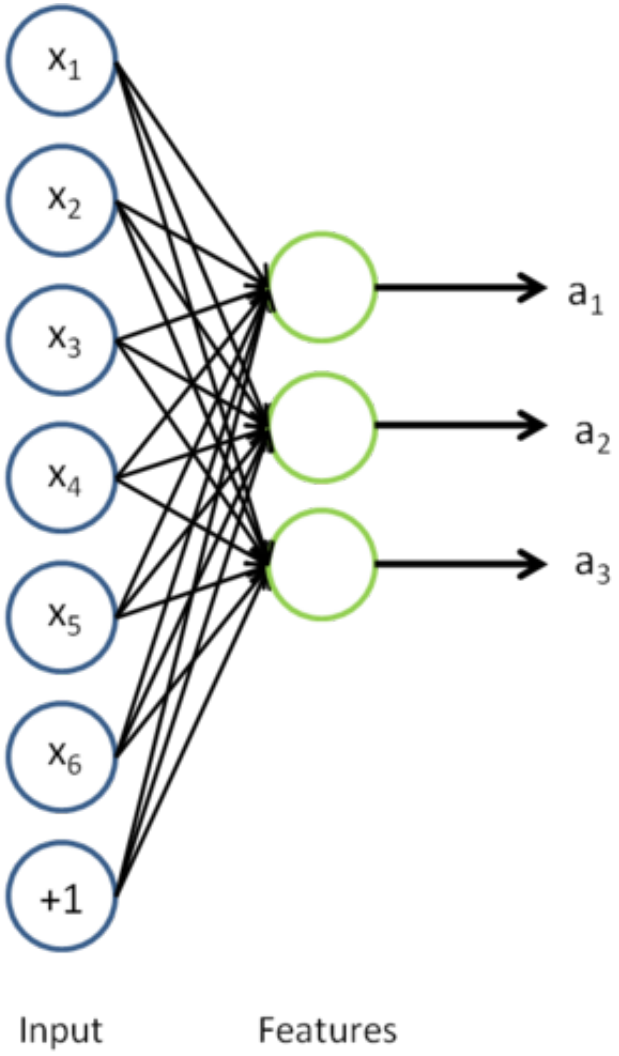
Self-Taught Learning to Deep Networks

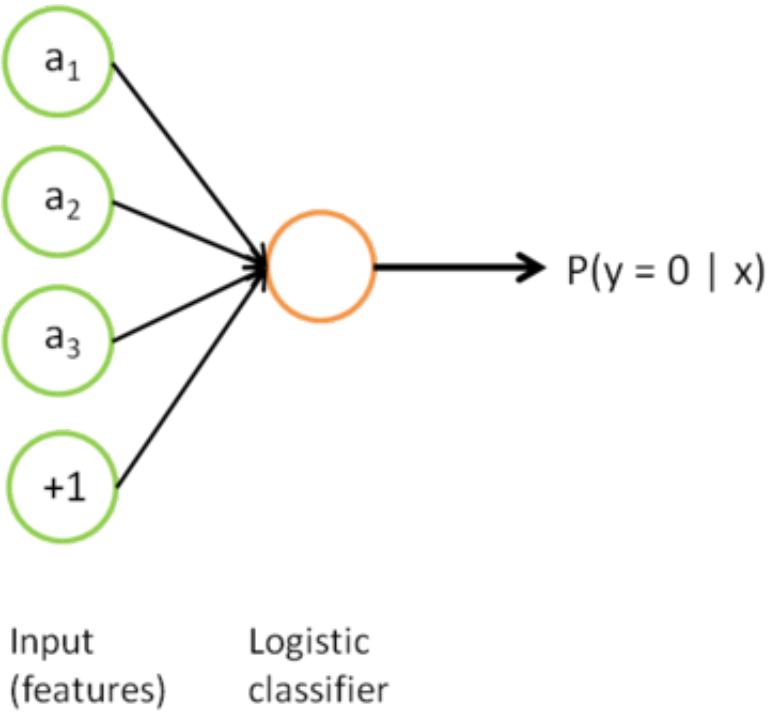
From Ufldl

In the previous section, you used an autoencoder to learn features that were then fed as input to a softmax or logistic regression classifier. In that method, the features were learned using only unlabeled data. In this section, we describe how you can **fine-tune** and further improve the learned features using labeled data. When you have a large amount of labeled training data, this can significantly improve your classifier's performance.

