Deep learning

3.4. Multi-Layer Perceptrons

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A linear classifier of the form

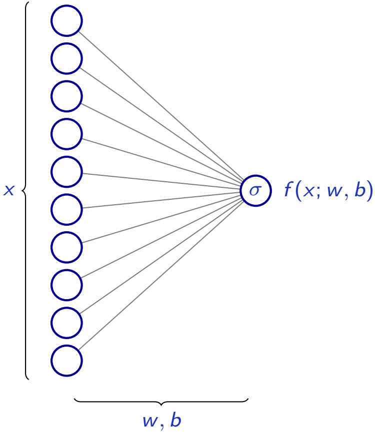
$$\begin{aligned} \mathbb{R}^D &\to \mathbb{R} \\ x &\mapsto \sigma(w \cdot x + b), \end{aligned}$$

with $w \in \mathbb{R}^D$, $b \in \mathbb{R}$, and $\sigma : \mathbb{R} \to \mathbb{R}$, can naturally be extended to a multi-dimension output by applying a similar transformation to every output

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

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

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



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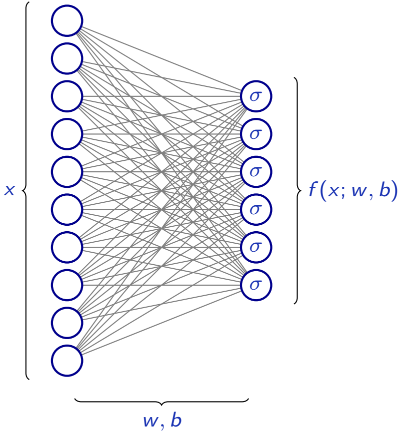

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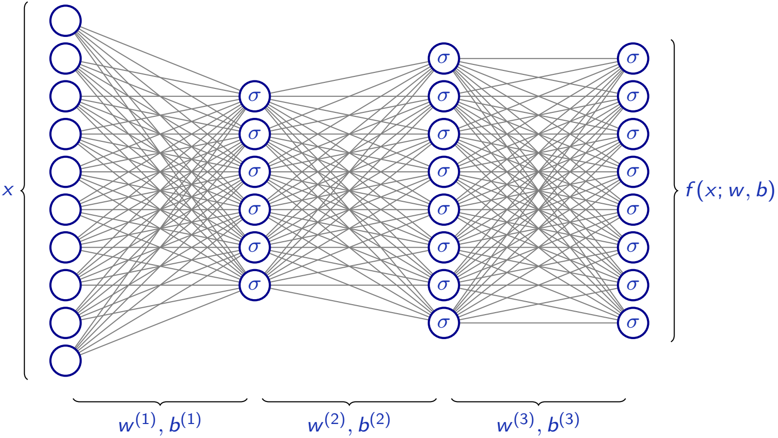

This latter structure can be formally defined, with $x^{(0)} = x$,

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

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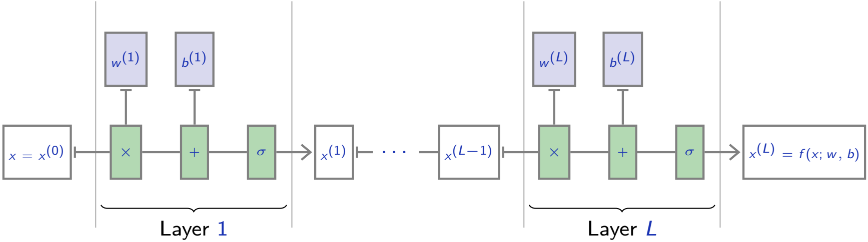

Such a model is a **Multi-Layer Perceptron (MLP).**

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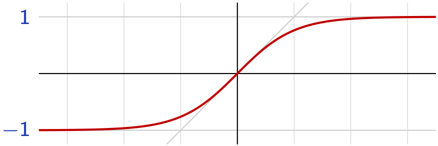
Consequently:

The activation function σ should not be affine. Otherwise the resulting MLP would be an affine mapping with a peculiar parametrization.

The two classical activation functions are the hyperbolic tangent

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



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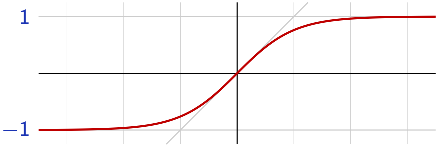
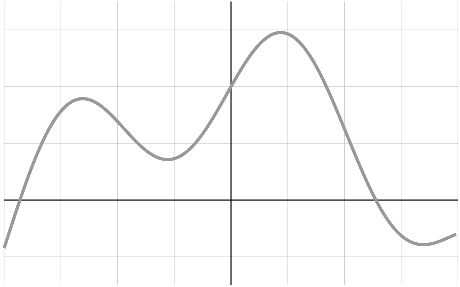


and the rectified linear unit (ReLU, Glorot et al., 2011)

