel_size=2, activation='relu',
                 input_shape=(img_rows, img_cols, 1),
                 padding='equal'))
# Second convolutional layer
model.add(Conv2D(10, kernel_size=2, activation='relu')
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```



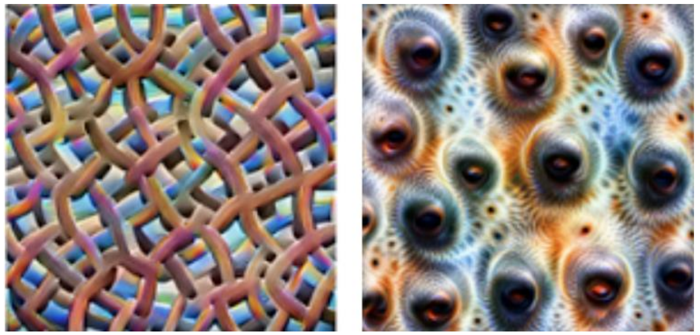


This is the architecture of a network developed by Google researchers in 2014. It has 22 layers of convolutions, and some other kinds of layers, like pooling layers. One way to understand why we would want a network this deep is by looking at the kinds of things that the kernels and feature maps in the different layers tend to respond to.

These are the kinds of things that layers in the early part of the network tend to respond to. Oriented lines, or simple textures.



Intermediate layers of the network tend to respond to more complex features, that include simple objects, such as eyes.



By the time the information travels up to higher layers of the network, the feature maps tend to extract specific types of objects. This allows the fully connected layers at the top of the network to extract useful information for object classification based on the responses of these layers.

In other words, having multiple layers of convolutions in the network allows the network to gradually build up representations of objects in the images from simple features to more complex features and up to sensitivity to distinct categories of objects.

How deep should your network be? Consider the following: despite the advantages mentioned above, depth does come at a computational cost. In addition, to train a very deep network you might need a larger amount of training data.

Creating a deep learning network

A deep convolutional neural network is a network that has more than one layer. Each layer in a deep network receives its input from the preceding layer, with the very first layer receiving its input from the images used as training or test data.

Here, you will create a network that has two convolutional layers.

```
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten

model = Sequential()

# Add a convolutional layer (15 units)
model.add(Conv2D(15, kernel_size=2, activation='relu',
                 input_shape=(img_rows, img_cols, 1)))

# Add another convolutional layer (5 units)
model.add(Conv2D(5, kernel_size=2, activation='relu'))

# Flatten and feed to output layer
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

You built a network with multiple convolution layers.

Train a deep CNN to classify clothing images

Training a deep learning model is very similar to training a single layer network. Once the model is constructed (as you have done in the previous exercise), the model needs to be compiled with the right set of parameters. Then, the model is fit by providing it with training data, as well as training labels. After training is done, the model can be evaluated on test data.

The `model` you built in the previous exercise is available in your workspace.

```
# Compile model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Fit the model to training data
model.fit(train_data, train_labels,
          validation_split=0.2,
          epochs=3, batch_size=10)

# Evaluate the model on test data
model.evaluate(test_data, test_labels, batch_size=10)
```

```
<script.py> output:
    Train on 40 samples, validate on 10 samples
    Epoch 1/3

    10/40 [======>.......................] - ETA: 2s - loss: 1.0957 - acc: 0.4000
    40/40 [==============================] - 1s 22ms/step - loss: 1.0861 - acc: 0.5750 - val_loss: 1.0630 - val_acc: 0.7000
    Epoch 2/3

    10/40 [======>.......................] - ETA: 0s - loss: 1.0665 - acc: 0.7000
    40/40 [==============================] - 0s 913us/step - loss: 1.0379 - acc: 0.8750 - val_loss: 0.9906 - val_acc: 1.0000
    Epoch 3/3

    10/40 [======>.......................] - ETA: 0s - loss: 1.0027 - acc: 1.0000
    40/40 [==============================] - 0s 955us/step - loss: 0.9559 - acc: 0.9750 - val_loss: 0.8835 - val_acc: 1.0000

    10/10 [==============================] - 0s 467us/step
```

Accuracy calculated on the test data is not subject to overfitting.

What is special about a deep network?

Networks with more convolution layers are called "deep" networks, and they may have more power to fit complex data, because of their ability to create hierarchical representations of the data that they fit.

What is a major difference between a deep CNN and a CNN with only one convolutional layer?

- ○ A deep network is inspired by the human visual system.
- [✓ A deep network requires more data and more computation to fit.]
- ○ A deep network has more dense layers.
- ○ A deep network has larger convolutions.

That's right!

How many parameters?

```
model = Sequential()
```

```
model.add(Dense(
        10, activation='relu',
        input_shape=(784,)))
```

$$parameters = 784 * 10 + 10$$

$$= 7850$$

```
model.add(Dense(
        10, activation='relu'))
```

$$parameters = 10 * 10 + 10$$

$$= 110$$

```
model.add(Dense(
        3, activation='softmax'))
```

$$parameters = 10 * 3 + 3$$

$$= 33$$

$$7850 + 110 + 33 = 7993$$

```
# Call the summary method
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 10)                7850
_________________________________________________________________
dense_2 (Dense)              (None, 10)                110
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 33
=================================================================
Total params: 7,993
Trainable params: 7,993
Non-trainable params: 0
_________________________________________________________________
```

```
model = Sequential()
```

```
model.add(
 Conv2D(10, kernel_size=3,
        activation='relu',
        input_shape=(28, 28, 1),
        padding='same'))
model.add(
 Conv2D(10, kernel_size=3,
        activation='relu',
        padding='same'))


model.add(Flatten())
```

```
model.add(Dense(
       3, activation='softmax'))
```

$$parameters = 9 * 10 + 10$$

$$= 100$$

$$parameters = 10 * 9 * 10 + 10$$

$$= 910$$

$$parameters = 0$$

$$parameters = 7840 * 3 + 3$$

$$= 23523$$

$$100 + 910 + 0 + 23523 = 24533$$

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 28, 28, 10)        100
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 28, 28, 10)        910
_________________________________________________________________
flatten_3 (Flatten)          (None, 7840)              0
_________________________________________________________________
dense_4 (Dense)              (None, 3)                 23523
=================================================================
Total params: 24,533
Trainable params: 24,533
Non-trainable params: 0
```

```
model = Sequential()

model.add(Dense(5, activation='relu',
                input_shape=(784,), padding='same'))

model.add(Dense(15, activation='relu', padding='same'))

model.add(Dense(3, activation='softmax'))
```

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 5)                 3925
_________________________________________________________________
dense_2 (Dense)              (None, 15)                90
_________________________________________________________________
dense_3 (Dense)              (None, 3)                 48
=================================================================
Total params: 4,063
Trainable params: 4,063
Non-trainable params: 0
_________________________________________________________________
```

```
model = Sequential()

model.add(Conv2D(5, kernel_size=3, activation='relu',
                 input_shape=(28, 28, 1),
                 padding="same"))

model.add(Conv2D(15, kernel_size=3, activation='relu',
                 padding="same"))

model.add(Flatten())

model.add(Dense(3, activation='softmax'))
```

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_12 (Conv2D)           (None, 28, 28, 5)         50
_________________________________________________________________
conv2d_13 (Conv2D)           (None, 28, 28, 15)        690
_________________________________________________________________
flatten_6 (Flatten)          (None, 11760)             0
_________________________________________________________________
dense_9 (Dense)              (None, 3)                 35283
=================================================================
Total params: 36,023
Trainable params: 36,023
Non-trainable params: 0
_________________________________________________________________
```

This is the convolutional network with the equivalent number of units in each layer. In contrast to the densely connected neural network, when we run the summary method on this network, we see that the first few layers use very few parameters, while the last layer uses a lot of parameters. One way to think about this is that the convolutions have more expressive power, so they require less parameters, but reading out these more expressive representations then requires many more parameters on the output side.

