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# Chapter 1

## 1.1

### 1.1.1 Estimating class probabilities in multiclass classification via the softmax function

The softmax function is a soft form of the argmax function; instead of giving a single class index, it provides the probability of each class. Therefore, it allows us to compute meaningful class probabilities in multiclass settings (multinomial logistic regression).

In softmax, the probability of a particular sample with net input  $z$  belonging to the  $i$ th class can be computed with a normalization term in the denominator, that is, the sum of the exponentially weighted linear functions:

$$p(z) = \sigma(z) = \frac{e^{z_i}}{\sum_{j=1}^M e^{z_j}} \quad (1.1)$$

### 1.1.2 Broadening the output spectrum using a hyperbolic tangent

Another sigmoidal function that is often used in the hidden layers of artificial NNs is the hyperbolic tangent (commonly known as tanh), which can be interpreted as a rescaled version of the logistic function:

$$\begin{aligned} \sigma_{\text{logistic}}(z) &= \frac{1}{1 + e^{-z}} \\ \sigma_{\text{tanh}}(z) &= 2 \times \sigma_{\text{logistic}}(2z) - 1 = \frac{e^z - e^{-z}}{e^z + e^{-z}} \end{aligned} \quad (1.2)$$

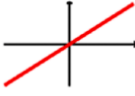
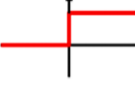
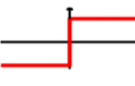




Activation function	Equation	Example	1D graph
Linear	$\sigma(z) = z$	Adaline, linear regression	
Unit step (Heaviside function)	$\sigma(z) = \begin{cases} 0 & z < 0 \\ 0.5 & z = 0 \\ 1 & z > 0 \end{cases}$	Perceptron variant	
Sign (signum)	$\sigma(z) = \begin{cases} -1 & z < 0 \\ 0 & z = 0 \\ 1 & z > 0 \end{cases}$	Perceptron variant	
Piece-wise linear	$\sigma(z) = \begin{cases} 0 & z \leq -\frac{1}{2} \\ z + \frac{1}{2} & -\frac{1}{2} \leq z \leq \frac{1}{2} \\ 1 & z \geq \frac{1}{2} \end{cases}$	Support vector machine	
Logistic (sigmoid)	$\sigma(z) = \frac{1}{1 + e^{-z}}$	Logistic regression, multilayer NN	
Hyperbolic tangent (tanh)	$\sigma(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	Multilayer NN, RNNs	
ReLU	$\sigma(z) = \begin{cases} 0 & z < 0 \\ z & z > 0 \end{cases}$	Multilayer NN, CNNs	

图 1.1: The activation functions covered

The advantage of the hyperbolic tangent over the logistic function is that it has a broader output spectrum ranging in the open interval  $(-1, 1)$ , which can improve the convergence of the backpropagation algorithm.

Note that using `torch.sigmoid(x)` produces results that are equivalent to `torch.nn.Sigmoid()(x)`. `torch.nn.Sigmoid` is a class to which you can pass in parameters to construct an object in order to control the behavior. In contrast, `torch.sigmoid` is a function.

## Chapter 2

# Classifying Images with Deep Convolutional Neural Networks

### 2.1 The building blocks of CNNs

#### 2.1.1 Discrete convolutions in one dimension

##### Determining the size of the convolution output

The output size of a convolution is determined by the total number of times that we shift the filter,  $\mathbf{w}$ , along the input vector. Let's assume that the input vector is of size  $n$  and the filter is of size  $m$ . Then, the size of the output resulting from  $\mathbf{y} = \mathbf{x} * \mathbf{w}$ , with padding  $p$  and stride  $s$ , would be determined as follows:

$$o = \left\lfloor \frac{n + 2p - m}{s} \right\rfloor + 1 \quad (2.1)$$