

# 28

## *Deep learning*

### 28.1 Introduction

Many of the models we have looked at in this book have a simple two-layer architecture of the form  $\mathbf{z} \rightarrow \mathbf{y}$  for unsupervised latent variable models, or  $\mathbf{x} \rightarrow \mathbf{y}$  for supervised models. However, when we look at the brain, we seem many levels of processing. It is believed that each level is learning features or representations at increasing levels of abstraction. For example, the **standard model** of the visual cortex (Hubel and Wiesel 1962; Serre et al. 2005; Ranzato et al. 2007) suggests that (roughly speaking) the brain first extracts edges, then patches, then surfaces, then objects, etc. (See e.g., (Palmer 1999; Kandel et al. 2000) for more information about how the brain might perform vision.)

This observation has inspired a recent trend in machine learning known as **deep learning** (see e.g., (Bengio 2009), [deeplearning.net](http://deeplearning.net), and the references therein), which attempts to replicate this kind of architecture in a computer. (Note the idea can be applied to non-vision problems as well, such as speech and language.)

In this chapter, we give a brief overview of this new field. However, we caution the reader that the topic of deep learning is currently evolving very quickly, so the material in this chapter may soon be outdated.

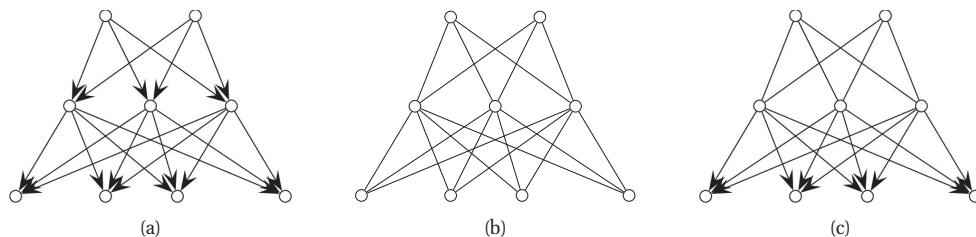
### 28.2 Deep generative models

Deep models often have millions of parameters. Acquiring enough labeled data to train such models is difficult, despite crowd sourcing sites such as Mechanical Turk. In simple settings, such as hand-written character recognition, it is possible to generate lots of labeled data by making modified copies of a small manually labeled training set (see e.g., Figure 16.13), but it seems unlikely that this approach will scale to complex scenes.<sup>1</sup>

To overcome the problem of needing labeled training data, we will focus on unsupervised learning. The most natural way to perform this is to use generative models. In this section, we discuss three different kinds of deep generative models: directed, undirected, and mixed.

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1. There have been some attempts to use computer graphics and video games to generate realistic-looking images of complex scenes, and then to use this as training data for computer vision systems. However, often graphics programs cut corners in order to make perceptually appealing images which are not reflective of the natural statistics of real-world images.



**Figure 28.1** Some deep multi-layer graphical models. Observed variables are at the bottom. (a) A directed model. (b) An undirected model (deep Boltzmann machine). (c) A mixed directed-undirected model (deep belief net).

### 28.2.1 Deep directed networks

Perhaps the most natural way to build a deep generative model is to construct a deep directed graphical model, as shown in Figure 28.1(a). The bottom level contains the observed pixels (or whatever the data is), and the remaining layers are hidden. We have assumed just 3 layers for notational simplicity. The number and size of layers is usually chosen by hand, although one can also use non-parametric Bayesian methods (Adams et al. 2010) or boosting (Chen et al. 2010) to infer the model structure.

We shall call models of this form **deep directed networks** or DDNs. If all the nodes are binary, and all CPDs are logistic functions, this is called a **sigmoid belief net** (Neal 1992). In this case, the model defines the following joint distribution:

$$p(\mathbf{h}_1, \mathbf{h}_2, \mathbf{h}_3, \mathbf{v} | \boldsymbol{\theta}) = \prod_i \text{Ber}(v_i | \text{sigm}(\mathbf{h}_1^T \mathbf{w}_{0i})) \prod_j \text{Ber}(h_{1j} | \text{sigm}(\mathbf{h}_2^T \mathbf{w}_{1j})) \quad (28.1)$$

$$\prod_k \text{Ber}(h_{2k} | \text{sigm}(\mathbf{h}_3^T \mathbf{w}_{2k})) \prod_l \text{Ber}(h_{3l} | w_{3l}) \quad (28.2)$$

Unfortunately, inference in directed models such as these is intractable because the posterior on the hidden nodes is correlated due to explaining away. One can use fast mean field approximations (Jaakkola and Jordan 1996a; Saul and Jordan 2000), but these may not be very accurate, since they approximate the correlated posterior with a factorial posterior. One can also use MCMC inference (Neal 1992; Adams et al. 2010), but this can be quite slow because the variables are highly correlated. Slow inference also results in slow learning.