How many parameters in a CNN?

We need to know how many parameters a CNN has, so we can adjust the model architecture, to reduce this number or shift parameters from one part of the network to another. How many parameters would a network have if its inputs are images with 28-by-28 pixels, there is one convolutional layer with 10 units kernels of 3-by-3 pixels, using zero padding (input has the same size as the output), and one densely connected layer with 2 units?

Possible Answers

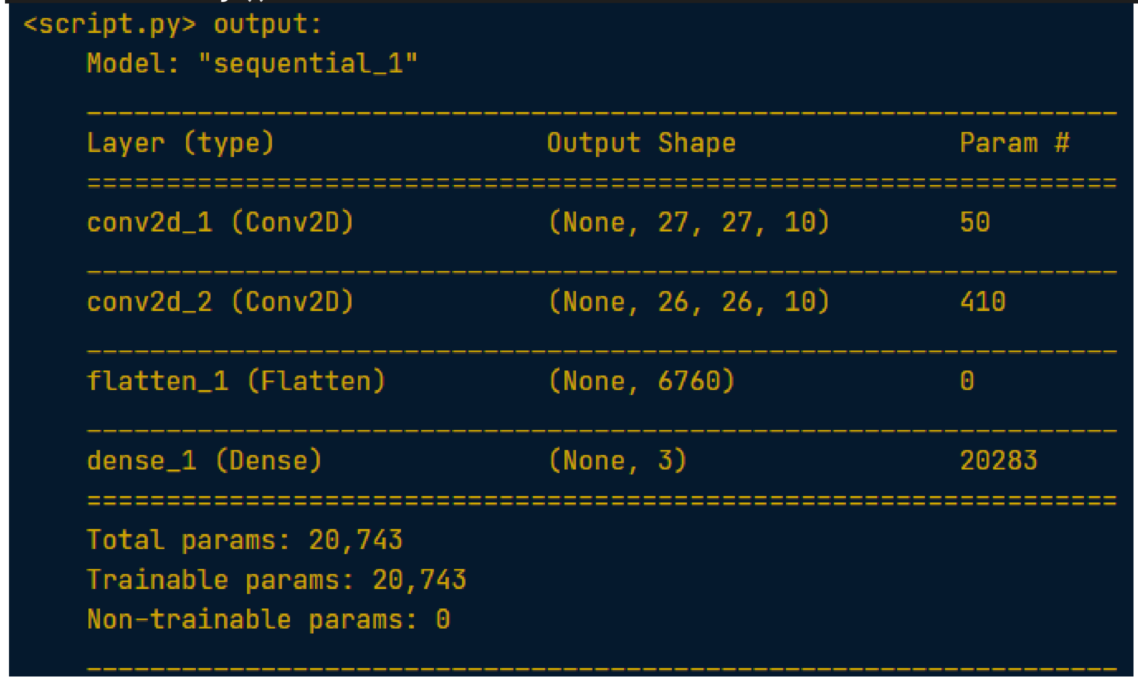
- 100
- 1668
- [✓ 15,782]
- 15,682

How many parameters in a deep CNN?

In this exercise, you will use Keras to calculate the total number of parameters along with the number of parameters in each layer of the network.

We have already provided code that builds a deep CNN for you.

```python
# CNN model
model = Sequential()
model.add(Conv2D(10, kernel_size=2, activation='relu',
                 input_shape=(28, 28, 1)))
model.add(Conv2D(10, kernel_size=2, activation='relu'))
model.add(Flatten())
model.add(Dense(3, activation='softmax'))

# Summarize the model
model.summary()
```

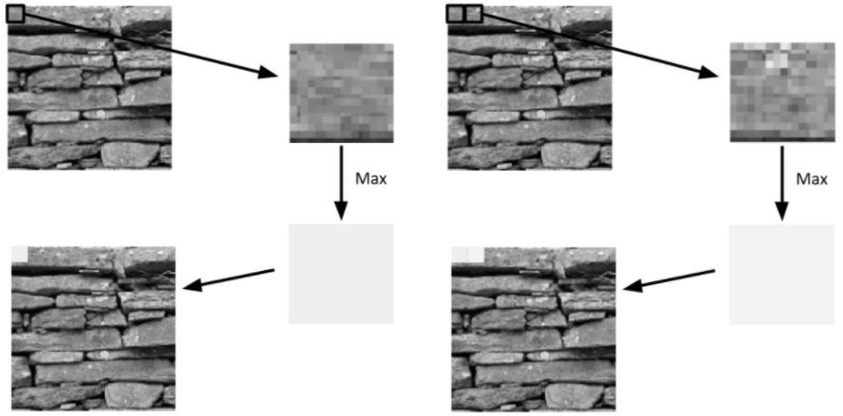


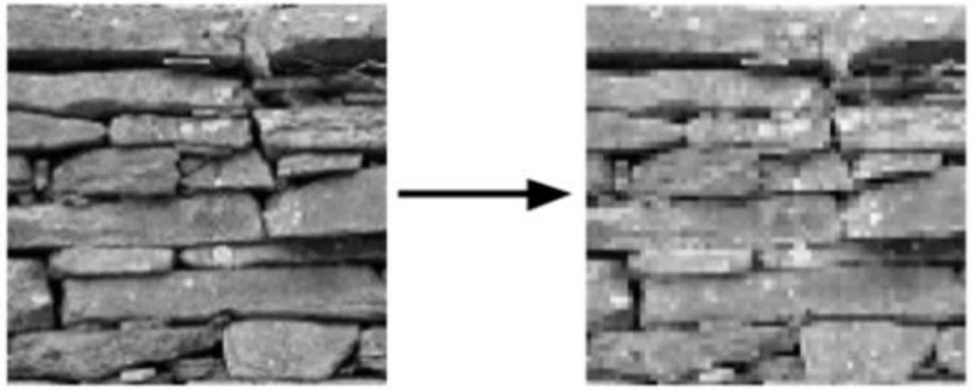
```
<script.py> output:
    Model: "sequential_1"
    _________________________________________________________________
    Layer (type)                 Output Shape              Param #
    =================================================================
    conv2d_1 (Conv2D)            (None, 27, 27, 10)        50
    _________________________________________________________________
    conv2d_2 (Conv2D)            (None, 26, 26, 10)        410
    _________________________________________________________________
    flatten_1 (Flatten)          (None, 6760)              0
    _________________________________________________________________
    dense_1 (Dense)              (None, 3)                 20283
    =================================================================
    Total params: 20,743
    Trainable params: 20,743
    Non-trainable params: 0
    _________________________________________________________________
```

This model has 20,743 parameters!