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

Universal approximation

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



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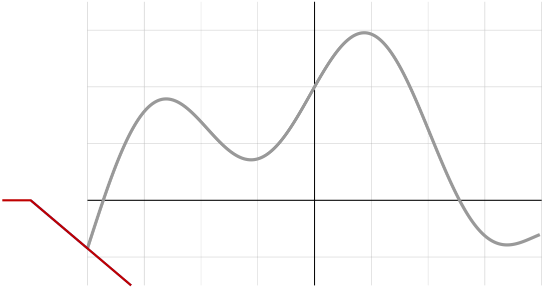

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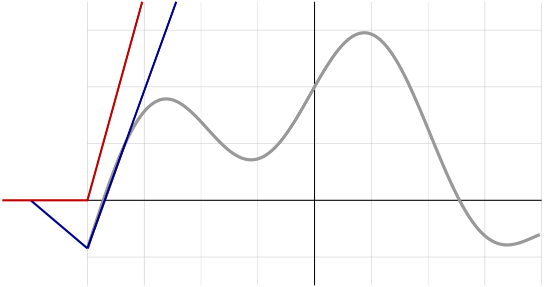

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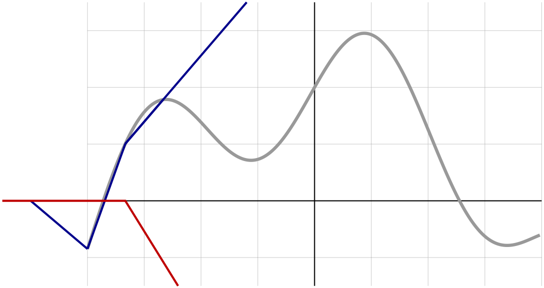

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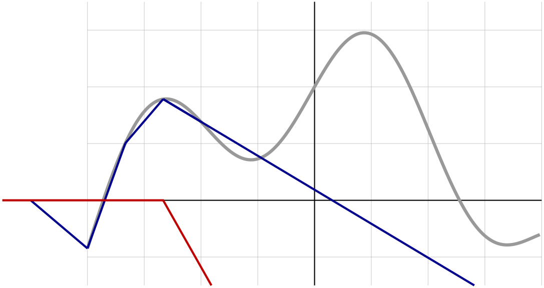

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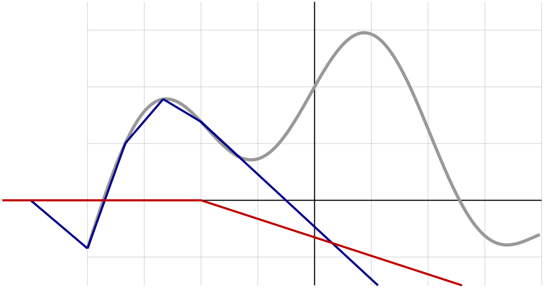

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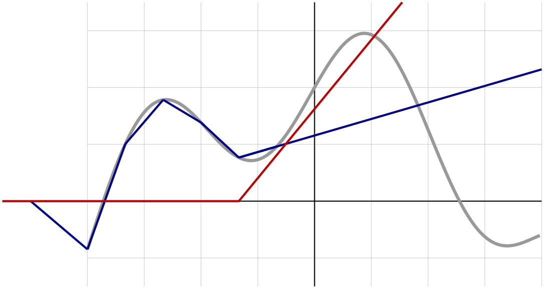

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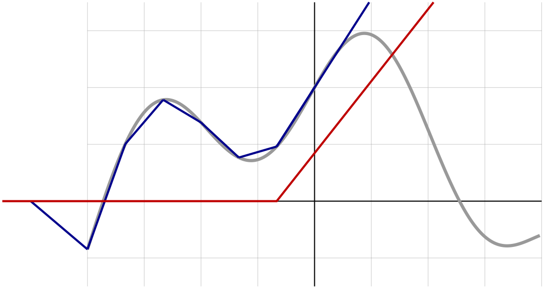

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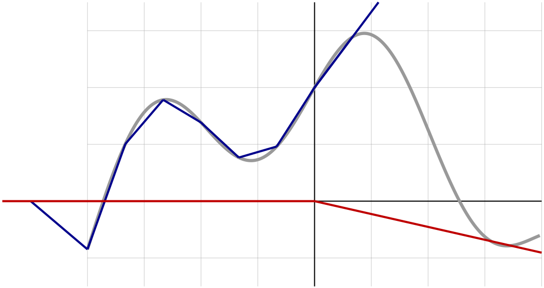

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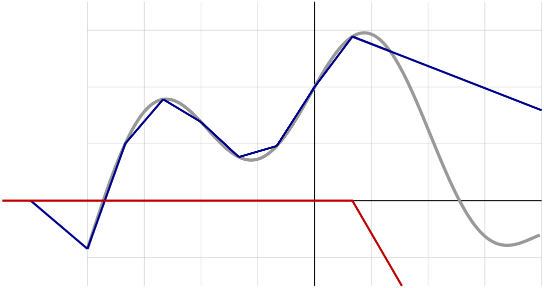

