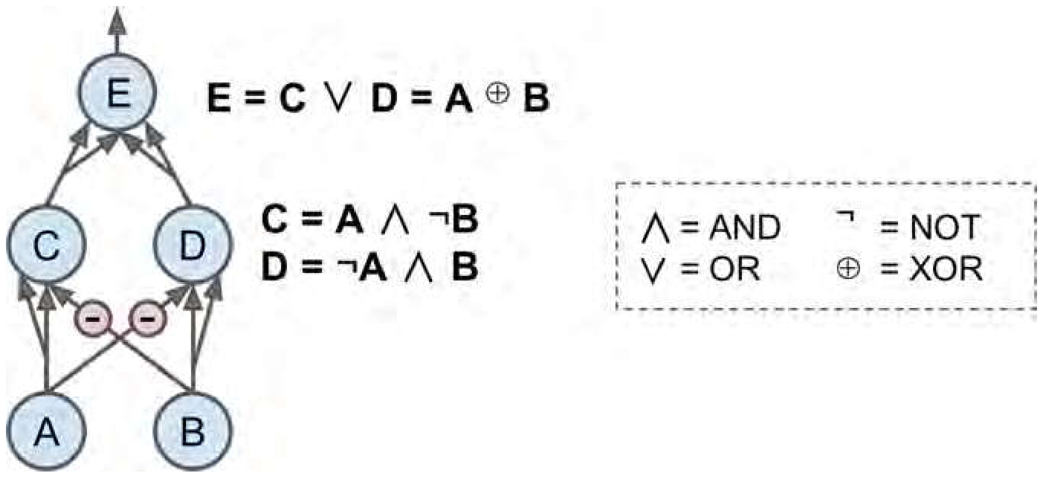
12. See the Jupyter notebooks available at *https://github.com/ageron/handson-ml*.

Chapter 10: Introduction to Artificial Neural Networks

1. Here is a neural network based on the original artificial neurons that computes $A \oplus B$ (where $\oplus$ represents the exclusive OR), using the fact that $A \oplus B = (A \wedge \neg B) \vee (\neg A \wedge B)$. There are other solutions—for example, using the fact that $A \oplus B = (A \vee B) \wedge \neg(A \wedge B)$, or the fact that $A \oplus B = (A \vee B) \wedge (\neg A \vee \wedge B)$, and so on.



2. A classical Perceptron will converge only if the dataset is linearly separable, and it won't be able to estimate class probabilities. In contrast, a Logistic Regression classifier will converge to a good solution even if the dataset is not linearly separable, and it will output class probabilities. If you change the Perceptron's activation function to the logistic activation function (or the softmax activation function if there are multiple neurons), and if you train it using Gradient Descent (or some other optimization algorithm minimizing the cost function, typically cross entropy), then it becomes equivalent to a Logistic Regression classifier.

3. The logistic activation function was a key ingredient in training the first MLPs because its derivative is always nonzero, so Gradient Descent can always roll down the slope. When the activation function is a step function, Gradient Descent cannot move, as there is no slope at all.

4. The step function, the logistic function, the hyperbolic tangent, the rectified linear unit (see Figure 10-8). See Chapter 11 for other examples, such as ELU and variants of the ReLU.

5. Considering the MLP described in the question: suppose you have an MLP composed of one input layer with 10 passthrough neurons, followed by one hidden layer with 50 artificial neurons, and finally one output layer with 3 artificial neurons. All artificial neurons use the ReLU activation function.

- The shape of the input matrix $\mathbf{X}$ is $m \times 10$, where m represents the training batch size.
- The shape of the hidden layer's weight vector $\mathbf{W}_h$ is 10×50 and the length of its bias vector $\mathbf{b}_h$ is 50.
- The shape of the output layer's weight vector $\mathbf{W}_o$ is 50×3, and the length of its bias vector $\mathbf{b}_o$ is 3.
- The shape of the network's output matrix $\mathbf{Y}$ is $m \times 3$.
- $\mathbf{Y} = (\mathbf{X} \cdot \mathbf{W}_h + \mathbf{b}_h) \cdot \mathbf{W}_o + \mathbf{b}_o$. Note that when you are adding a bias vector to a matrix, it is added to every single row in the matrix, which is called *broadcasting*.