### 28.2.2 Deep Boltzmann machines

A natural alternative to a directed model is to construct a deep undirected model. For example, we can stack a series of RBMs on top of each other, as shown in Figure 28.1(b). This is known as a **deep Boltzmann machine** or **DBM** (Salakhutdinov and Hinton 2009). If we have 3 hidden layers, the model is defined as follows:

$$p(\mathbf{h}_1, \mathbf{h}_2, \mathbf{h}_3, \mathbf{v} | \boldsymbol{\theta}) = \frac{1}{Z(\boldsymbol{\theta})} \exp \left( \sum_{ij} v_i h_{1j} W_{1ij} + \sum_{jk} h_{1j} h_{2k} W_{2jk} + \sum_{kl} h_{2k} h_{3l} W_{3kl} \right) \quad (28.3)$$

where we are ignoring constant offset or bias terms.

The main advantage over the directed model is that one can perform efficient block (layer-wise) Gibbs sampling, or block mean field, since all the nodes in each layer are conditionally independent of each other given the layers above and below (Salakhutdinov and Larochelle 2010). The main disadvantage is that training undirected models is more difficult, because of the partition function. However, below we will see a greedy layer-wise strategy for learning deep undirected models.

### 28.2.3 Deep belief networks

An interesting compromise is to use a model that is partially directed and partially undirected. In particular, suppose we construct a layered model which has directed arrows, except at the top, where there is an undirected bipartite graph, as shown in Figure 28.1(c). This model is known as a **deep belief network** (Hinton et al. 2006) or **DBN**.<sup>2</sup> If we have 3 hidden layers, the model is defined as follows:

$$p(\mathbf{h}_1, \mathbf{h}_2, \mathbf{h}_3, \mathbf{v} | \boldsymbol{\theta}) = \prod_i \text{Ber}(v_i | \text{sigm}(\mathbf{h}_1^T \mathbf{w}_{1i})) \prod_j \text{Ber}(h_{1j} | \text{sigm}(\mathbf{h}_2^T \mathbf{w}_{2j})) \quad (28.4)$$

$$\frac{1}{Z(\boldsymbol{\theta})} \exp \left( \sum_{kl} h_{2k} h_{3l} W_{3kl} \right) \quad (28.5)$$

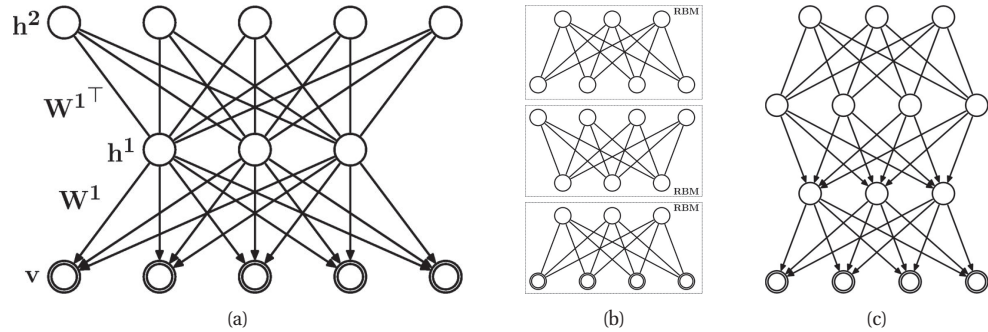
Essentially the top two layers act as an associative memory, and the remaining layers then generate the output.

The advantage of this peculiar architecture is that we can infer the hidden states in a fast, bottom-up fashion. To see why, suppose we only have two hidden layers, and that  $\mathbf{W}_2 = \mathbf{W}_1^T$ , so the second level weights are tied to the first level weights (see Figure 28.2(a)). This defines a model of the form  $p(\mathbf{h}_1, \mathbf{h}_2, \mathbf{v} | \mathbf{W}_1)$ . One can show that the distribution  $p(\mathbf{h}_1, \mathbf{v} | \mathbf{W}_1) = \sum_{\mathbf{h}_2} p(\mathbf{h}_1, \mathbf{h}_2, \mathbf{v} | \mathbf{W}_1)$  has the form  $p(\mathbf{h}_1, \mathbf{v} | \mathbf{W}_1) = \frac{1}{Z(\mathbf{W}_1)} \exp(\mathbf{v}^T \mathbf{W}_1 \mathbf{h}_1)$ , which is equivalent to an RBM. Since the DBN is equivalent to the RBM as far as  $p(\mathbf{h}_1, \mathbf{v} | \mathbf{W}_1)$  is concerned, we can infer the posterior  $p(\mathbf{h}_1 | \mathbf{v}, \mathbf{W}_1)$  in the DBN exactly as in the RBM. This posterior is exact, even though it is fully factorized.

