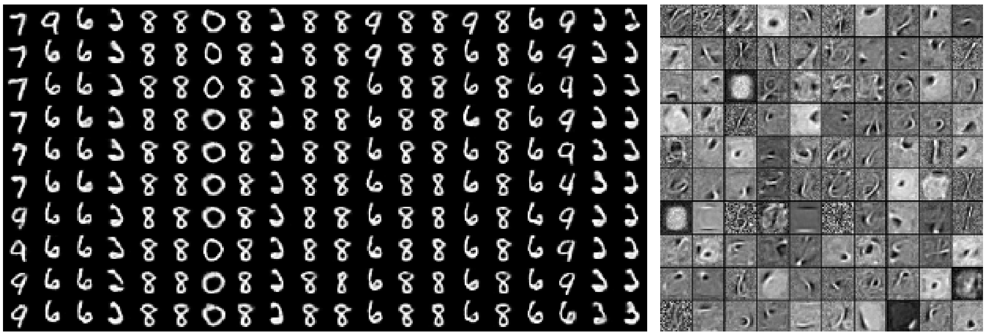

Figure 16.15: Samples from a trained RBM, and its weights. Image reproduced with permission from LISA (2008). *(Left)*Samples from a model trained on MNIST, drawn using Gibbs sampling. Each column is a separate Gibbs sampling process. Each row represents the output of another 1,000 steps of Gibbs sampling. Successive samples are highly correlated with one another. *(Right)*The corresponding weight vectors. Compare this to the samples and weights of a linear factor model, shown in figure 13.2. The samples here are much better because the RBM prior $p(\boldsymbol{h})$ is not constrained to be factorial. The RBM can learn which features should appear together when sampling. On the other hand, the RBM posterior $p(\boldsymbol{h} \mid \boldsymbol{v})$ is factorial, while the sparse coding posterior $p(\boldsymbol{h} \mid \boldsymbol{v})$ is not, so the sparse coding model may be better for feature extraction. Other models are able to have both a non-factorial $p(\boldsymbol{h})$ and a non-factorial $p(\boldsymbol{h} \mid \boldsymbol{v})$.