Once a prediction for each pixel is made, various methods can be used to further process these predictions in order to obtain a segmentation of the image into regions (Briggman *et al.*, 2009; Turaga *et al.*, 2010; Farabet *et al.*, 2013). The general idea is to assume that large groups of contiguous pixels tend to be associated with the same label. Graphical models can describe the probabilistic relationships between neighboring pixels. Alternatively, the convolutional network can be trained to maximize an approximation of the graphical model training objective (Ning *et al.*, 2005; Thompson *et al.*, 2014).

9.7 Data Types

The data used with a convolutional network usually consists of several channels, each channel being the observation of a different quantity at some point in space or time. See table 9.1 for examples of data types with different dimensionalities and number of channels.

For an example of convolutional networks applied to video, see Chen *et al.* (2010).

So far we have discussed only the case where every example in the train and test data has the same spatial dimensions. One advantage to convolutional networks is that they can also process inputs with varying spatial extents. These kinds of input simply cannot be represented by traditional, matrix multiplication-based neural networks. This provides a compelling reason to use convolutional networks even when computational cost and overfitting are not significant issues.

For example, consider a collection of images, where each image has a different width and height. It is unclear how to model such inputs with a weight matrix of fixed size. Convolution is straightforward to apply; the kernel is simply applied a different number of times depending on the size of the input, and the output of the convolution operation scales accordingly. Convolution may be viewed as matrix multiplication; the same convolution kernel induces a different size of doubly block circulant matrix for each size of input. Sometimes the output of the network is allowed to have variable size as well as the input, for example if we want to assign a class label to each pixel of the input. In this case, no further design work is necessary. In other cases, the network must produce some fixed-size output, for example if we want to assign a single class label to the entire image. In this case we must make some additional design steps, like inserting a pooling layer whose pooling regions scale in size proportional to the size of the input, in order to maintain a fixed number of pooled outputs. Some examples of this kind of strategy are shown in figure 9.11.