Now the only way to get a factored posterior is if the prior  $p(\mathbf{h}_1 | \mathbf{W}_1)$  is a **complementary prior**. This is a prior which, when multiplied by the likelihood  $p(\mathbf{v} | \mathbf{h}_1)$ , results in a perfectly factored posterior. Thus we see that the top level RBM in a DBN acts as a complementary prior for the bottom level directed sigmoidal likelihood function.

If we have multiple hidden levels, and/or if the weights are not tied, the correspondence between the DBN and the RBM does not hold exactly any more, but we can still use the factored inference rule as a form of approximate bottom-up inference. Below we show that this is a valid variational lower bound. This bound also suggests a layer-wise training strategy, that we will explain in more detail later. Note, however, that top-down inference in a DBN is not tractable, so DBNs are usually only used in a feedforward manner.

2. Unfortunately the acronym “DBN” also stands for “dynamic Bayes net” (Section 17.6.7). Geoff Hinton, who invented deep belief networks, has suggested the acronyms **DeeBNs** and **DyBNs** for these two different meanings. However, this terminology is non-standard.



**Figure 28.2** (a) A DBN with two hidden layers and tied weights that is equivalent to an RBM. Source: Figure 2.2 of (Salakhutdinov 2009). (b) A stack of RBMs trained greedily. (c) The corresponding DBN. Source: Figure 2.3 of (Salakhutdinov 2009). Used with kind permission of Ruslan Salakhutdinov.

### 28.2.4 Greedy layer-wise learning of DBNs

The equivalence between DBNs and RBMs suggests the following strategy for learning a DBN.

- Fit an RBM to learn  $W_1$  using methods described in Section 27.7.2.
- Unroll the RBM into a DBN with 2 hidden layers, as in Figure 28.2(a). Now “freeze” the directed weights  $W_1$  and let  $W_2$  be “untied” so it is no longer forced to be equal to  $W_1^T$ . We will now learn a better prior for  $p(h_1|W_2)$  by fitting a second RBM. The input data to this new RBM is the activation of the hidden units  $\mathbb{E}[h_1|v, W_1]$  which can be computed using a factorial approximation.
- Continue to add more hidden layers until some stopping criterion is satisfied, e.g., you run out of time or memory, or you start to overfit the validation set. Construct the DBN from these RBMs, as illustrated in Figure 28.2(c).

One can show (Hinton et al. 2006) that this procedure always increases a lower bound the observed data likelihood. Of course this procedure might result in overfitting, but that is a different matter.

In practice, we want to be able to use any number of hidden units in each level. This means we will not be able to initialize the weights so that  $W_\ell = W_{\ell-1}^T$ . This voids the theoretical guarantee. Nevertheless the method works well in practice, as we will see. The method can also be extended to train DBMs in a greedy way (Salakhutdinov and Larochelle 2010).

After using the greedy layer-wise training strategy, it is standard to “fine tune” the weights, using a technique called **backfitting**. This works as follows. Perform an upwards sampling pass to the top. Then perform brief Gibbs sampling in the top level RBM, and perform a CD update of the RBM parameters. Finally, perform a downwards ancestral sampling pass (which is an approximate sample from the posterior), and update the logistic CPD parameters using a small gradient step. This is called the **up-down** procedure (Hinton et al. 2006). Unfortunately this procedure is very slow.

## 28.3 Deep neural networks

Given that DBNs are often only used in a feed-forward, or bottom-up, mode, they are effectively acting like neural networks. In view of this, it is natural to dispense with the generative story and try to fit deep neural networks directly, as we discuss below. The resulting training methods are often simpler to implement, and can be faster.

Note, however, that performance with deep neural nets is sometimes not as good as with probabilistic models (Bengio et al. 2007). One reason for this is that probabilistic models support top-down inference as well as bottom-up inference. (DBNs do not support efficient top-down inference, but DBMs do, and this has been shown to help (Salakhutdinov and Larochelle 2010).) Top-down inference is useful when there is a lot of ambiguity about the correct interpretation of the signal.

It is interesting to note that in the mammalian visual cortex, there are many more feedback connections than there are feedforward connections (see e.g., (Palmer 1999; Kandel et al. 2000)). The role of these feedback connections is not precisely understood, but they presumably provide contextual prior information (e.g., coming from the previous “frame” or retinal glance) which can be used to disambiguate the current bottom-up signals (Lee and Mumford 2003).

Of course, we can simulate the effect of top-down inference using a neural network. However the models we discuss below do not do this.