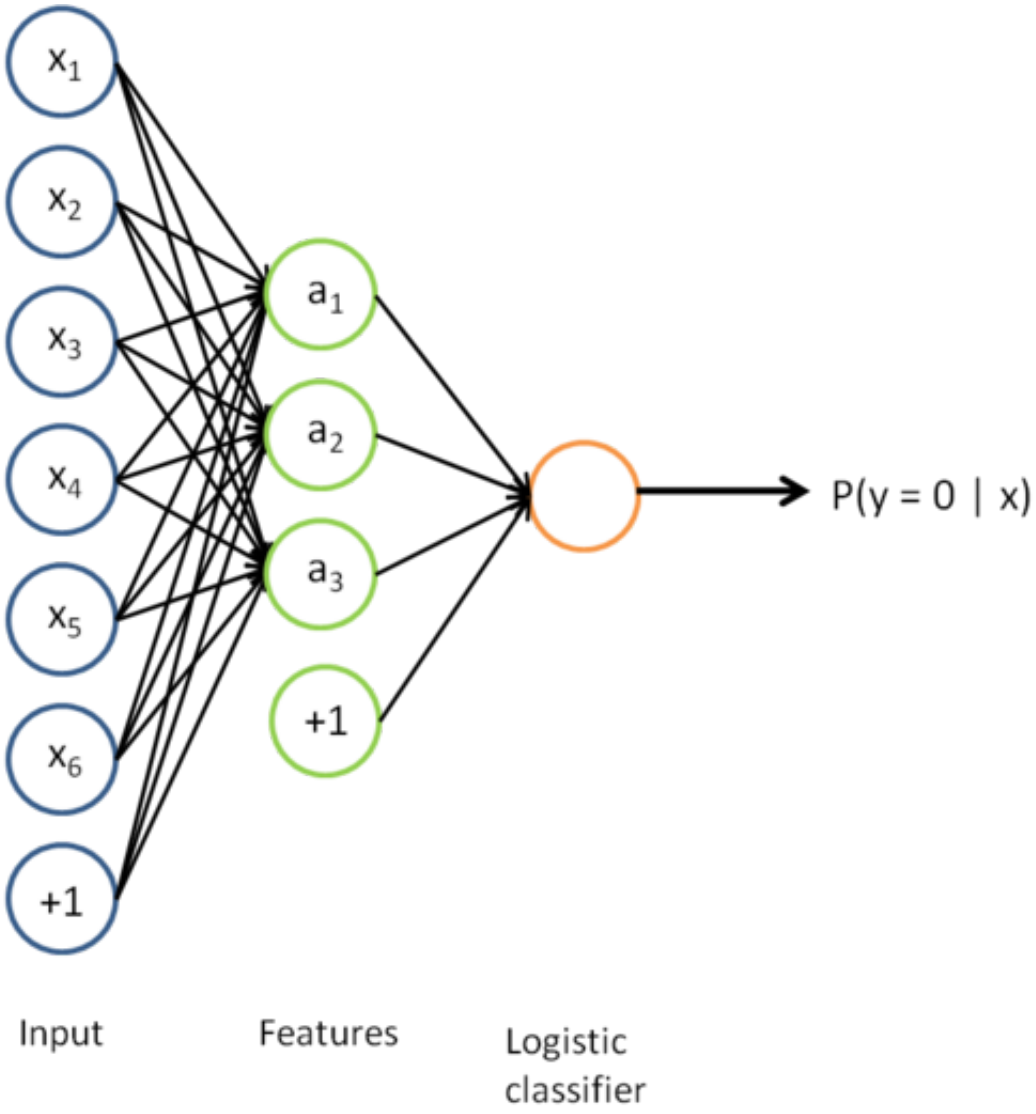
In self-taught learning, we first trained a sparse autoencoder on the unlabeled data. Then, given a new example x, we used the hidden layer to extract features a. This is illustrated in the following diagram:



We are interested in solving a classification task, where our goal is to predict labels y. We have a labeled training set $\{(x_l^{(1)}, y^{(1)}), (x_l^{(2)}, y^{(2)}), \ldots (x_l^{(m_l)}, y^{(m_l)})\}$ of m_l labeled examples. We showed previously that we can replace the original features $x^{(i)}$ with features $a^{(l)}$ computed by the sparse autoencoder (the "replacement" representation). This gives us a training set $\{(a^{(1)}, y^{(1)}), \ldots (a^{(m_l)}, y^{(m_l)})\}$. Finally, we train a logistic classifier to map from the features $a^{(i)}$ to the classification label $y^{(i)}$. To illustrate this step, similar to our earlier notes, we can draw our logistic regression unit (shown in orange) as follows:



Now, consider the overall classifier (i.e., the input-output mapping) that we have learned using this method. In particular, let us examine the function that our classifier uses to map from from a new test example x to a new prediction $p(y = 1 \mid x)$. We can draw a representation of this function by putting together the two pictures from above. In particular, the final classifier looks like this:



The parameters of this model were trained in two stages: The first layer of weights $W^{(1)}$ mapping from the input x to the hidden unit activations a were trained as part of the sparse autoencoder training process. The second layer of weights $W^{(2)}$ mapping from the activations a to the output y was trained using logistic regression (or softmax regression).

But the form of our overall/final classifier is clearly just a whole big neural network. So, having trained up an initial set of parameters for our model (training the first layer using an autoencoder, and the second layer via logistic/softmax regression), we can further modify all the parameters in our model to try to further reduce the training error. In particular, we can **fine-tune** the parameters, meaning perform gradient descent (or use L-BFGS) from the current setting of the parameters to try to reduce the training error on our labeled training set $\{(x_l^{(1)}, y^{(1)}), (x_l^{(2)}, y^{(2)}), \ldots (x_l^{(m_l)}, y^{(m_l)})\}$.

When fine-tuning is used, sometimes the original unsupervised feature learning steps (i.e., training the autoencoder and the logistic classifier) are called **pre-training.** The effect of fine-tuning is that the labeled data can be used to modify the weights $W^{(1)}$ as well, so that adjustments can be made to the features a extracted by the layer of hidden units.

So far, we have described this process assuming that you used the "replacement" representation, where the training

examples seen by the logistic classifier are of the form $(a^{(i)}, y^{(i)})$, rather than the "concatenation" representation, where the examples are of the form $((x^{(i)}, a^{(i)}), y^{(i)})$. It is also possible to perform fine-tuning too using the "concatenation" representation. (This corresponds to a neural network where the input units x_i also feed directly to the logistic classifier in the output layer. You can draw this using a slightly different type of neural network diagram than the ones we have seen so far; in particular, you would have edges that go directly from the first layer input nodes to the third layer output node, "skipping over" the hidden layer.) However, so long as we are using finetuning, usually the "concatenation" representation has little advantage over the "replacement" representation. Thus, if we are using fine-tuning usually we will do so with a network built using the replacement representation. (If you are not using fine-tuning however, then sometimes the concatenation representation can give much better performance.)

When should we use fine-tuning? It is typically used only if you have a large labeled training set; in this setting, fine-tuning can significantly improve the performance of your classifier. However, if you have a large *unlabeled* dataset (for unsupervised feature learning/pre-training) and only a relatively small labeled training set, then fine-tuning is significantly less likely to help.

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