## Caching the Frozen Layers

Since the frozen layers won't change, it is possible to cache the output of the topmost frozen layer for each training instance. Since training goes through the whole dataset many times, this will give you a huge speed boost as you will only need to go through the frozen layers once per training instance (instead of once per epoch). For example, you could first run the whole training set through the lower layers (assuming you have enough RAM):

```
hidden2_outputs = sess.run(hidden2, feed_dict={X: X_train})
```

Then during training, instead of building batches of training instances, you would build batches of outputs from hidden layer 2 and feed them to the training operation:

```
import numpy as np

n_epochs = 100
n_batches = 500

for epoch in range(n_epochs):
    shuffled_idx = rnd.permutation(len(hidden2_outputs))
    hidden2_batches = np.array_split(hidden2_outputs[shuffled_idx], n_batches)
    y_batches = np.array_split(y_train[shuffled_idx], n_batches)
    for hidden2_batch, y_batch in zip(hidden2_batches, y_batches):
        sess.run(training_op, feed_dict={hidden2: hidden2_batch, y: y_batch})
```

The last line runs the training operation defined earlier (which freezes layers 1 and 2), and feeds it a batch of outputs from the second hidden layer (as well as the targets for that batch). Since we give TensorFlow the output of hidden layer 2, it does not try to evaluate it (or any node it depends on).

## Tweaking, Dropping, or Replacing the Upper Layers

The output layer of the original model should usually be replaced since it is most likely not useful at all for the new task, and it may not even have the right number of outputs for the new task.

Similarly, the upper hidden layers of the original model are less likely to be as useful as the lower layers, since the high-level features that are most useful for the new task may differ significantly from the ones that were most useful for the original task. You want to find the right number of layers to reuse.

Try freezing all the copied layers first, then train your model and see how it performs. Then try unfreezing one or two of the top hidden layers to let backpropagation tweak them and see if performance improves. The more training data you have, the more layers you can unfreeze.

If you still cannot get good performance, and you have little training data, try dropping the top hidden layer(s) and freeze all remaining hidden layers again. You can iterate until you find the right number of layers to reuse. If you have plenty of training data, you may try replacing the top hidden layers instead of dropping them, and even add more hidden layers.

## Model Zoos

Where can you find a neural network trained for a task similar to the one you want to tackle? The first place to look is obviously in your own catalog of models. This is one good reason to save all your models and organize them so you can retrieve them later easily. Another option is to search in a *model zoo*. Many people train Machine Learning models for various tasks and kindly release their pretrained models to the public.

TensorFlow has its own model zoo available at *https://github.com/tensorflow/models*. In particular, it contains most of the state-of-the-art image classification nets such as VGG, Inception, and ResNet (see Chapter 13, and check out the *models/slim* directory), including the code, the pretrained models, and tools to download popular image datasets.

Another popular model zoo is Caffe's Model Zoo. It also contains many computer vision models (e.g., LeNet, AlexNet, ZFNet, GoogLeNet, VGGNet, inception) trained on various datasets (e.g., ImageNet, Places Database, CIFAR10, etc.). Saumitro Dasgupta wrote a converter, which is available at *https://github.com/ethereon/caffe-tensorflow*.

## Unsupervised Pretraining

Suppose you want to tackle a complex task for which you don't have much labeled training data, but unfortunately you cannot find a model trained on a similar task. Don't lose all hope! First, you should of course try to gather more labeled training data, but if this is too hard or too expensive, you may still be able to perform *unsupervised pretraining* (see Figure 11-5). That is, if you have plenty of unlabeled training data, you can try to train the layers one by one, starting with the lowest layer and then going up, using an unsupervised feature detector algorithm such as *Restricted Boltzmann Machines* (RBMs; see Appendix E) or autoencoders (see Chapter 15). Each layer is trained on the output of the previously trained layers (all layers except the one being trained are frozen). Once all layers have been trained this way, you can fine-tune the network using supervised learning (i.e., with backpropagation).

This is a rather long and tedious process, but it often works well; in fact, it is this technique that Geoffrey Hinton and his team used in 2006 and which led to the revival of neural networks and the success of Deep Learning. Until 2010, unsupervised pretraining (typically using RBMs) was the norm for deep nets, and it was only after the vanishing gradients problem was alleviated that it became much more common to train DNNs purely using backpropagation. However, unsupervised pretraining (today typically using autoencoders rather than RBMs) is still a good option when