Pooling operations

One of the challenges in fitting neural networks is the large number of parameters. One way to mitigate this is to summarize the output of convolutional layers in concise manner. To do this, we can use pooling operations.





We might summarize a group of pixels based on its maximal value. This is called "max pooling". We might start with the top left corner, extracting the pixels in this part of the image and, calculating the maximal value of the pixels there. In the output, we replace these pixels with one large pixel that stores this maximal value. If we repeat this operation in multiple windows of size 2 by 2, we end up with an image that has a quarter of the number of the original pixels, and retains only the brightest feature in each part of the image.
We can integrate max pooling operations into a Keras convolutional neural network, using the MaxPool2D object.

```python
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten, MaxPool2D
model = Sequential()
model.add(Conv2D(5, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)))
model.add(MaxPool2D(2))
model.add(Conv2D(15, kernel_size=3, activation='relu',
                 input_shape=(img_rows, img_cols, 1)))
model.add(MaxPool2D(2))
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 5)         50
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 5)         0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 11, 11, 15)        690
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 5, 5, 15)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 375)               0
_________________________________________________________________
dense_1 (Dense)              (None, 3)                 1128
=================================================================
```

Running the summary method for this model, we can see that using the pooling operation dramatically reduces the number of parameters in the model. Instead of more than 30,000 parameters that this model had with no pooling operations, we now have less than 2,000 parameters.
There are of course trade-offs to reducing the number of parameters. Let's see how this plays out with some examples.

Write your own pooling operation

As we have seen before, CNNs can have a lot of parameters. Pooling layers are often added between the convolutional layers of a neural network to summarize their outputs in a condensed manner, and reduce the number of parameters in the next layer in the network. This can help us if we want to train the network more rapidly, or if we don't have enough data to learn a very large number of parameters.

A pooling layer can be described as a particular kind of convolution. For every window in the input it finds the maximal pixel value and passes only this pixel through. In this exercise, you will write your own max pooling operation, based on the code that you previously used to write a two-dimensional convolution operation.

```
# Result placeholder
result = np.zeros((im.shape[0]//2, im.shape[1]//2))

# Pooling operation
for ii in range(result.shape[0]):
    for jj in range(result.shape[1]):
        result[ii, jj] = np.max(im[ii*2:ii*2+2, jj*2:jj*2+2])
```

The resulting image is smaller, but retains the salient features in every location

Keras pooling layers

Keras implements a pooling operation as a layer that can be added to CNNs between other layers. In this exercise, you will construct a convolutional neural network similar to the one you have constructed before:

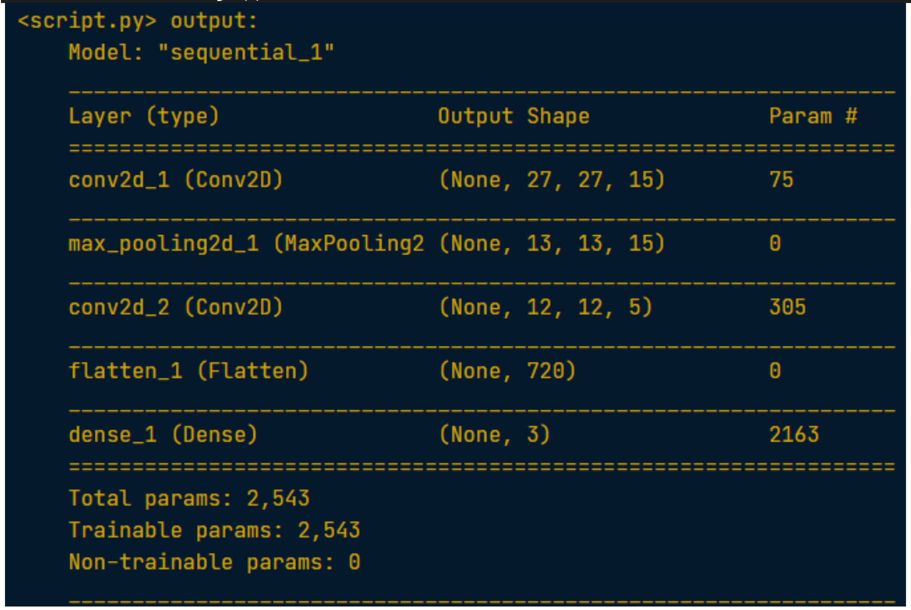
Convolution => Convolution => Flatten => Dense

However, you will also add a pooling layer. The architecture will add a single max-pooling layer between the convolutional layer and the dense layer with a pooling of 2x2:

Convolution => Max pooling => Convolution => Flatten => Dense

A Sequential `model` along with `Dense`, `Conv2D`, `Flatten`, and `MaxPool2D` objects are available in your workspace.

```
# Add a convolutional layer
model.add(Conv2D(15, kernel_size=2, activation='relu',
                 input_shape=(img_rows, img_cols, 1)))

# Add a pooling operation
model.add(MaxPool2D(2))

# Add another convolutional layer
model.add(Conv2D(5, kernel_size=2, activation='relu'))

# Flatten and feed to output layer
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
model.summary()
```



```
<script.py> output:
    Model: "sequential_1"
    _________________________________________________________________
    Layer (type)                 Output Shape              Param #
    =================================================================
    conv2d_1 (Conv2D)            (None, 27, 27, 15)        75
    _________________________________________________________________
    max_pooling2d_1 (MaxPooling2 (None, 13, 13, 15)        0
    _________________________________________________________________
    conv2d_2 (Conv2D)            (None, 12, 12, 5)         305
    _________________________________________________________________
    flatten_1 (Flatten)          (None, 720)               0
    _________________________________________________________________
    dense_1 (Dense)              (None, 3)                 2163
    =================================================================
    Total params: 2,543
    Trainable params: 2,543
    Non-trainable params: 0
    _________________________________________________________________
```

