8.7.4 Supervised Pretraining

Sometimes, directly training a model to solve a specific task can be too ambitious if the model is complex and hard to optimize or if the task is very difficult. It is sometimes more effective to train a simpler model to solve the task, then make the model more complex. It can also be more effective to train the model to solve a simpler task, then move on to confront the final task. These strategies that involve training simple models on simple tasks before confronting the challenge of training the desired model to perform the desired task are collectively known as **pretraining**.

Greedy algorithms break a problem into many components, then solve for the optimal version of each component in isolation. Unfortunately, combining the individually optimal components is not guaranteed to yield an optimal complete solution. However, greedy algorithms can be computationally much cheaper than algorithms that solve for the best joint solution, and the quality of a greedy solution is often acceptable if not optimal. Greedy algorithms may also be followed by a **fine-tuning** stage in which a joint optimization algorithm searches for an optimal solution to the full problem. Initializing the joint optimization algorithm with a greedy solution can greatly speed it up and improve the quality of the solution it finds.

Pretraining, and especially greedy pretraining, algorithms are ubiquitous in deep learning. In this section, we describe specifically those pretraining algorithms that break supervised learning problems into other simpler supervised learning problems. This approach is known as **greedy supervised pretraining**.

In the original (Bengio *et al.*, 2007) version of greedy supervised pretraining, each stage consists of a supervised learning training task involving only a subset of the layers in the final neural network. An example of greedy supervised pretraining is illustrated in figure 8.7, in which each added hidden layer is pretrained as part of a shallow supervised MLP, taking as input the output of the previously trained hidden layer. Instead of pretraining one layer at a time, Simonyan and Zisserman (2015) pretrain a deep convolutional network (eleven weight layers) and then use the first four and last three layers from this network to initialize even deeper networks (with up to nineteen layers of weights). The middle layers of the new, very deep network are initialized randomly. The new network is then jointly trained. Another option, explored by Yu *et al.* (2010) is to use the *outputs* of the previously trained MLPs, as well as the raw input, as inputs for each added stage.

Why would greedy supervised pretraining help? The hypothesis initially discussed by Bengio *et al.* (2007) is that it helps to provide better guidance to the