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- Most neurons in C3 maps are connected to neurons in only three or four S2 maps (instead of all six S2 maps). See table 1 in the original paper for details.
- The output layer is a bit special: instead of computing the dot product of the inputs and the weight vector, each neuron outputs the square of the Euclidian distance between its input vector and its weight vector. Each output measures how much the image belongs to a particular digit class. The cross entropy cost function is now preferred, as it penalizes bad predictions much more, producing larger gradients and thus converging faster.

Yann LeCun's [website](#) ("LENET" section) features great demos of LeNet-5 classifying digits.

AlexNet

The *AlexNet CNN architecture*⁹ won the 2012 ImageNet ILSVRC challenge by a large margin: it achieved 17% top-5 error rate while the second best achieved only 26%! It was developed by Alex Krizhevsky (hence the name), Ilya Sutskever, and Geoffrey Hinton. It is quite similar to LeNet-5, only much larger and deeper, and it was the first to stack convolutional layers directly on top of each other, instead of stacking a pooling layer on top of each convolutional layer. Table 13-2 presents this architecture.

Table 13-2. AlexNet architecture

Layer	Type	Maps	Size	Kernel size	Stride	Padding	Activation
Out	Fully Connected	—	1,000	—	—	—	Softmax
F9	Fully Connected	—	4,096	—	—	—	ReLU
F8	Fully Connected	—	4,096	—	—	—	ReLU
C7	Convolution	256	13 × 13	3 × 3	1	SAME	ReLU
C6	Convolution	384	13 × 13	3 × 3	1	SAME	ReLU
C5	Convolution	384	13 × 13	3 × 3	1	SAME	ReLU
S4	Max Pooling	256	13 × 13	3 × 3	2	VALID	—
C3	Convolution	256	27 × 27	5 × 5	1	SAME	ReLU
S2	Max Pooling	96	27 × 27	3 × 3	2	VALID	—
C1	Convolution	96	55 × 55	11 × 11	4	SAME	ReLU
In	Input	3 (RGB)	224 × 224	—	—	—	—

To reduce overfitting, the authors used two regularization techniques we discussed in previous chapters: first they applied dropout (with a 50% dropout rate) during training to the outputs of layers F8 and F9. Second, they performed data augmentation by

⁹ "ImageNet Classification with Deep Convolutional Neural Networks," A. Krizhevsky et al. (2012).

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 randomly shifting the training images by various offsets, flipping them horizontally, and changing the lighting conditions.

AlexNet also uses a competitive normalization step immediately after the ReLU step of layers C1 and C3, called *local response normalization*. This form of normalization makes the neurons that most strongly activate inhibit neurons at the same location but in neighboring feature maps (such competitive activation has been observed in biological neurons). This encourages different feature maps to specialize, pushing them apart and forcing them to explore a wider range of features, ultimately improving generalization. Equation 13-2 shows how to apply LRN.

Equation 13-2. Local response normalization

$$b_i = a_i \left(k + \alpha \sum_{j=j_{\text{low}}}^{j_{\text{high}}} a_j^2 \right)^{-\beta} \quad \text{with} \quad \begin{cases} j_{\text{high}} = \min \left(i + \frac{r}{2}, f_n - 1 \right) \\ j_{\text{low}} = \max \left(0, i - \frac{r}{2} \right) \end{cases}$$

- b_i is the normalized output of the neuron located in feature map i , at some row u and column v (note that in this equation we consider only neurons located at this row and column, so u and v are not shown).
- a_i is the activation of that neuron after the ReLU step, but before normalization.
- k , α , β , and r are hyperparameters. k is called the *bias*, and r is called the *depth radius*.
- f_n is the number of feature maps.

For example, if $r = 2$ and a neuron has a strong activation, it will inhibit the activation of the neurons located in the feature maps immediately above and below its own.

In AlexNet, the hyperparameters are set as follows: $r = 2$, $\alpha = 0.00002$, $\beta = 0.75$, and $k = 1$. This step can be implemented using TensorFlow's `local_response_normalization()` operation.

A variant of AlexNet called *ZF Net* was developed by Matthew Zeiler and Rob Fergus and won the 2013 ILSVRC challenge. It is essentially AlexNet with a few tweaked hyperparameters (number of feature maps, kernel size, stride, etc.).

GoogLeNet

The **GoogLeNet architecture** was developed by Christian Szegedy et al. from Google Research,¹⁰ and it won the ILSVRC 2014 challenge by pushing the top-5 error rate

¹⁰ "Going Deeper with Convolutions," C. Szegedy et al. (2015).