Typically, the output variables are treated as being conditionally independent given h so that this probability distribution is inexpensive to evaluate, but some techniques such as mixture density outputs allow tractable modeling of outputs with correlations.

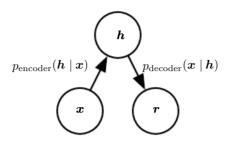


Figure 14.2: The structure of a stochastic autoencoder, in which both the encoder and the decoder are not simple functions but instead involve some noise injection, meaning that their output can be seen as sampled from a distribution, $p_{\text{encoder}}(\boldsymbol{h} \mid \boldsymbol{x})$ for the encoder and $p_{\text{decoder}}(\boldsymbol{x} \mid \boldsymbol{h})$ for the decoder.

To make a more radical departure from the feedforward networks we have seen previously, we can also generalize the notion of an **encoding function** f(x) to an **encoding distribution** $p_{\text{encoder}}(h \mid x)$, as illustrated in figure 14.2.

Any latent variable model $p_{\text{model}}(\boldsymbol{h}, \boldsymbol{x})$ defines a stochastic encoder

$$p_{\text{encoder}}(\boldsymbol{h} \mid \boldsymbol{x}) = p_{\text{model}}(\boldsymbol{h} \mid \boldsymbol{x}) \tag{14.12}$$

and a stochastic decoder

$$p_{\text{decoder}}(\boldsymbol{x} \mid \boldsymbol{h}) = p_{\text{model}}(\boldsymbol{x} \mid \boldsymbol{h}). \tag{14.13}$$

In general, the encoder and decoder distributions are not necessarily conditional distributions compatible with a unique joint distribution $p_{\text{model}}(\boldsymbol{x}, \boldsymbol{h})$. Alain *et al.* (2015) showed that training the encoder and decoder as a denoising autoencoder will tend to make them compatible asymptotically (with enough capacity and examples).

14.5 Denoising Autoencoders

The **denoising autoencoder** (DAE) is an autoencoder that receives a corrupted data point as input and is trained to predict the original, uncorrupted data point as its output.

The DAE training procedure is illustrated in figure 14.3. We introduce a corruption process $C(\tilde{\mathbf{x}} \mid \mathbf{x})$ which represents a conditional distribution over