

# EE-559 – Deep learning

## 3.4. Multi-Layer Perceptrons

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So far we have seen linear classifiers of the form

$$\begin{aligned}\mathbb{R}^D &\rightarrow \mathbb{R} \\ x &\mapsto \sigma(w \cdot x + b),\end{aligned}$$

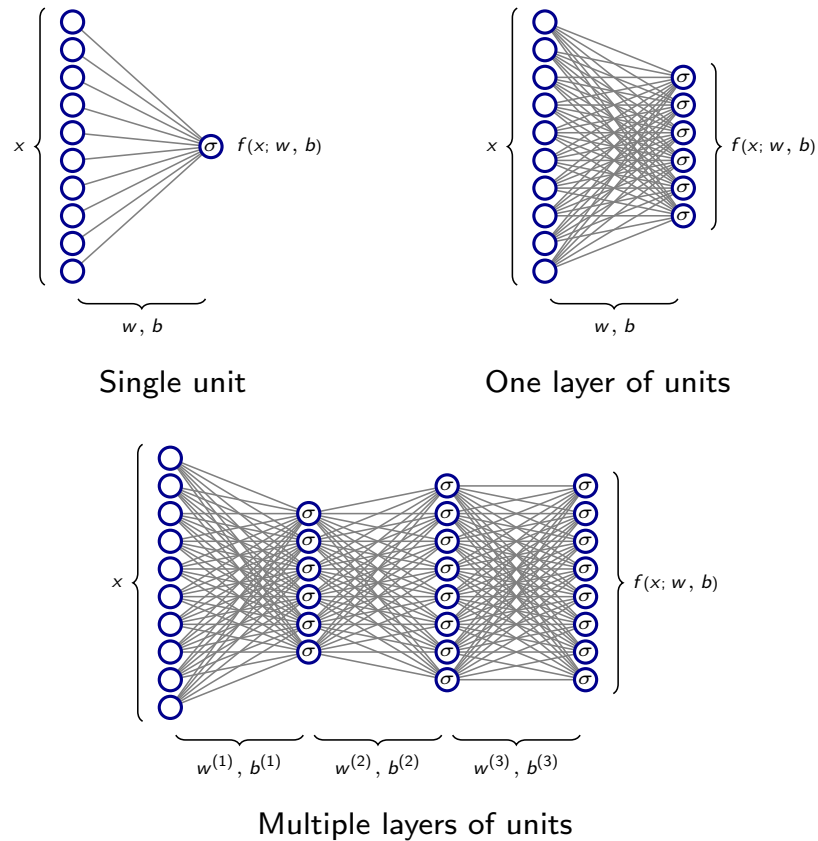
with  $w \in \mathbb{R}^D$ ,  $b \in \mathbb{R}$ , and  $\sigma : \mathbb{R} \rightarrow \mathbb{R}$ .

This can naturally be extended to a multi-dimension output by applying a similar transformation to every output, which leads to

$$\begin{aligned}\mathbb{R}^D &\rightarrow \mathbb{R}^C \\ x &\mapsto \sigma(wx + b),\end{aligned}$$

with  $w \in \mathbb{R}^{C \times D}$ ,  $b \in \mathbb{R}^C$ , and  $\sigma$  is applied component-wise.

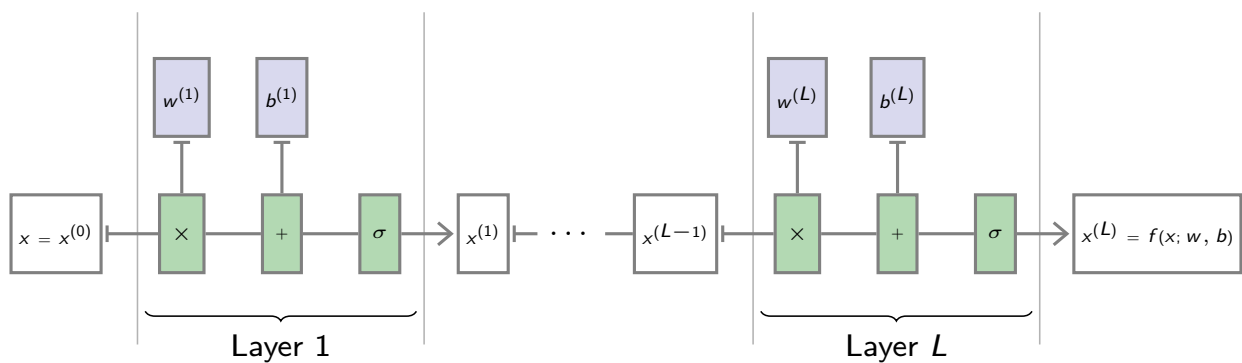
Even though it has no practical value implementation-wise, we can represent such a model as a combination of units, and extend it.



This latter structure can be formally defined, with  $x^{(0)} = x$ ,

$$\forall l = 1, \dots, L, x^{(l)} = \sigma \left( w^{(l)} x^{(l-1)} + b^{(l)} \right)$$


and  $f(x; w, b) = x^{(L)}$ .



Such a model is a **Multi-Layer Perceptron (MLP)**.

Note that if  $\sigma$  is an affine transformation, the full MLP is a composition of affine mappings, and itself an affine mapping.

Consequently:

 **The activation function  $\sigma$  should be non-linear**, or the resulting MLP is an affine mapping with a peculiar parametrization.