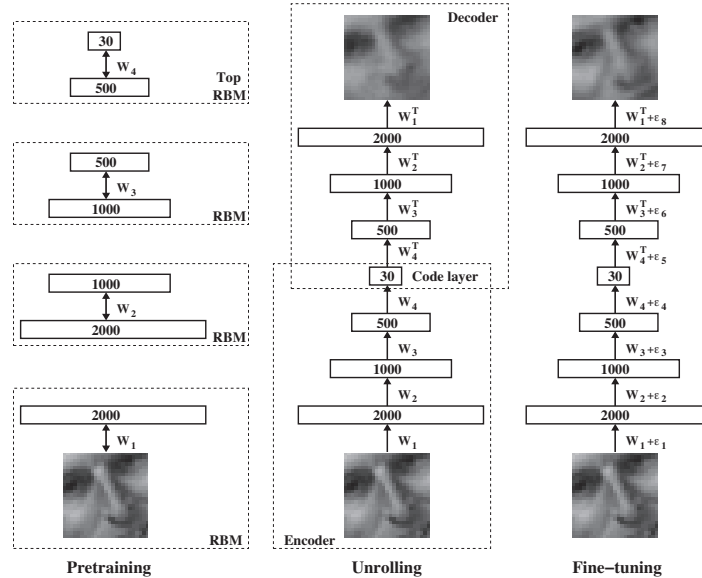
### 28.3.1 Deep multi-layer perceptrons

Many decision problems can be reduced to classification, e.g., predict which object (if any) is present in an image patch, or predict which phoneme is present in a given acoustic feature vector. We can solve such problems by creating a deep feedforward neural network or multi-layer perceptron (MLP), as in Section 16.5, and then fitting the parameters using gradient descent (aka back-propagation).

Unfortunately, this method does not work very well. One problem is that the gradient becomes weaker the further we move away from the data; this is known as the “**vanishing gradient**” problem (Bengio and Frasconi 1995). A related problem is that there can be large plateaus in the error surface, which cause simple first-order gradient-based methods to get stuck (Glorot and Bengio 2010).

Consequently early attempts to learn deep neural networks proved unsuccessful. Recently there has been some progress, due to the adoption of GPUs (Ciresan et al. 2010) and second-order optimization algorithms (Martens 2010). Nevertheless, such models remain difficult to train.

Below we discuss a way to initialize the parameters using unsupervised learning; this is called **generative pre-training**. The advantage of performing unsupervised learning first is that the model is forced to model a high-dimensional response, namely the input feature vector, rather than just predicting a scalar response. This acts like a data-induced regularizer, and helps backpropagation find local minima with good generalization properties (Erhan et al. 2010; Glorot and Bengio 2010).



**Figure 28.3** Training a deep autoencoder. (a) First we greedily train some RBMs. (b) Then we construct the auto-encoder by replicating the weights. (c) Finally we fine-tune the weights using back-propagation. From Figure 1 of (Hinton and Salakhutdinov 2006). Used with kind permission of Ruslan Salakhutdinov.

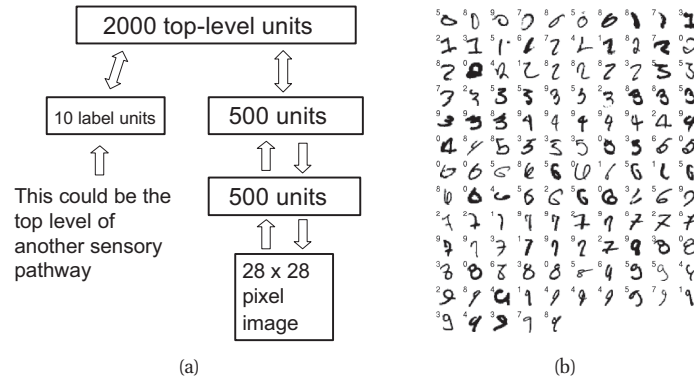
### 28.3.2 Deep auto-encoders

An **auto-encoder** is a kind of unsupervised neural network that is used for dimensionality reduction and feature discovery. More precisely, an auto-encoder is a feedforward neural network that is trained to predict the input itself. To prevent the system from learning the trivial identity mapping, the hidden layer in the middle is usually constrained to be a narrow **bottleneck**. The system can minimize the reconstruction error by ensuring the hidden units capture the most relevant aspects of the data.

Suppose the system has one hidden layer, so the model has the form  $\mathbf{v} \rightarrow \mathbf{h} \rightarrow \mathbf{v}$ . Further, suppose all the functions are linear. In this case, one can show that the weights to the  $K$  hidden units will span the same subspace as the first  $K$  principal components of the data (Karhunen and Joutsensalo 1995; Japkowicz et al. 2000). In other words, linear auto-encoders are equivalent to PCA. However, by using nonlinear activation functions, one can discover nonlinear representations of the data.

