Deep Learning

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FAST DISCOVERING THE FUTURE

Activation functions

1. Sigmoid: $\sigma(x) = \dfrac{1}{1 + e^{-x}}$

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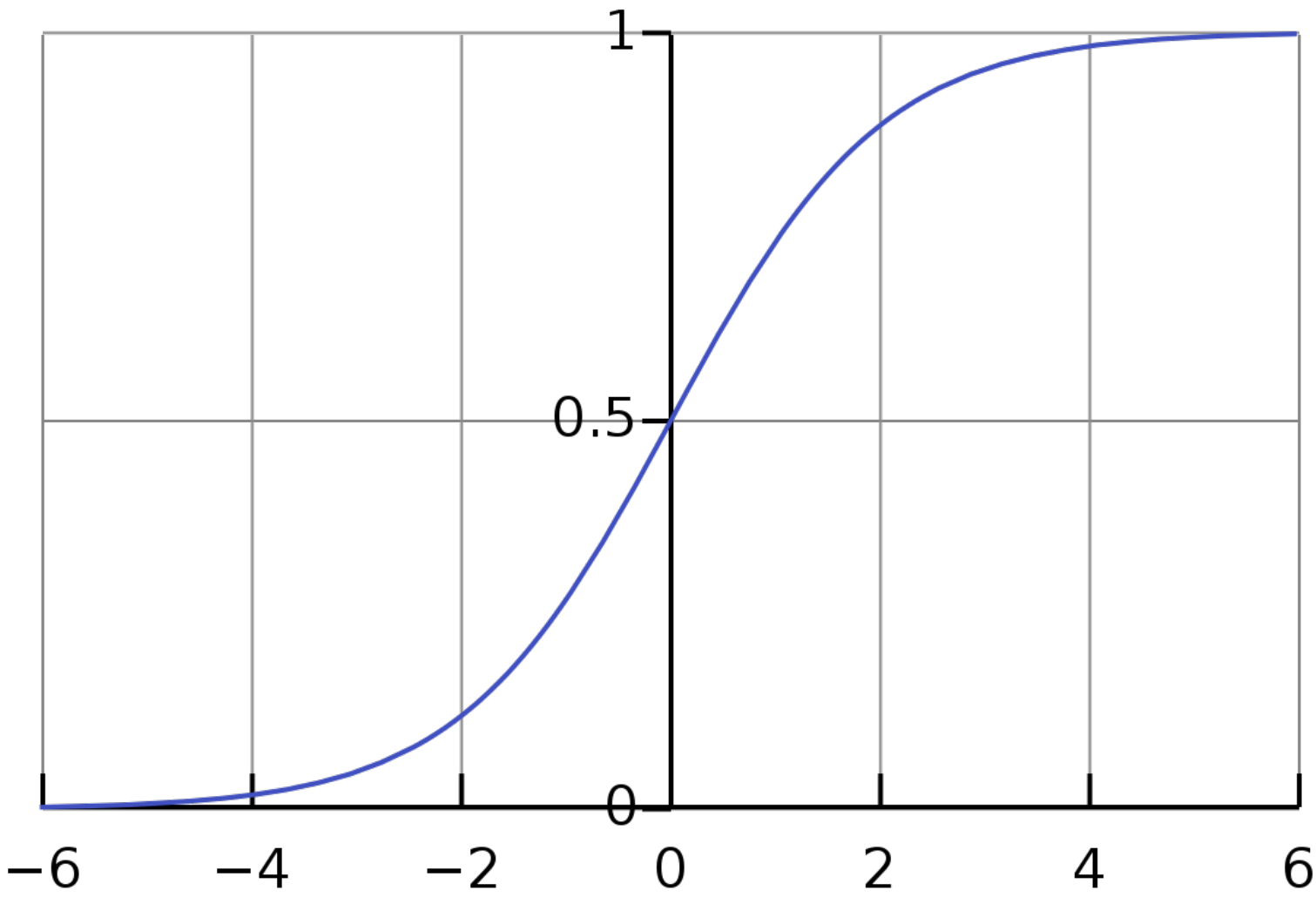