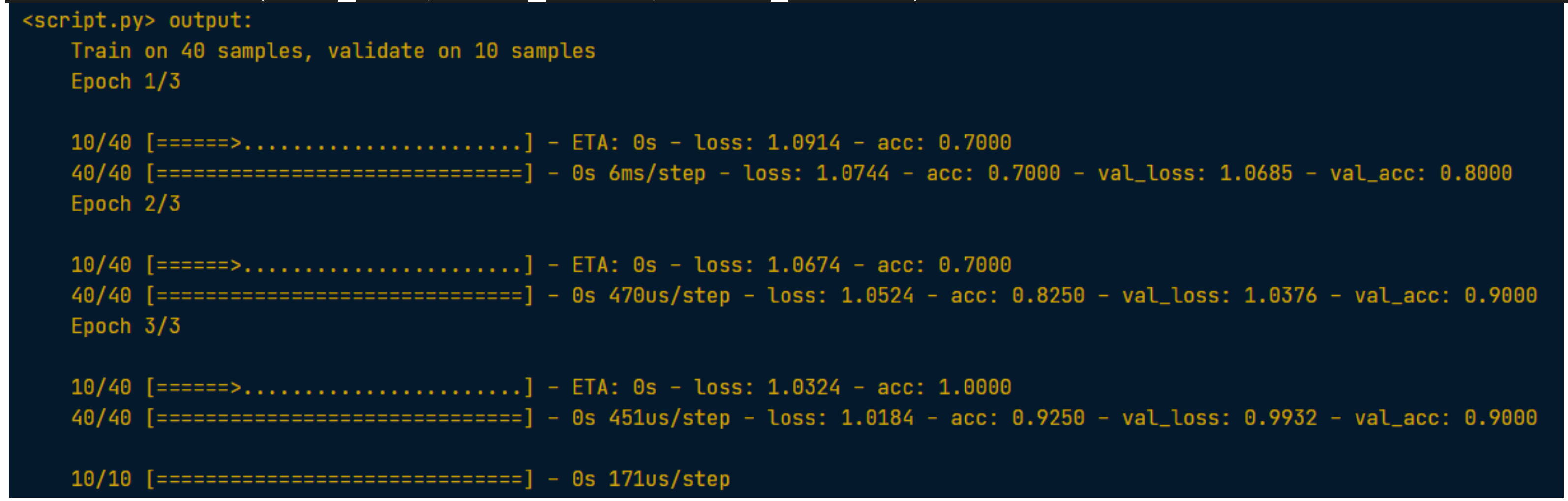
This model is even deeper, but has fewer parameters.

Train a deep CNN with pooling to classify images

Training a CNN with pooling layers is very similar to training of the deep networks that y have seen before. Once the network is constructed (as you did in the previous exercise), the model needs to be appropriately compiled, and then training data needs to be provided, together with the other arguments that control the fitting procedure. The following `model` from the previous exercise is available in your workspace:

Convolution => Max pooling => Convolution => Flatten => Dense

```
# Compile model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])

# Fit the model to training data
model.fit(train_data, train_labels,
          validation_split=0.2,
          epochs=3, batch_size=10)

# Evaluate the model on test data
model.evaluate(test_data, test_labels, batch_size=10)
```



```
<script.py> output:
    Train on 40 samples, validate on 10 samples
    Epoch 1/3

    10/40 [======>.......................] - ETA: 0s - loss: 1.0914 - acc: 0.7000
    40/40 [==============================] - 0s 6ms/step - loss: 1.0744 - acc: 0.7000 - val_loss: 1.0685 - val_acc: 0.8000
    Epoch 2/3

    10/40 [======>.......................] - ETA: 0s - loss: 1.0674 - acc: 0.7000
    40/40 [==============================] - 0s 470us/step - loss: 1.0524 - acc: 0.8250 - val_loss: 1.0376 - val_acc: 0.9000
    Epoch 3/3

    10/40 [======>.......................] - ETA: 0s - loss: 1.0324 - acc: 1.0000
    40/40 [==============================] - 0s 451us/step - loss: 1.0184 - acc: 0.9250 - val_loss: 0.9932 - val_acc: 0.9000

    10/10 [==============================] - 0s 171us/step
```

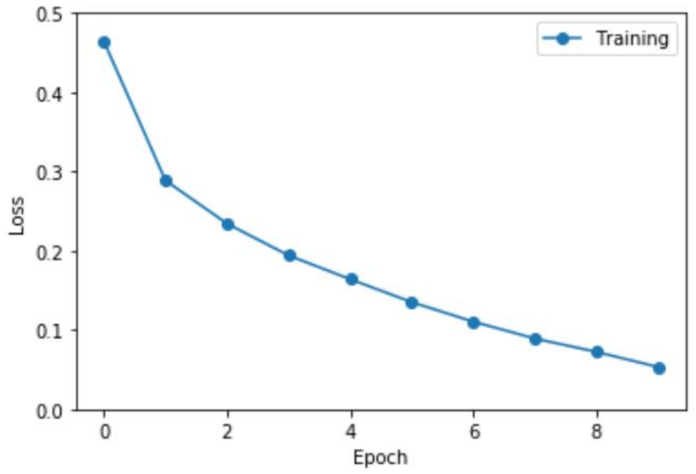
This model is also very accurate!

Chapter 4. Understanding and Improving Deep Convolutional Networks

There are many ways to improve training by neural networks. In this chapter, we will focus on our ability to track how well a network is doing, and explore approaches towards improving convolutional neural networks.

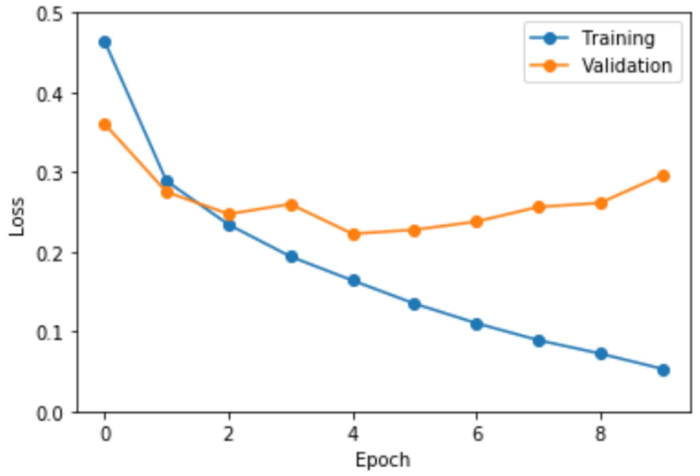
Tracking learning

During learning, the weights used by the network change, and as they change, the network becomes more attuned to the features of the images that discriminate between classes. This means that the loss function we use for training becomes smaller and smaller.
As long as learning is progressing well, we might expect the loss function to keep going down.

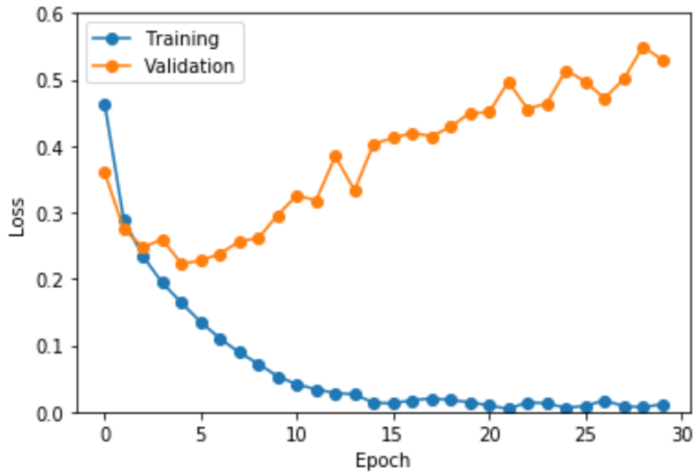


For example, here is a curve showing the categorical cross-entropy loss in a network that is learning to classify different types of clothing, measured on the training set. You can see that loss rapidly decreases in the first few epochs of training, after which learning slows down. This is a sign that learning is going rather well.