More powerful representations can be learned by using **deep auto-encoders**. Unfortunately training such models using back-propagation does not work well, because the gradient signal becomes too small as it passes back through multiple layers, and the learning algorithm often gets stuck in poor local minima.

One solution to this problem is to greedily train a series of RBMs and to use these to initialize an auto-encoder, as illustrated in Figure 28.3. The whole system can then be fine-tuned using backprop in the usual fashion. This approach, first suggested in (Hinton and Salakhutdinov



**Figure 28.4** (a) A DBN architecture for classifying MNIST digits. Source: Figure 1 of (Hinton et al. 2006). Used with kind permission of Geoff Hinton. (b) These are the 125 errors made by the DBN on the 10,000 test cases of MNIST. Above each image is the estimated label. Source: Figure 6 of (Hinton et al. 2006). Used with kind permission of Geoff Hinton. Compare to Figure 16.15.

2006), works much better than trying to fit the deep auto-encoder directly starting with random weights.

### 28.3.3 Stacked denoising auto-encoders

A standard way to train an auto-encoder is to ensure that the hidden layer is narrower than the visible layer. This prevents the model from learning the identity function. But there are other ways to prevent this trivial solution, which allow for the use of an over-complete representation. One approach is to impose sparsity constraints on the activation of the hidden units (Ranzato et al. 2006). Another approach is to add noise to the inputs; this is called a **denoising auto-encoder** (Vincent et al. 2010). For example, we can corrupt some of the inputs, for example by setting them to zero, so the model has to learn to predict the missing entries. This can be shown to be equivalent to a certain approximate form of maximum likelihood training (known as score matching) applied to an RBM (Vincent 2011).

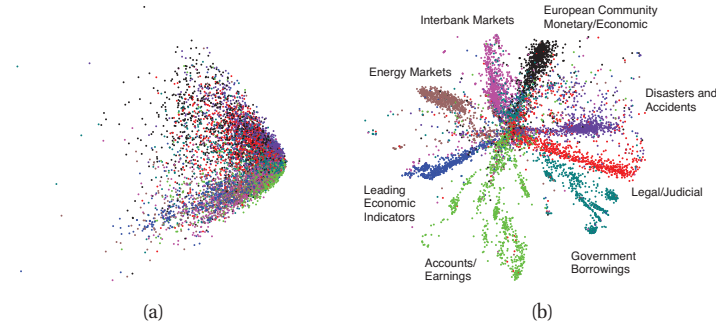
Of course, we can stack these models on top of each other to learn a deep stacked denoising auto-encoder, which can be discriminatively fine-tuned just like a feedforward neural network, if desired.

## 28.4 Applications of deep networks

In this section, we mention a few applications of the models we have been discussing.

### 28.4.1 Handwritten digit classification using DBNs

Figure 28.4(a) shows a DBN (from (Hinton et al. 2006)) consisting of 3 hidden layers. The visible layer corresponds to binary images of handwritten digits from the MNIST data set. In addition, the top RBM is connected to a softmax layer with 10 units, representing the class label.



**Figure 28.5** 2d visualization of some bag of words data from the Reuters RCV1-v2 corpus. (a) Results of using LSA. (b) results of using a deep auto-encoder. Source: Figure 4 of (Hinton and Salakhutdinov 2006). Used with kind permission of Ruslan Salakhutdinov.

The first 2 hidden layers were trained in a greedy unsupervised fashion from 50,000 MNIST digits, using 30 epochs (passes over the data) and stochastic gradient descent, with the CD heuristic. This process took “a few hours per layer” (Hinton et al. 2006, p1540). Then the top layer was trained using as input the activations of the lower hidden layer, as well as the class labels. The corresponding generative model had a test error of about 2.5%. The network weights were then carefully fine-tuned on all 60,000 training images using the up-down procedure. This process took “about a week” (Hinton et al. 2006, p1540). The model can be used to classify by performing a deterministic bottom-up pass, and then computing the free energy for the top-level RBM for each possible class label. The final error on the test set was about 1.25%. The misclassified examples are shown in Figure 28.4(b).