Activation functions

2. Tanh: $\tanh(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}}$

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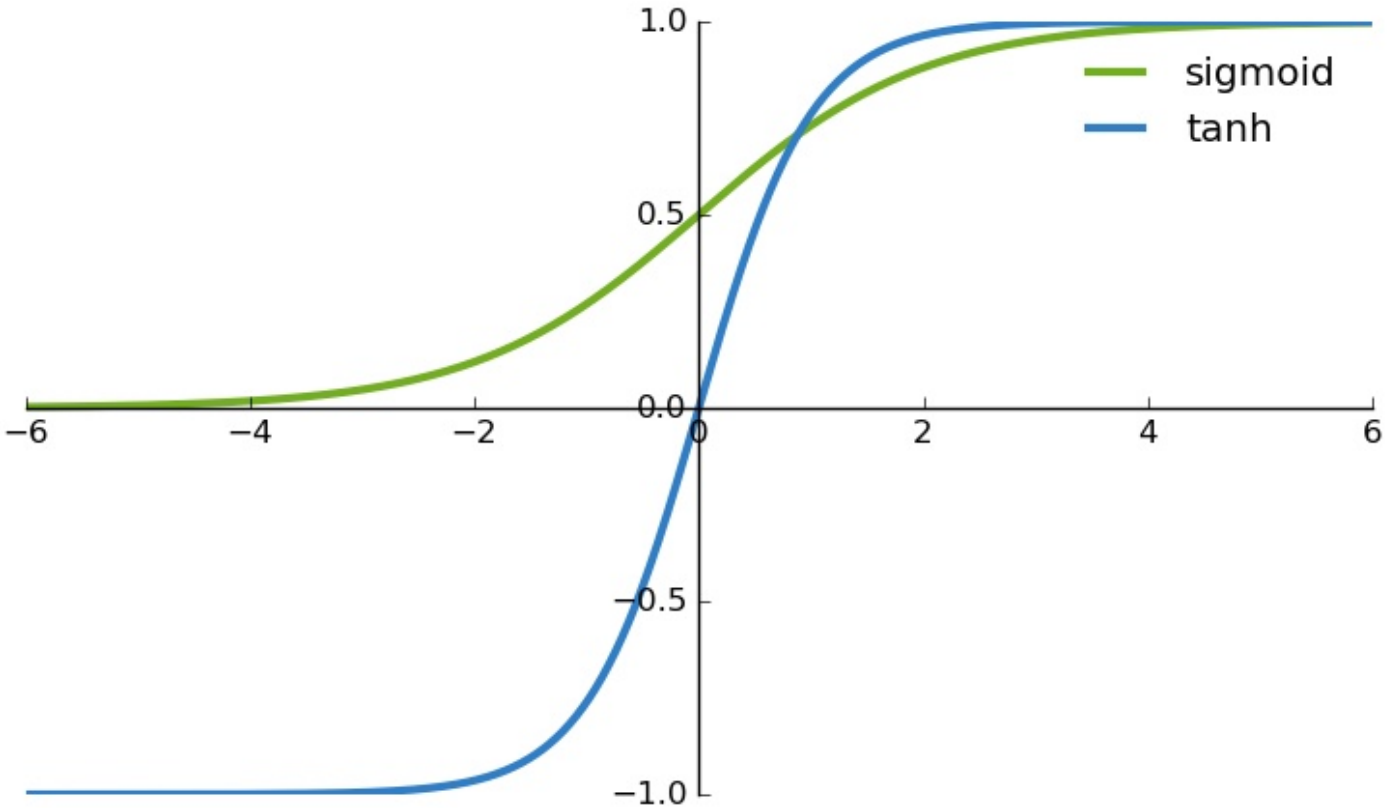

