

binarization step share a file containing the results of the random binarization, so that there is no difference in results based on different outcomes of the binarization step.

Because being able to generate realistic samples from the data distribution is one of the goals of a generative model, practitioners often evaluate generative models by visually inspecting the samples. In the best case, this is done not by the researchers themselves, but by experimental subjects who do not know the source of the samples (Denton *et al.*, 2015). Unfortunately, it is possible for a very poor probabilistic model to produce very good samples. A common practice to verify if the model only copies some of the training examples is illustrated in figure 16.1. The idea is to show for some of the generated samples their nearest neighbor in the training set, according to Euclidean distance in the space of \mathbf{x} . This test is intended to detect the case where the model overfits the training set and just reproduces training instances. It is even possible to simultaneously underfit and overfit yet still produce samples that individually look good. Imagine a generative model trained on images of dogs and cats that simply learns to reproduce the training images of dogs. Such a model has clearly overfit, because it does not produce images that were not in the training set, but it has also underfit, because it assigns no probability to the training images of cats. Yet a human observer would judge each individual image of a dog to be high quality. In this simple example, it would be easy for a human observer who can inspect many samples to determine that the cats are absent. In more realistic settings, a generative model trained on data with tens of thousands of modes may ignore a small number of modes, and a human observer would not easily be able to inspect or remember enough images to detect the missing variation.

Since the visual quality of samples is not a reliable guide, we often also evaluate the log-likelihood that the model assigns to the test data, when this is computationally feasible. Unfortunately, in some cases the likelihood seems not to measure any attribute of the model that we really care about. For example, real-valued models of MNIST can obtain arbitrarily high likelihood by assigning arbitrarily low variance to background pixels that never change. Models and algorithms that detect these constant features can reap unlimited rewards, even though this is not a very useful thing to do. The potential to achieve a cost approaching negative infinity is present for any kind of maximum likelihood problem with real values, but it is especially problematic for generative models of MNIST because so many of the output values are trivial to predict. This strongly suggests a need for developing other ways of evaluating generative models.

Theis *et al.* (2015) review many of the issues involved in evaluating generative