Slides and notebooks: `https://ml4ns.github.io`

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Lecture 6. Neural Networks

In lecture 6, we cover the basic concept behind the design and use of neural networks. In machine learning, we are interested in modelling biologically inspired networks known as artificial neural networks to help us solve learning and decision-making problems. Our previous lectures have focused on linear models; however, linearity implies the weaker assumption of monotonicity (i.e., that any increase in a feature will always result in an increase or decrease in the model's output). Such an assumption is not always true in real-world applications.

The simplest kind of neural network is a single-layer perceptron model, which consists of a single layer of output nodes to which the inputs are directly fed via a set of weights. In each node, the sum of the products of the inputs and their respective weights is calculated, and if the value exceeds a threshold, the neuron fires and takes the activated value. Otherwise, the neuron takes the deactivated value. Neurons with this type of activation function are also called artificial neurons or linear threshold units.

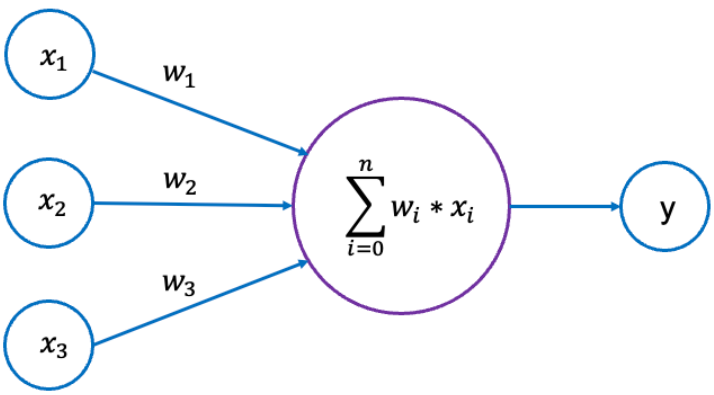

Figure 6.1. A simple illustration of an artificial neuron

Figure 6.1 illustrates a single artificial neuron (a type of single-layer perceptron that acts as a binary classifier).

In this lecture, we discuss how the limitations of linear models can be overcome by incorporating one or more hidden layers (with activation functions) into a neural network. We define network depth and width as the number of hidden layers and the number of nodes in the hidden layers, respectively. We also introduce two commonly used activation functions for adding nonlinearity to neural networks: the $sigmoid$ function and rectified linear units (ReLU). Networks with multiple layers of computational units are known as multi-layer perceptrons (MLPs).

Figure 6.2 illustrates the architecture of a fully connected, feed-forward multilayer perceptron.

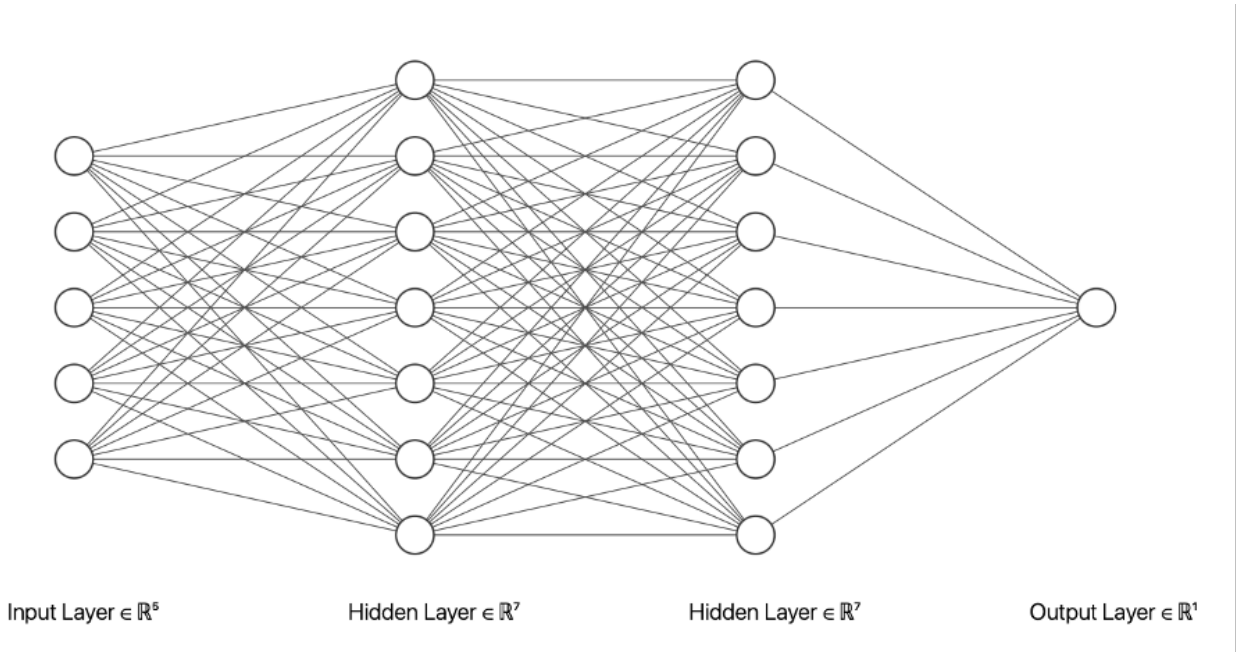

Figure 6.2. A sample multilayer perceptron architecture
Created using: https://alexlenail.me/NN-SVG/

MLPs are often interconnected in a feed-forward way, which is where the connections between nodes do not form a cycle as in recurrent neural networks (RNNs).

We further expand on how we train feed-forward neural networks using forward propagation and backpropagation. Finally, we consider how to design our neural networks, including selecting an appropriate number of hidden layers and a suitable learning rate. We also introduce and explain the objective of different adaptive learning rate optimisation algorithms.

The tutorial aims to build your familiarity with the machine learning framework $PyTorch$ and will also demonstrate the basics of building and training simple neural networks.