# Chapter 19

# Approximate Inference

Many probabilistic models are difficult to train because it is difficult to perform inference in them. In the context of deep learning, we usually have a set of visible variables $\boldsymbol{v}$ and a set of latent variables $\boldsymbol{h}$. The challenge of inference usually refers to the difficult problem of computing $p(\boldsymbol{h} \mid \boldsymbol{v})$ or taking expectations with respect to it. Such operations are often necessary for tasks like maximum likelihood learning.

Many simple graphical models with only one hidden layer, such as restricted Boltzmann machines and probabilistic PCA, are defined in a way that makes inference operations like computing $p(\boldsymbol{h} \mid \boldsymbol{v})$, or taking expectations with respect to it, simple. Unfortunately, most graphical models with multiple layers of hidden variables have intractable posterior distributions. Exact inference requires an exponential amount of time in these models. Even some models with only a single layer, such as sparse coding, have this problem.

In this chapter, we introduce several of the techniques for confronting these intractable inference problems. Later, in chapter 20, we will describe how to use these techniques to train probabilistic models that would otherwise be intractable, such as deep belief networks and deep Boltzmann machines.

Intractable inference problems in deep learning usually arise from interactions between latent variables in a structured graphical model. See figure 19.1 for some examples. These interactions may be due to direct interactions in undirected models or "explaining away" interactions between mutual ancestors of the same visible unit in directed models.