This was the best error rate of any method on the permutation-invariant version of MNIST at that time. (By permutation-invariant, we mean a method that does not exploit the fact that the input is an image. Generic methods work just as well on permuted versions of the input (see Figure 1.5), and can therefore be applied to other kinds of datasets.) The only other method that comes close is an SVM with a degree 9 polynomial kernel, which has achieved an error rate of 1.4% (Decoste and Schoelkopf 2002). By way of comparison, 1-nearest neighbor (using all 60,000 examples) achieves 3.1% (see `mnist1NNdemo`). This is not as good, although 1-NN is much simpler.<sup>3</sup>

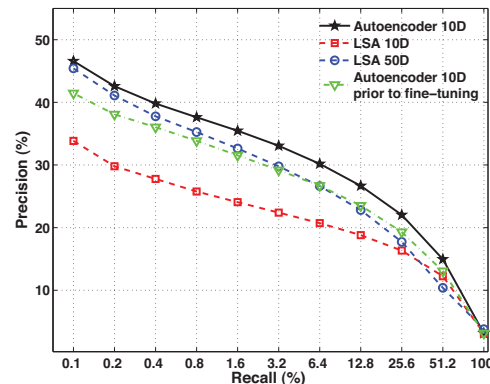
### 28.4.2 Data visualization and feature discovery using deep auto-encoders

Deep autoencoders can learn informative features from raw data. Such features are often used as input to standard supervised learning methods.

To illustrate this, consider fitting a deep auto-encoder with a 2d hidden bottleneck to some

3. One can get much improved performance on this task by exploiting the fact that the input is an image. One way to do this is to create distorted versions of the input, adding small shifts and translations (see Figure 16.13 for some examples). Applying this trick reduced the SVM error rate to 0.56%. Similar error rates can be achieved using convolutional neural networks (Section 16.5.1) trained on distorted images ((Simard et al. 2003) got 0.4%). However, the point of DBNs is that they offer a way to learn such prior knowledge, without it having to be hand-crafted.





**Figure 28.6** Precision-recall curves for document retrieval in the Reuters RCV1-v2 corpus. Source: Figure 3.9 of (Salakhutdinov 2009). Used with kind permission of Ruslan Salakhutdinov.

text data. The results are shown in Figure 28.5. On the left we show the 2d embedding produced by LSA (Section 27.2.2), and on the right, the 2d embedding produced by the auto-encoder. It is clear that the low-dimensional representation created by the auto-encoder has captured a lot of the meaning of the documents, even though class labels were not used.<sup>4</sup>

Note that various other ways of learning low-dimensional continuous embeddings of words have been proposed. See e.g., (Turian et al. 2010) for details.

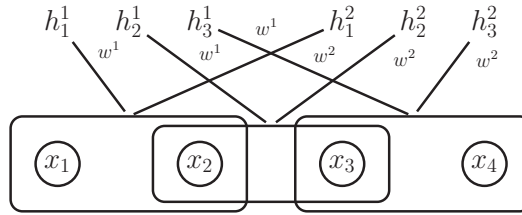
### 28.4.3 Information retrieval using deep auto-encoders (semantic hashing)

In view of the success of RBMs for information retrieval discussed in Section 27.7.3.1, it is natural to wonder if deep models can do even better. In fact they can, as is shown in Figure 28.6.

More interestingly, we can use a binary low-dimensional representation in the middle layer of the deep auto-encoder, rather than a continuous representation as we used above. This enables very fast retrieval of related documents. For example, if we use a 20-bit code, we can precompute the binary representation for all the documents, and then create a hash-table mapping codewords to documents. This approach is known as **semantic hashing**, since the binary representation of semantically similar documents will be close in Hamming distance.

For the 402,207 test documents in Reuters RCV1-v2, this results in about 0.4 documents per entry in the table. At test time, we compute the codeword for the query, and then simply retrieve the relevant documents in *constant time* by looking up the contents of the relevant address in memory. To find other related documents, we can compute all the codewords within a

4. Some details. Salakhutdinov and Hinton used the Reuters RCV1-v2 data set, which consists of 804,414 newswire articles, manually classified into 103 topics. They represent each document by counting how many times each of the top 2000 most frequent words occurs. They trained a deep auto-encoder with 2000-500-250-125-2 layers on half of the data. The 2000 visible units use a replicated softmax distribution, the 2 hidden units in the middle layer have a Gaussian distribution, and the remaining units have the usual Bernoulli-logistic distribution. When fine tuning the auto-encoder, a cross-entropy loss function (equivalent to maximum likelihood under a multinoulli distribution) was used. See (Hinton and Salakhutdinov 2006) for further details.



**Figure 28.7** A small 1d convolutional RBM with two groups of hidden units, each associated with a filter of size 2.  $h_1^1$  and  $h_2^1$  are two different “views” of the data in the first window,  $(x_1, x_2)$ . The first view is computed using the filter  $\mathbf{w}^1$ , the second view using filter  $\mathbf{w}^2$ . Similarly,  $h_1^2$  and  $h_2^2$  are the views of the data in the second window,  $(x_2, x_3)$ , computed using  $\mathbf{w}^1$  and  $\mathbf{w}^2$  respectively.

Hamming distance of, say, 4. This results in retrieving about  $6196 \times 0.4 \approx 2500$  documents<sup>5</sup>. The key point is that the total time is independent of the size of the corpus.