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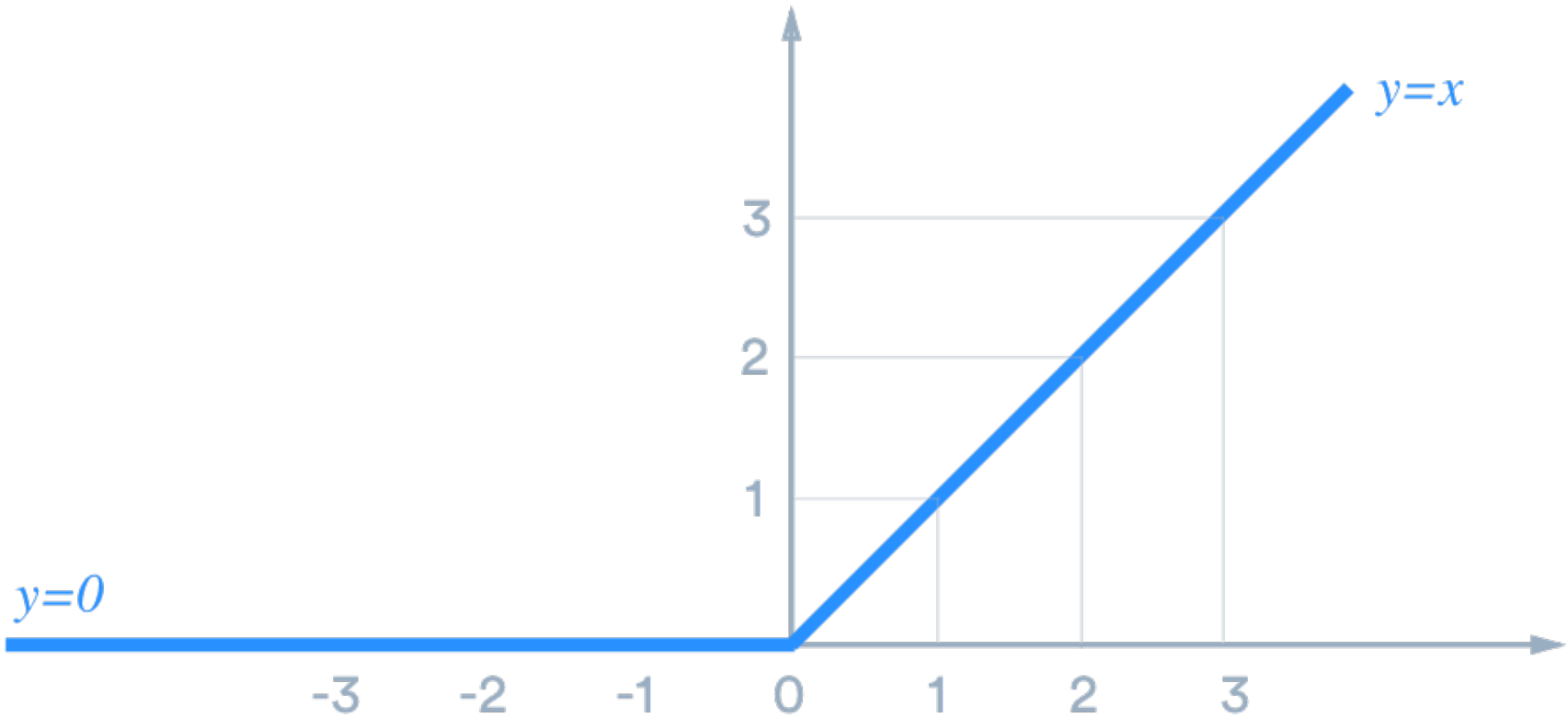