On the other hand, if we add the validation loss to this plot, we can see that learning is progressing to some level of loss and then flattens out. What is going on?



This is a form of overfitting. Because neural networks have so many parameters that can be adjusted, the weights can be adjusted to accurately classify, but this performance does not generalize well outside of the training set. When validated against a separate set of data, loss cannot become better.



In fact, if we keep training for many epochs, the validation accuracy can start increasing back up again. This is a sign that we have passed the point at which the model weights are being adjusted in a useful way, and we are starting to over-fit to the specifics of the training data.

```
training = model.fit(train_data, train_labels,
                     epochs=3, validation_split=0.2)
import matplotlib.pyplot as plt
plt.plot(training.history['loss'])
plt.plot(training.history['val_loss'])
plt.show()
```

How do we use the best parameters before the network starts over-fitting? By using the callbacks module from Keras which contains functions that can be executed at the end of each training epoch. One of these callbacks is a ModelCheckpoint object that can be used to store the weights of a network at the end of each epoch of learning. When it is initialized, an hdf5 file is created. Here we call it weights dot hdf5.

```
from keras.callbacks import ModelCheckpoint

# This checkpoint object will store the model parameters
# in the file "weights.hdf5"
checkpoint = ModelCheckpoint('weights.hdf5', monitor='val_loss',
                             save_best_only=True)
```

The callback monitors the validation loss, and will only overwrite the weights whenever the validation loss shows improvement. That is, the validation loss decreases. This means that if the network overfits, the weights will be stored for the epoch at which the validation loss was the smallest, before it started rising back up. The checkpoint object is stored in a list and passed as input to the model fitting procedure. After all epochs of fitting are done, this file contains the best weights.

```
# Store in a list to be used during training
callbacks_list = [checkpoint]
# Fit the model on a training set, using the checkpoint as a
#callback
model.fit(train_data, train_labels, validation_split=0.2,
          epochs=3, callbacks=callbacks_list)
```

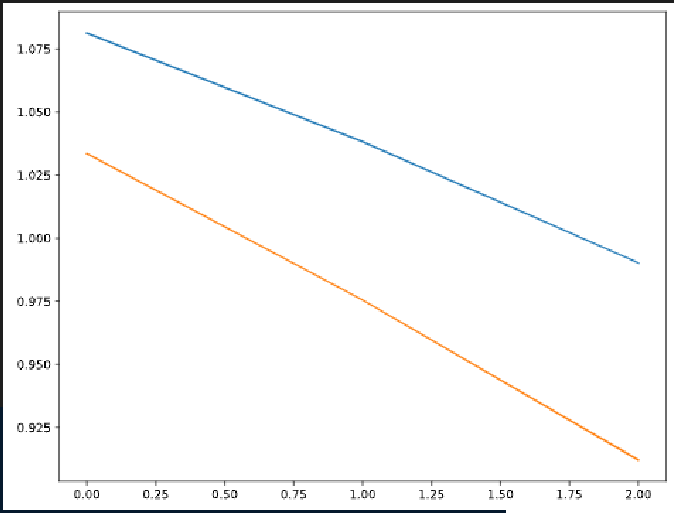
To use these weights, we'll need to initialize the model again with the same architecture, the same layers, with the same number of units in each. We can then use the model's load_weights() method to bring the model weights back to their value when the model was at its best during training. We can then use the weights in all kinds of ways. For example, we can use the model weights to predict the classes of a separate test image data set, using the predict_classes() method. Each entry in the result is the column corresponding to the clothing article in the one-hot encoded array.

```
model.load_weights('weights.hdf5')
model.predict_classes(test_data)
array([2, 2, 1, 2, 0, 1, 0, 1, 2, 0])
```

Plot the learning curves

During learning, the model will store the loss function evaluated in each epoch. Looking at the learning curves can tell us quite a bit about the learning process. In this exercise, you will plot the learning and validation loss curves for a model that you will train.

```python
import matplotlib.pyplot as plt

# Train the model and store the training object
training = model.fit(train_data, train_labels, validation_split=0.2, epochs=3, batch_size=10)

# Extract the history from the training object
history = training.history

# Plot the training loss
plt.plot(history['loss'])
# Plot the validation loss
plt.plot(history['val_loss'])

# Show the figure
plt.show()
```



```
 <script.py> output:
     Train on 40 samples, validate on 10 samples
     Epoch 1/3

     10/40 [======>.......................] - ETA: 0s - loss: 1.0841 - acc: 0.2000
     40/40 [==============================] - 0s 8ms/step - loss: 1.0812 - acc: 0.2750 - val_loss: 1.0335 - val_acc: 0.6000
     Epoch 2/3

     10/40 [======>.......................] - ETA: 0s - loss: 1.0681 - acc: 0.6000
     40/40 [==============================] - 0s 458us/step - loss: 1.0382 - acc: 0.5000 - val_loss: 0.9755 - val_acc: 0.8000
     Epoch 3/3

     10/40 [======>.......................] - ETA: 0s - loss: 1.0370 - acc: 0.3000
     40/40 [==============================] - 0s 501us/step - loss: 0.9902 - acc: 0.5750 - val_loss: 0.9121 - val_acc: 0.8000
```

If you continue for many epochs, the validation loss will start going back up.

Using stored weights to predict in a test set

Model weights stored in an `hdf5` file can be reused to populate an untrained model. Once the weights are loaded into this model, it behaves just like a model that has been trained to reach these weights. For example, you can use this model to make predictions from an unseen data set (e.g. `test_data`).

```
# Load the weights from file
model.load_weights('weights.hdf5')

# Predict from the first three images in the test data
model.predict(test_data[:3])
```

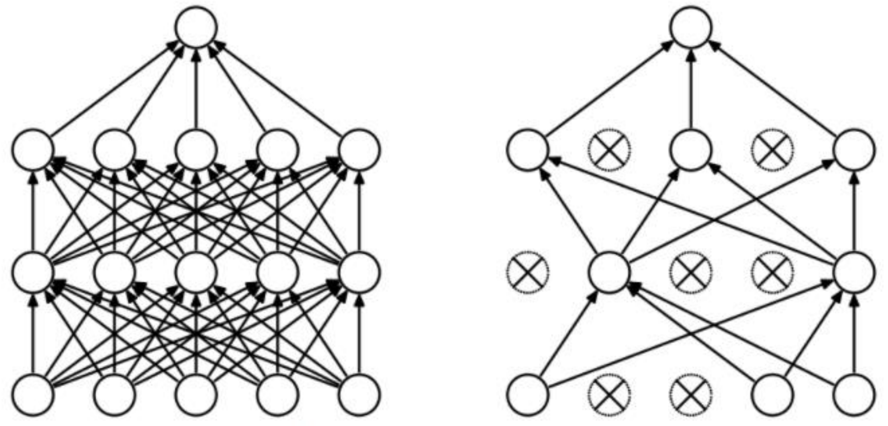
How would you use these weights to evaluate the model instead?