Of course, there are other techniques for fast document retrieval, such as inverted indices. These rely on the fact that individual words are quite informative, so we can simply intersect all the documents that contain each word. However, when performing image retrieval, it is clear that we do not want to work at the pixel level. Recently (Krizhevsky and Hinton 2010) showed that a deep autoencoder could learn a good semantic hashing function that outperformed previous techniques (Torralba et al. 2008; Weiss et al. 2008) on the 80 million tiny images dataset. It is hard to apply inverted indexing techniques to real-valued data (although one could imagine vector quantizing image patches).

#### 28.4.4 Learning audio features using 1d convolutional DBNs

To apply DBNs to time series of unbounded length, it is necessary to use some form of parameter tying. One way to do this is to use **convolutional DBNs** (Lee et al. 2009; Desjardins and Bengio 2008), which use convolutional RBMs as their basic unit. These models are a generative version of convolutional neural nets discussed in Section 16.5.1. The basic idea is illustrated in Figure 28.7. The hidden activation vector for each group is computed by convolving the input vector with that group’s filter (weight vector or matrix). In other words, each node within a hidden group is a weighted combination of a subset of the inputs. We compute the activation of all the hidden nodes by “sliding” this weight vector over the input. This allows us to model **translation invariance**, since we use the same weights no matter where in the input vector the pattern occurs.<sup>6</sup> Each group has its own filter, corresponding to its own pattern detector.

5. Note that  $6196 = \sum_{k=0}^4 \binom{20}{k}$  is the number of bit vectors that are up to a Hamming distance of 4 away.

6. It is often said that the goal of deep learning is to discover **invariant features**, e.g., a representation of an object that does not change even as nuisance variables, such as the lighting, do change. However, sometimes these so-called “nuisance variables” may be the variables of interest. For example if the task is to determine if a photograph was taken in the morning or the evening, then lighting is one of the more salient features, and object identity may be less relevant. As always, one task’s “signal” is another task’s “noise”, so it is unwise to “throw away” apparently irrelevant information.

More formally, for binary 1d signals, we can define the full conditionals in a convolutional RBM as follows (Lee et al. 2009):

$$p(h_t^k = 1 | \mathbf{v}) = \text{sigm}((\mathbf{w}^k \otimes \mathbf{v})_t + b_t) \quad (28.6)$$

$$p(v_s = 1 | \mathbf{h}) = \text{sigm}\left(\sum_k (\mathbf{w}^k \otimes \mathbf{h}^k)_s + c_s\right) \quad (28.7)$$

where  $\mathbf{w}^k$  is the weight vector for group  $k$ ,  $b_t$  and  $c_s$  are bias terms, and  $\mathbf{a} \otimes \mathbf{b}$  represents the convolution of vectors  $\mathbf{a}$  and  $\mathbf{b}$ .

It is common to add a **max pooling** layer as well as a convolutional layer, which computes a local maximum over the filtered response. This allows for a small amount of translation invariance. It also reduces the size of the higher levels, which speeds up computation considerably. Defining this for a neural network is simple, but defining this in a way which allows for information flow backwards as well as forwards is a bit more involved. The basic idea is similar to a noisy-OR CPD (Section 10.2.3), where we define a probabilistic relationship between the max node and the parts it is maxing over. See (Lee et al. 2009) for details. Note, however, that the top-down generative process will be difficult, since the max pooling operation throws away so much information.

(Lee et al. 2009) applies 1d convolutional DBNs of depth 2 to auditory data. When the input consists of speech signals, the method recovers a representation that is similar to phonemes. When applied to music classification and speaker identification, their method outperforms techniques using standard features such as MFCC. (All features were fed into the same discriminative classifier.)

In (Seide et al. 2011), a deep neural net was used in place of a GMM inside a conventional HMM. The use of DNNs significantly improved performance on conversational speech recognition. In an interview, the tech lead of this project said “historically, there have been very few individual technologies in speech recognition that have led to improvements of this magnitude”.<sup>7</sup>

### 28.4.5 Learning image features using 2d convolutional DBNs

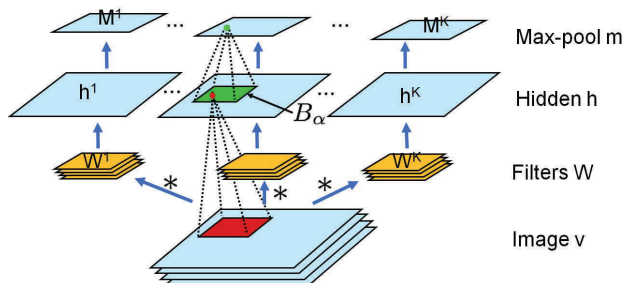
We can extend a convolutional DBN from 1d to 2d in a straightforward way (Lee et al. 2009), as illustrated in Figure 28.8. The results of a 3 layer system trained on four classes of visual objects (cars, motorbikes, faces and airplanes) from the Caltech 101 dataset are shown in Figure 28.9. We only show the results for layers 2 and 3, because layer 1 learns Gabor-like filters that are very similar to those learned by sparse coding, shown in Figure 13.21(b). We see that layer 2 has learned some generic visual parts that are shared amongst object classes, and layer 3 seems to have learned filters that look like grandmother cells, that are specific to individual object classes, and in some cases, to individual objects.