Activation functions

4. Leaky ReLU: $LR(x) = \begin{cases} 0.01x, & \text{for } x < 0 \\ x, & \text{for } x \geq 0 \end{cases}$

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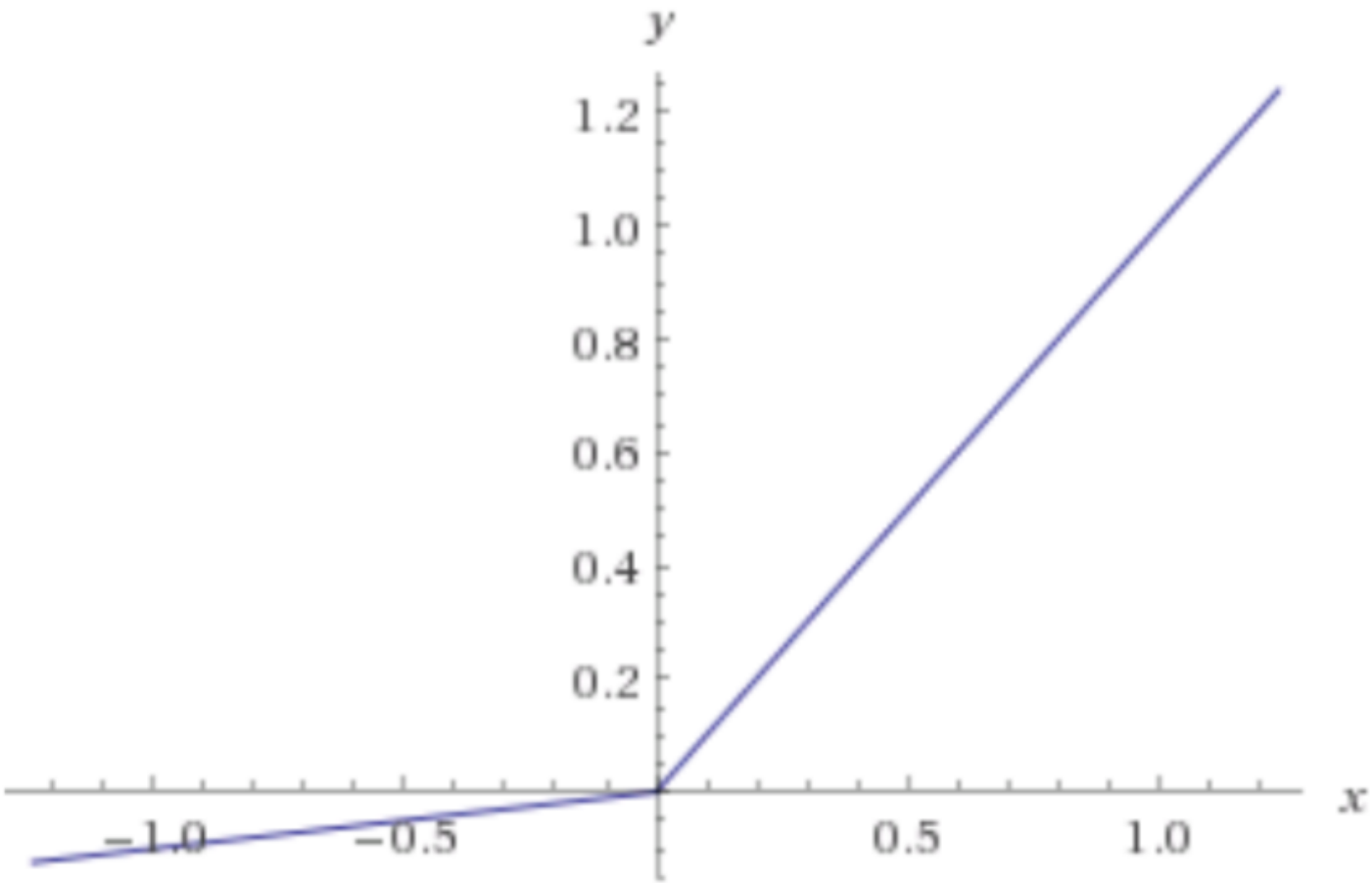