Regularization

To prevent overfitting

Dropout

In each step of learning, we choose a random subset of the units in a layer and we ignore it. This group of units would be ignored both on the forward pass through the network, as well as in the back-propagation stage.



(a) Standard Neural Net (b) After applying dropout.

On the left is a fully connected network, and on the right is this network with dropout applied to it during one step of training. This might sound strange, but this regularization strategy can work really well. This is because it allows us to train many different networks on different parts of the data. Each time, the network that is trained is randomly chosen from the full network.

This way, if part of the network becomes too sensitive to some noise in the data, other parts will compensate for this, because they haven't seen the samples with this noise. It also helps prevent different units in the network from becoming overly correlated in their activity. One way to think about this is that if one unit learns to prefer horizontal orientations, another unit would be trained to prefer vertical ones.

```python
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten, Dropout
model = Sequential()
model.add(Conv2D(5, kernel_size=3, activation='relu',
              input_shape=(img_rows, img_cols, 1)))
model.add(Dropout(0.25))
model.add(Conv2D(15, kernel_size=3, activation='relu'))
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

When using dropout we'll need to choose what proportion of the units in the layer to ignore in each learning step. For example, here I have chosen to drop 25% of the units in the first layer. The rest of the model that follows is unchanged. Compiling and training the model is also unchanged.

Batch normalization

This operation takes the output of a particular layer, and rescales it so that it always has 0 mean and standard deviation of 1 in every batch of training. The algorithm solves the problem where different batches of input might produce wildly different distributions of outputs in any given layer in the network. Because the adjustments to the weights through back-propagation depends on the activation of the units in every step of learning, this means that the network may progress very slowly through training.

```python
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten, BatchNormalization

model = Sequential()
model.add(Conv2D(5, kernel_size=3, activation='relu',
              input_shape=(img_rows, img_cols, 1)))
model.add(BatchNormalization())
```

To add a single batch normalization operation after the first layer. The rest of the network is unchanged.

```
model.add(Conv2D(15, kernel_size=3, activation='relu'))
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

Sometimes dropout and batch normalization do not work well together. This is because while dropout slows down learning, making it more incremental and careful, batch normalization tends to make learning go faster. Their effects together may in fact counter each other, and networks sometimes perform worse when both of these methods are used together than they would if neither were used. This has been called "**the disharmony of batch normalization and dropout**".

Adding dropout to your network

Dropout is a form of regularization that removes a different random subset of the units in a layer in each round of training. In this exercise, we will add dropout to the convolutional neural network that we have used in previous exercises:

1. Convolution (15 units, kernel size 2, 'relu' activation)
2. Dropout (20%)
3. Convolution (5 units, kernel size 2, 'relu' activation)
4. Flatten
5. Dense (3 units, 'softmax' activation)

A Sequential `model` along with `Dense`, `Conv2D`, `Flatten`, and `Dropout` objects are available in your workspace.

```
# Add a convolutional layer
model.add(Conv2D(15, kernel_size=2, activation='relu',
                 input_shape=(img_rows, img_cols, 1)))

# Add a dropout layer
model.add(Dropout(0.2))

# Add another convolutional layer
model.add(Conv2D(5, kernel_size=2, activation='relu'))
```

```
# Flatten and feed to output layer
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

Now the kernels will be more different from each other.

Add batch normalization to your network

Batch normalization is another form of regularization that rescales the outputs of a layer to make sure that they have mean 0 and standard deviation 1. In this exercise, we will add batch normalization to the convolutional neural network that we have used in previous exercises:

1. Convolution (15 units, kernel size 2, 'relu' activation)
2. Batch normalization
3. Convolution (5 unites, kernel size 2, 'relu' activation)
4. Flatten
5. Dense (3 units, 'softmax' activation)

A Sequential `model` along with `Dense`, `Conv2D`, `Flatten`, and `Dropout` objects are available in your workspace.

```
# Add a convolutional layer
model.add(Conv2D(15, kernel_size=2, activation='relu',
                 input_shape=(img_rows, img_cols, 1)))

# Add batch normalization layer
model.add(BatchNormalization())

# Add another convolutional layer
model.add(Conv2D(5, kernel_size=2, activation='relu'))

# Flatten and feed to output layer
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

That should improve training.

Interpreting the model

Convolutional neural networks are "black boxes" and that even when they work very well, it is hard to understand why they work so well. Here, I will show you how to take apart a trained convolutional network, select particular parts of the network and analyze their behavior. For example, here is a network with 2 convolutional layers, followed by a flattening operation and readout with a dense layer.

```
model.layers
```

```
[<keras.layers.convolutional.Conv2D at 0x109f10c18>,
 <keras.layers.convolutional.Conv2D at 0x109ec5ba8>,
 <keras.layers.core.Flatten at 0x1221ffcc0>,
 <keras.layers.core.Dense at 0x1221ffef0>]
```

```
conv1 = model.layers[0]
weights1 = conv1.get_weights()
len(weights1)
```

```
2
```

If we want to look at the first convolutional layer, we can pull it out by indexing the first item in this list. The weights for this layer are accessible through the get_weights() method.
This method returns a list with two items. The first item in this list is an array that holds the values of the weights for the convolutional kernels for this layer. The kernels array has the shape 3 by 3 by 1 by 5. The first 2 dimensions denote the kernel size. This network was initialized with kernel size of 3. The third dimension denotes the number of channels in the kernels. This is one, because the network was looking at black and white data. The last dimension denotes the number of kernels in this layer: 5. To pull out the first kernel in this layer, we would use the index 0 into the last dimension. Because there is only one channel, we can also index on the channel dimension, to collapse that dimension. This would return the 3 by 3 array containing this convolutional kernel.

```
kernels1 = weights1[0]
kernels1.shape
```

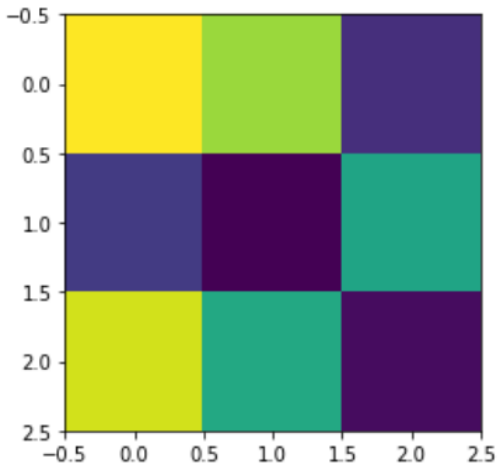
```
(3, 3, 1, 5)
```

```
kernel1_1 = kernels1[:, :,
                     0, 0]
kernel1_1.shape
```