## 28.5 Discussion

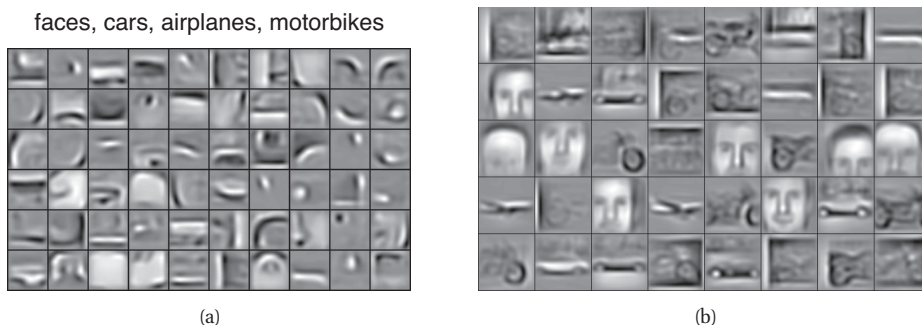
So far, we have been discussing models inspired by low-level processing in the brain. These models have produced useful features for simple classification tasks. But can this pure bottom-up

too early.

7. Source: <http://research.microsoft.com/en-us/news/features/speechrecognition-082911.aspx>.



**Figure 28.8** A 2d convolutional RBM with max-pooling layers. The input signal is a stack of 2d images (e.g., color planes). Each input layer is passed through a different set of filters. Each hidden unit is obtained by convolving with the appropriate filter, and then summing over the input planes. The final layer is obtained by computing the local maximum within a small window. Source: Figure 1 of (Chen et al. 2010) . Used with kind permission of Bo Chen.



**Figure 28.9** Visualization of the filters learned by a convolutional DBN in layers two and three. Source: Figure 3 of (Lee et al. 2009). Used with kind permission of Honglak Lee.

approach scale to more challenging problems, such as scene interpretation or natural language understanding?

To put the problem in perspective, consider the DBN for handwritten digit classification in Figure 28.4(a). This has about 1.6M free parameters ( $28 \times 28 \times 500 + 500 \times 500 + 510 \times 2000 = 1,662,000$ ). Although this is a lot, it is tiny compared to the number of neurons in the brain. As Hinton says,

This is about as many parameters as 0.002 cubic millimetres of mouse cortex, and several hundred networks of this complexity could fit within a single voxel of a high-resolution fMRI scan. This suggests that much bigger networks may be required to compete with human shape recognition abilities. — (Hinton et al. 2006, p1547).

To scale up to more challenging problems, various groups are using GPUs (see e.g., (Raina et al. 2009)) and/or parallel computing. But perhaps a more efficient approach is to work at a higher level of abstraction, where inference is done in the space of objects or their parts, rather

than in the space of bits and pixels. That is, we want to bridge the **signal-to-symbol** divide, where by “symbol” we mean something atomic, that can be combined with other symbols in a compositional way.

The question of how to convert low level signals into a more structured/ “semantic” representation is known as the **symbol grounding** problem (Harnard 1990). Traditionally such symbols are associated with words in natural language, but it seems unlikely we can jump directly from low-level signals to high-level semantic concepts. Instead, what we need is an intermediate level of symbolic or atomic parts.

A very simple way to create such parts from real-valued signals, such as images, is to apply vector quantization. This generates a set of **visual words**. These can then be modelled using some of the techniques from Chapter 27 for modeling bags of words. Such models, however, are still quite “shallow”.

It is possible to define, and learn, deep models which use discrete latent parts. Here we just mention a few recent approaches, to give a flavor of the possibilities. (Salakhutdinov et al. 2011) combine RBMs with hierarchical latent Dirichlet allocation methods, trained in an unsupervised way. (Zhu et al. 2010) use latent and-or graphs, trained in a manner similar to a latent structural SVM. A similar approach, based on grammars, is described in (Girshick et al. 2011). What is interesting about these techniques is that they apply data-driven machine learning methods to rich structured/symbolic “AI-style” models. This seems like a promising future direction for machine learning.