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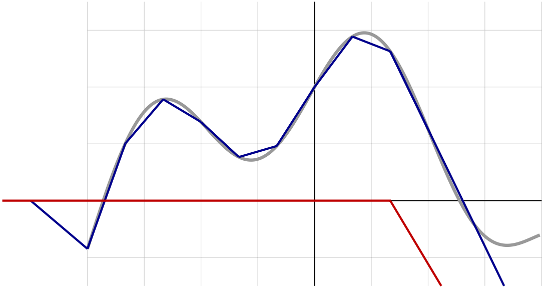

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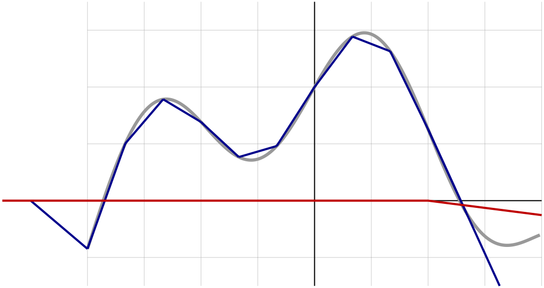

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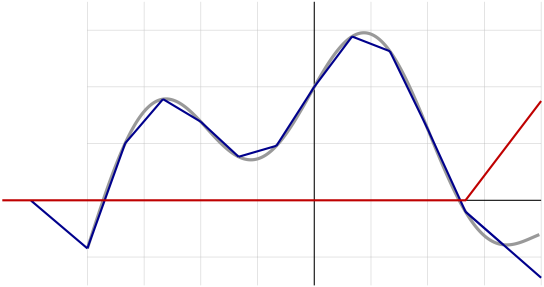

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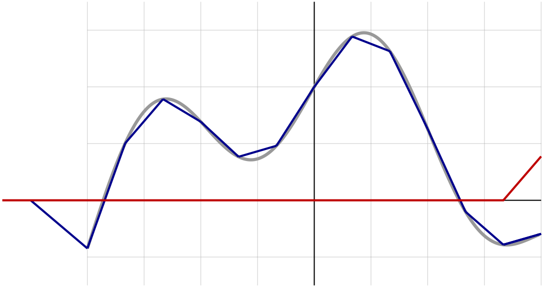

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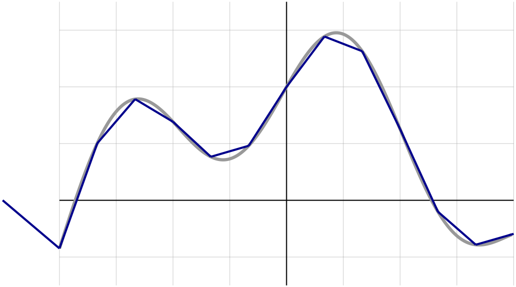

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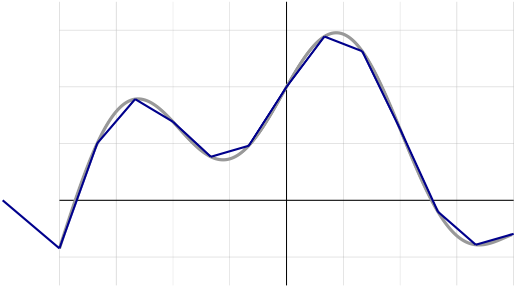


This is true for other activation functions under mild assumptions.

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

We can approximate the sin function with the previous scheme, and use the density of Fourier series to get the final result:

$$\forall \epsilon > 0, \exists K, w \in \mathbb{R}^{K \times D}, b \in \mathbb{R}^K, \omega \in \mathbb{R}^K, \text{ s.t.}$$
$$\max_{x \in [0,1]^D} |\psi(x) - \omega \cdot \sigma(w\,x + b)| \leq \epsilon.$$

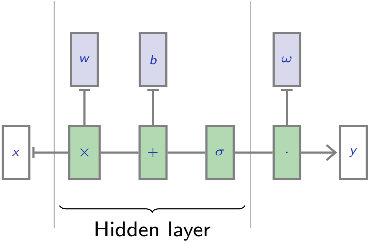
So we can approximate any continuous function

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

with a one hidden layer perceptron

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

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



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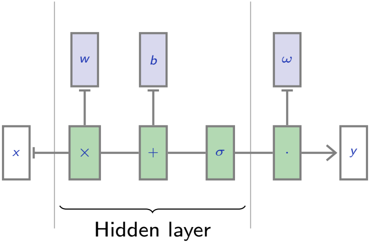

This is the **universal approximation theorem.**

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

So this results states that we can make the **training error** as low as we want by using a larger hidden layer. It states nothing about the **test error**.

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Deploying MLP in practice is often a balancing act between under-fitting and over-fitting.

The end

References

X. Glorot, A. Bordes, and Y. Bengio. **Deep sparse rectifier neural networks**. In International Conference on Artificial Intelligence and Statistics (AISTATS), 2011.