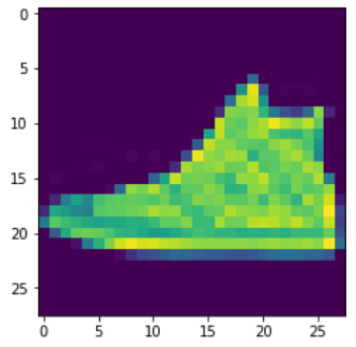
```
(3, 3)
```

Visualizing the kernel
We can then visualize this kernel directly, but understanding what kinds of features this kernel is responding to may be hard just from direct observation. To understand what this kernel does, it might sometimes be even more useful to convolve one of the images from our test set with this kernel and see what aspects of the image are emphasized by this kernel. Here, we pick the fourth image from the test_set, an image of a shoe.

```
plt.imshow(kernel1_1)
```

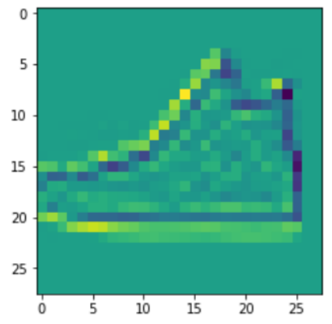


```
test_image = test_data[3, :, :, 0]
plt.imshow(test_image)
```



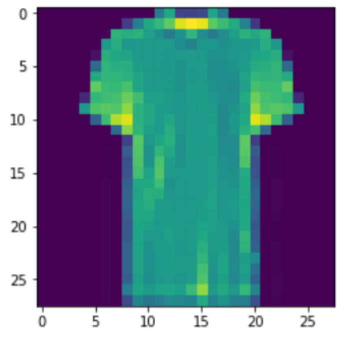
We convolve it with the kernel using the function that we created previously, and create a filtered image that is the result of this convolution. This filter seems to like the external edges of this image:

```
filtered_image = convolution(test_image, kernel1_1)
plt.imshow(filtered_image)
```



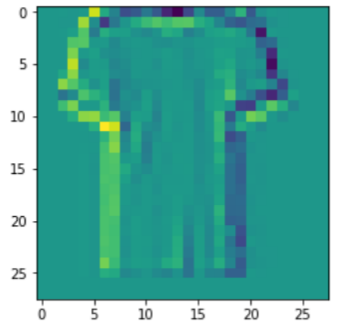
We can confirm this by running the convolution over another image. Here, we've picked the fifth image from the set, an image of a t-shirt.

```
test_image = test_data[4, :, :, 1]
plt.imshow(test_image)
```



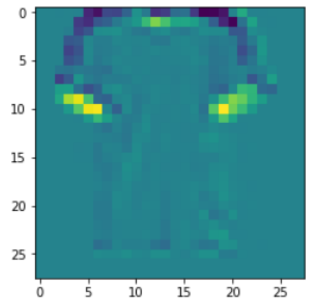
We see that here as well, vertical edges on the left side of the object are emphasized and on the right side are de-emphasized.

```
filtered_image = convolution(test_image, kernel1_1)
plt.imshow(filtered_img)
```



We can do the same thing with another one of our kernels. Here, we select the second kernel, and convolve the t-shirt image with this kernel. This kernel seems to have learned to detect horizontal edges, particularly on the bottom of the object.

```
kernel1_2 = kernels[:, :, 0, 1]
filtered_image = convolution(test_image, kernel1_2)
plt.imshow(filtered_img)
```



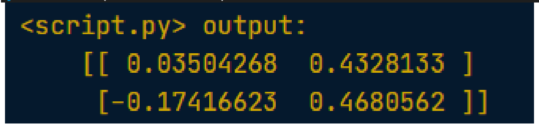
Taken together, this gives as an intuition for the kinds of things that the first layer of the network has learned, and can help interpreting the results you see from using this network for a particular task.

Extracting a kernel from a trained network

One way to interpret models is to examine the properties of the kernels in the convolutional layers. In this exercise, you will extract one of the kernels from a convolutional neural network with weights that you saved in a `hdf5` file.

```
# Load the weights into the model
```

```python
model.load_weights('weights.hdf5')

# Get the first convolutional layer from the model
c1 = model.layers[0]

# Get the weights of the first convolutional layer
weights1 = c1.get_weights()

# Pull out the first channel of the first kernel in the first layer
kernel = weights1[0][...,0, 0]
print(kernel)
```

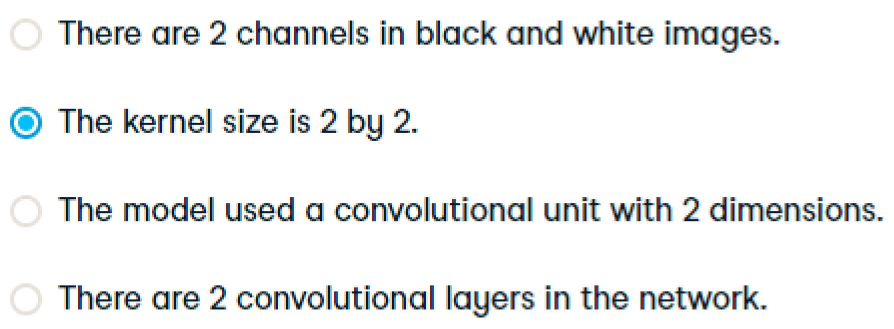


```
<script.py> output:
    [[ 0.03504268  0.4328133 ]
     [-0.17416623  0.4680562 ]]
```

You can extract the weights from other layers too.

Shape of the weights

A `Keras` neural network stores its layers in a list called `model.layers`. For the convolutional layers, you can get the weights using the `.get_weights()` method. This returns a list, and the first item in this list is an array representing the weights of the convolutional kernels. If the shape of this array is `(2, 2, 1, 5)`, what does the first number (`2`) represent?



- There are 2 channels in black and white images.
- [✓ The kernel size is 2 by 2.]
- The model used a convolutional unit with 2 dimensions.
- There are 2 convolutional layers in the network.

Each of the 2s in this shape is one of the dimensions of the kernel.

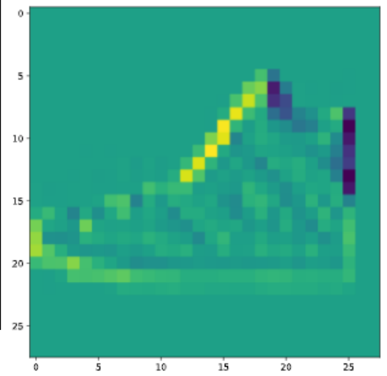
Visualizing kernel responses

One of the ways to interpret the weights of a neural network is to see how the kernels stored in these weights "see" the world. That is, what properties of an image are emphasized by this kernel. In this exercise, we will do that by convolving an image with the kernel and visualizing the result. Given images in the `test_data` variable, a function called `extract_kernel()` that extracts a kernel from the provided network, and the function called `convolution()` that we defined in the first chapter, extract the kernel, load the data from a file and visualize it with `matplotlib`.

