

not readily apparent how this schedule could support Monte Carlo training of an undirected model. Learning algorithms based on maximizing \mathcal{L} can be run with prolonged periods of improving q and prolonged periods of improving θ , however. If the role of biological dreaming is to train networks for predicting q , then this explains how animals are able to remain awake for several hours (the longer they are awake, the greater the gap between \mathcal{L} and $\log p(\mathbf{v})$, but \mathcal{L} will remain a lower bound) and to remain asleep for several hours (the generative model itself is not modified during sleep) without damaging their internal models. Of course, these ideas are purely speculative, and there is no hard evidence to suggest that dreaming accomplishes either of these goals. Dreaming may also serve reinforcement learning rather than probabilistic modeling, by sampling synthetic experiences from the animal's transition model, on which to train the animal's policy. Or sleep may serve some other purpose not yet anticipated by the machine learning community.

19.5.2 Other Forms of Learned Inference

This strategy of learned approximate inference has also been applied to other models. [Salakhutdinov and Larochelle \(2010\)](#) showed that a single pass in a learned inference network could yield faster inference than iterating the mean field fixed point equations in a DBM. The training procedure is based on running the inference network, then applying one step of mean field to improve its estimates, and training the inference network to output this refined estimate instead of its original estimate.

We have already seen in section [14.8](#) that the predictive sparse decomposition model trains a shallow encoder network to predict a sparse code for the input. This can be seen as a hybrid between an autoencoder and sparse coding. It is possible to devise probabilistic semantics for the model, under which the encoder may be viewed as performing learned approximate MAP inference. Due to its shallow encoder, PSD is not able to implement the kind of competition between units that we have seen in mean field inference. However, that problem can be remedied by training a deep encoder to perform learned approximate inference, as in the ISTA technique ([Gregor and LeCun, 2010b](#)).

Learned approximate inference has recently become one of the dominant approaches to generative modeling, in the form of the variational autoencoder ([Kingma, 2013](#); [Rezende *et al.*, 2014](#)). In this elegant approach, there is no need to construct explicit targets for the inference network. Instead, the inference network is simply used to define \mathcal{L} , and then the parameters of the inference network are adapted to increase \mathcal{L} . This model is described in depth later, in section [20.10.3](#).