6. To classify email into spam or ham, you just need one neuron in the output layer of a neural network—for example, indicating the probability that the email is spam. You would typically use the logistic activation function in the output layer when estimating a probability. If instead you want to tackle MNIST, you need 10 neurons in the output layer, and you must replace the logistic function with the softmax activation function, which can handle multiple classes, outputting one probability per class. Now, if you want your neural network to predict housing prices like in Chapter 2, then you need one output neuron, using no activation function at all in the output layer.[4]
7. Backpropagation is a technique used to train artificial neural networks. It first computes the gradients of the cost function with regards to every model parameter (all the weights and biases), and then it performs a Gradient Descent step using these gradients. This backpropagation step is typically performed thousands or millions of times, using many training batches, until the model parameters converge to values that (hopefully) minimize the cost function. To compute the gradients, backpropagation uses reverse-mode autodiff (although it wasn't called that when backpropagation was invented, and it has been reinvented several times). Reverse-mode autodiff performs a forward pass through a computation graph, computing every node's value for the current training batch, and then it performs a reverse pass, computing all the gradients at once (see Appendix D for more details). So what's the difference? Well, backpropagation refers to the whole process of training an artificial neural network using multiple backpropagation steps, each of which computes gradients and uses them to perform a Gradient Descent step. In contrast, reverse-mode autodiff is a simply a technique to compute gradients efficiently, and it happens to be used by backpropagation.

4 When the values to predict can vary by many orders of magnitude, then you may want to predict the logarithm of the target value rather than the target value directly. Simply computing the exponential of the neural network's output will give you the estimated value (since $\exp(\log v) = v$).

8. Here is a list of all the hyperparameters you can tweak in a basic MLP: the number of hidden layers, the number of neurons in each hidden layer, and the activation function used in each hidden layer and in the output layer.[5] In general, the ReLU activation function (or one of its variants; see Chapter 11) is a good default for the hidden layers. For the output layer, in general you will want the logistic activation function for binary classification, the softmax activation function for multiclass classification, or no activation function for regression.

   If the MLP overfits the training data, you can try reducing the number of hidden layers and reducing the number of neurons per hidden layer.

9. See the Jupyter notebooks available at *https://github.com/ageron/handson-ml*.

Chapter 11: Training Deep Neural Nets

1. No, all weights should be sampled independently; they should not all have the same initial value. One important goal of sampling weights randomly is to break symmetries: if all the weights have the same initial value, even if that value is not zero, then symmetry is not broken (i.e., all neurons in a given layer are equivalent), and backpropagation will be unable to break it. Concretely, this means that all the neurons in any given layer will always have the same weights. It's like having just one neuron per layer, and much slower. It is virtually impossible for such a configuration to converge to a good solution.
2. It is perfectly fine to initialize the bias terms to zero. Some people like to initialize them just like weights, and that's okay too; it does not make much difference.
3. A few advantages of the ELU function over the ReLU function are:

   - It can take on negative values, so the average output of the neurons in any given layer is typically closer to 0 than when using the ReLU activation function (which never outputs negative values). This helps alleviate the vanishing gradients problem.
   - It always has a nonzero derivative, which avoids the dying units issue that can affect ReLU units.

5 In Chapter 11 we discuss many techniques that introduce additional hyperparameters: type of weight initialization, activation function hyperparameters (e.g., amount of leak in leaky ReLU), Gradient Clipping threshold, type of optimizer and its hyperparameters (e.g., the momentum hyperparameter when using a `MomentumOptimizer`), type of regularization for each layer, and the regularization hyperparameters (e.g., dropout rate when using dropout) and so on.