A deep CNN `model`, a function `convolution()`, along with the `kernel` you extracted in an earlier exercise is available in your workspace.

Ready to take your deep learning to the next level? Check out **Advanced Deep Learning with Keras in Python** to see how the Keras functional API lets you build domain knowledge to solve new types of problems.

```python
import matplotlib.pyplot as plt

# Convolve with the fourth image in test_data
out = convolution(test_data[3, :, :, 0], kernel)

# Visualize the result
plt.imshow(out)
plt.show()
```



You can keep going and visualize the kernel responses for all the kernels in this layer!

Course completed!

Recap topics covered:

- image classification - a particularly useful task and one that convolutional neural networks excel at

- how to set up a training set, a validation set and a test set and how to use them in training a model for classification and how to evaluate it.

- the fundamental operations of these networks: convolutions. The development of convolutional layers for neural networks ushered in the current golden age of computation with neural networks, so understanding how they work is particularly valuable, even if you continue to learn about other kinds of neural networks.

- CNNs - they have a very large number of parameters. This is one of the reasons that large amounts of data are usually required to effectively and accurately train a neural network.

- approaches to reduce the number of parameters:
    - to tweak your convolutions, and adapt them to your problem, example, using strided convolutions.
    - to use pooling layers.

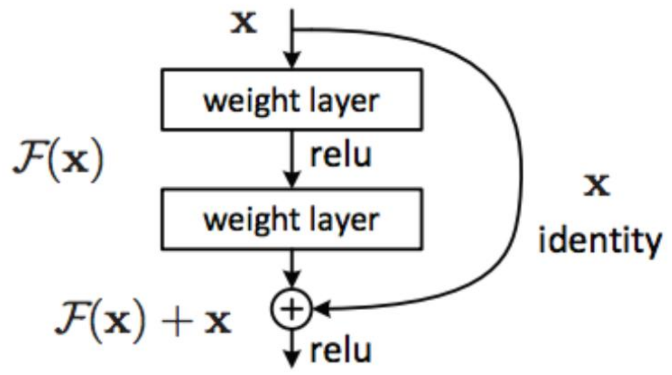
- approaches to improve your network, using regularization.

- ways to understand your network
    - visualize the progress of learning
    - visualize the final result of learning: the parameters of the trained network

Next Steps

- Even deeper networks - there are other architectures that provide a variety of computational benefits.

- Residual networks

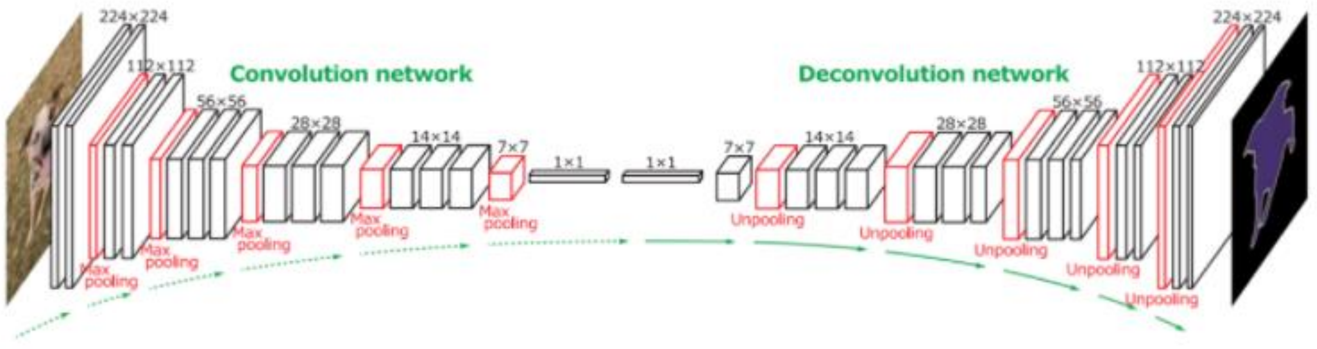

x
weight layer
$\mathcal{F}(\mathbf{x})$
relu
weight layer
x
identity
$\mathcal{F}(\mathbf{x}) + \mathbf{x}$
relu

These include connections that skip over several layers, and they are called residual networks because the network will use this skipped connection to compute a difference between the input of a stack of layers and their output. Learning this difference, or residual, turns out to often be easier than learning the output. This means that these networks have been surprisingly effective at tasks such as classification.

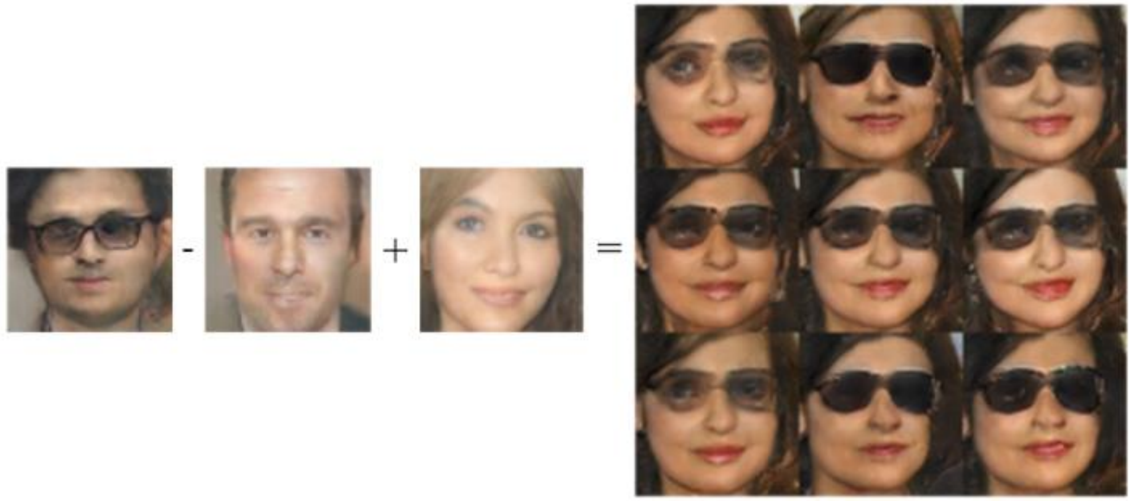
- Transfer learning
  In this approach an already-trained network is adapted to a new task. You've already learned how to read in weights into a network that you've defined. Now imagine training it again on another classification task. It's a great strategy for cases where you don't have a lot of data.

- Fully convolutional networks
  In addition to convolutional networks that perform classification, there are so-called fully convolutional networks that take an image as input and produce another image as output.

  For example, these networks can be used to find the part of an image that contains a particular kind of object, doing segmentation rather than classification.



- Generative adversarial networks
  These complex architectures can be used to train a network to create new images that didn't exist before.



Happy learning!