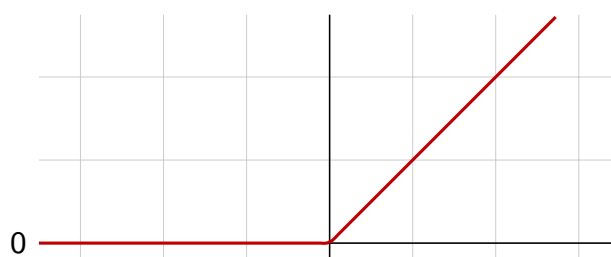
The two classical activation functions are the hyperbolic tangent

$$x \mapsto \frac{2}{1 + e^{-2x}} - 1$$



and the rectified linear unit (ReLU)

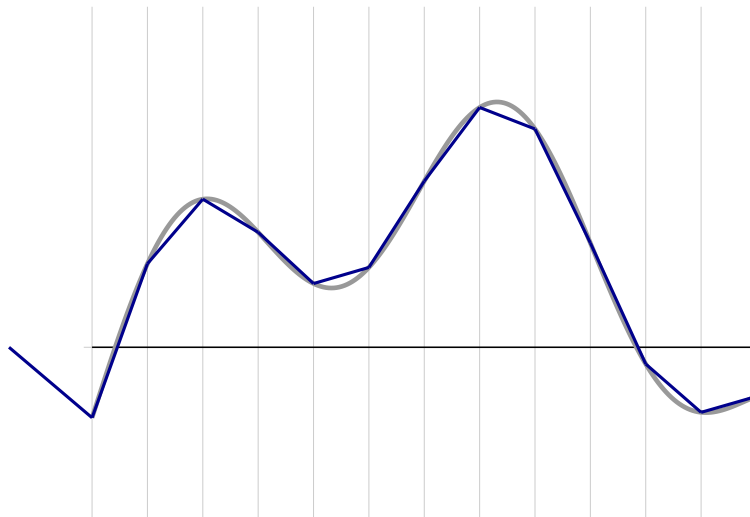
$$x \mapsto \max(0, x)$$



## Universal approximation

We can approximate any  $\psi \in \mathcal{C}([a, b], \mathbb{R})$  with a linear combination of translated/scaled ReLU functions.

$$f(x) = \sigma(w_1x + b_1) + \sigma(w_2x + b_2) + \sigma(w_3x + b_3) + \dots$$



This is true for other activation functions under mild assumptions.

Extending this result to any  $\psi \in \mathcal{C}([0, 1]^D, \mathbb{R})$  requires a bit of work.

First, we can use the previous result for the sin function

$$\forall A > 0, \epsilon > 0, \exists N, (\alpha_n, a_n) \in \mathbb{R} \times \mathbb{R}, n = 1, \dots, N,$$

$$\text{s.t. } \max_{x \in [-A, A]} \left| \sin(x) - \sum_{n=1}^N \alpha_n \sigma(x - a_n) \right| \leq \epsilon.$$

And the density of Fourier series provides

$$\forall \psi \in \mathcal{C}([0, 1]^D, \mathbb{R}), \delta > 0, \exists M, (v_m, \gamma_m, c_m) \in \mathbb{R}^D \times \mathbb{R} \times \mathbb{R}, m = 1, \dots, M,$$

$$\text{s.t. } \max_{x \in [0, 1]^D} \left| \psi(x) - \sum_{m=1}^M \gamma_m \sin(v_m \cdot x + c_m) \right| \leq \delta.$$

So,  $\forall \xi > 0$ , with

$$\delta = \frac{\xi}{2}, A = \max_{1 \leq m \leq M} \max_{x \in [0, 1]^D} |v_m \cdot x + c_m|, \text{ and } \epsilon = \frac{\xi}{2 \sum_m |\gamma_m|}$$

we get,  $\forall x \in [0, 1]^D$ ,

$$\left| \psi(x) - \sum_{m=1}^M \gamma_m \left( \sum_{n=1}^N \alpha_n \sigma(v_m \cdot x + c_m - a_n) \right) \right|$$

$$\leq \underbrace{\left| \psi(x) - \sum_{m=1}^M \gamma_m \sin(v_m \cdot x + c_m) \right|}_{\leq \frac{\xi}{2}}$$

$$+ \underbrace{\sum_{m=1}^M |\gamma_m| \left| \sin(v_m \cdot x + c_m) - \sum_{n=1}^N \alpha_n \sigma(v_m \cdot x + c_m - a_n) \right|}_{\leq \frac{\xi}{2 \sum_m |\gamma_m|}}$$

$$\leq \frac{\xi}{2}$$

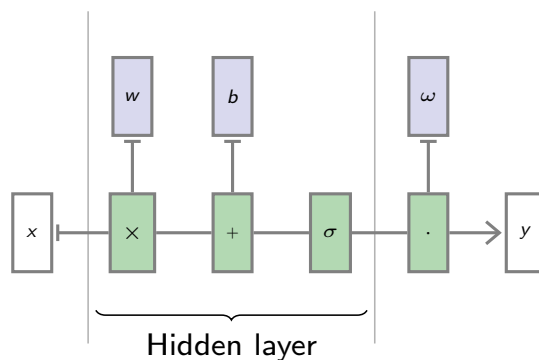
So we can approximate any continuous function

$$\psi : [0, 1]^D \rightarrow \mathbb{R}$$

with a one hidden layer perceptron

$$x \mapsto \omega \cdot \sigma(wx + b),$$

where  $b \in \mathbb{R}^K$ ,  $w \in \mathbb{R}^{K \times D}$ , and  $\omega \in \mathbb{R}^K$ .



This is the **universal approximation theorem**.



A better approximation requires a larger hidden layer (larger  $K$ ), and this theorem says nothing about the relation between the two.