personalization, it is possible to train a model once, then deploy it to be used by billions of users. In many cases, the end user is more resource-constrained than the developer. For example, one might train a speech recognition network with a powerful computer cluster, then deploy it on mobile phones.

A key strategy for reducing the cost of inference is **model compression** (Buciluǎ *et al.*, 2006). The basic idea of model compression is to replace the original, expensive model with a smaller model that requires less memory and runtime to store and evaluate.

Model compression is applicable when the size of the original model is driven primarily by a need to prevent overfitting. In most cases, the model with the lowest generalization error is an ensemble of several independently trained models. Evaluating all n ensemble members is expensive. Sometimes, even a single model generalizes better if it is large (for example, if it is regularized with dropout).

These large models learn some function $f(\boldsymbol{x})$, but do so using many more parameters than are necessary for the task. Their size is necessary only due to the limited number of training examples. As soon as we have fit this function $f(\boldsymbol{x})$, we can generate a training set containing infinitely many examples, simply by applying f to randomly sampled points $\boldsymbol{x}$. We then train the new, smaller, model to match $f(\boldsymbol{x})$ on these points. In order to most efficiently use the capacity of the new, small model, it is best to sample the new $\boldsymbol{x}$ points from a distribution resembling the actual test inputs that will be supplied to the model later. This can be done by corrupting training examples or by drawing points from a generative model trained on the original training set.

Alternatively, one can train the smaller model only on the original training points, but train it to copy other features of the model, such as its posterior distribution over the incorrect classes (Hinton *et al.*, 2014, 2015).

12.1.5 Dynamic Structure

One strategy for accelerating data processing systems in general is to build systems that have **dynamic structure** in the graph describing the computation needed to process an input. Data processing systems can dynamically determine which subset of many neural networks should be run on a given input. Individual neural networks can also exhibit dynamic structure internally by determining which subset of features (hidden units) to compute given information from the input. This form of dynamic structure inside neural networks is sometimes called **conditional computation** (Bengio, 2013; Bengio *et al.*, 2013b). Since many components of the architecture may be relevant only for a small amount of possible inputs, the