

(section 20.11.1). As with the denoising autoencoder, diffusion inversion trains a transition operator that attempts to probabilistically undo the effect of adding some noise. The difference is that diffusion inversion requires undoing only one step of the diffusion process, rather than traveling all the way back to a clean data point. This addresses the following dilemma present with the ordinary reconstruction log-likelihood objective of denoising autoencoders: with small levels of noise the learner only sees configurations near the data points, while with large levels of noise it is asked to do an almost impossible job (because the denoising distribution is highly complex and multi-modal). With the diffusion inversion objective, the learner can learn the shape of the density around the data points more precisely as well as remove spurious modes that could show up far from the data points.

Another approach to sample generation is the **approximate Bayesian computation** (ABC) framework (Rubin *et al.*, 1984). In this approach, samples are rejected or modified in order to make the moments of selected functions of the samples match those of the desired distribution. While this idea uses the moments of the samples like in moment matching, it is different from moment matching because it modifies the samples themselves, rather than training the model to automatically emit samples with the correct moments. Bachman and Precup (2015) showed how to use ideas from ABC in the context of deep learning, by using ABC to shape the MCMC trajectories of GSNs.

We expect that many other possible approaches to generative modeling await discovery.

20.14 Evaluating Generative Models

Researchers studying generative models often need to compare one generative model to another, usually in order to demonstrate that a newly invented generative model is better at capturing some distribution than the pre-existing models.

This can be a difficult and subtle task. In many cases, we can not actually evaluate the log probability of the data under the model, but only an approximation. In these cases, it is important to think and communicate clearly about exactly what is being measured. For example, suppose we can evaluate a stochastic estimate of the log-likelihood for model A, and a deterministic lower bound on the log-likelihood for model B. If model A gets a higher score than model B, which is better? If we care about determining which model has a better internal representation of the distribution, we actually cannot tell, unless we have some way of determining how loose the bound for model B is. However, if we care about how well we can use the model in practice, for example to perform anomaly detection, then it is fair to