Activation functions

5. Parametric ReLU: $PR(x) = \begin{cases} ax, & \text{for } x < 0 \\ x, & \text{for } x \geq 0 \end{cases}$

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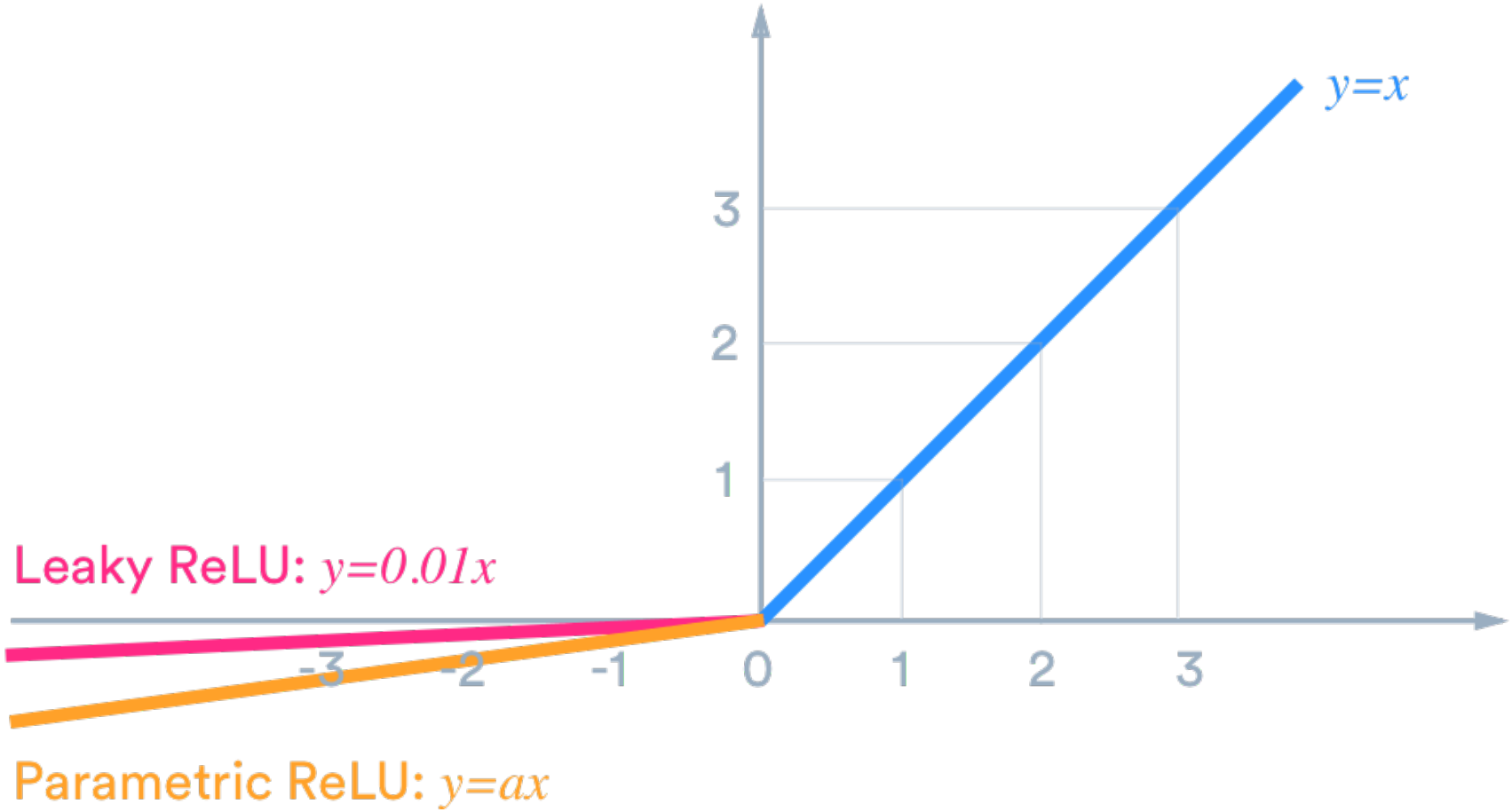

Activation functions

6. Exponential linear unit: $ELU(x) = \begin{cases} a(e^x - 1), & \text{for } x < 0 \\ x, & \text{for } x \geq 0 \end{cases}$

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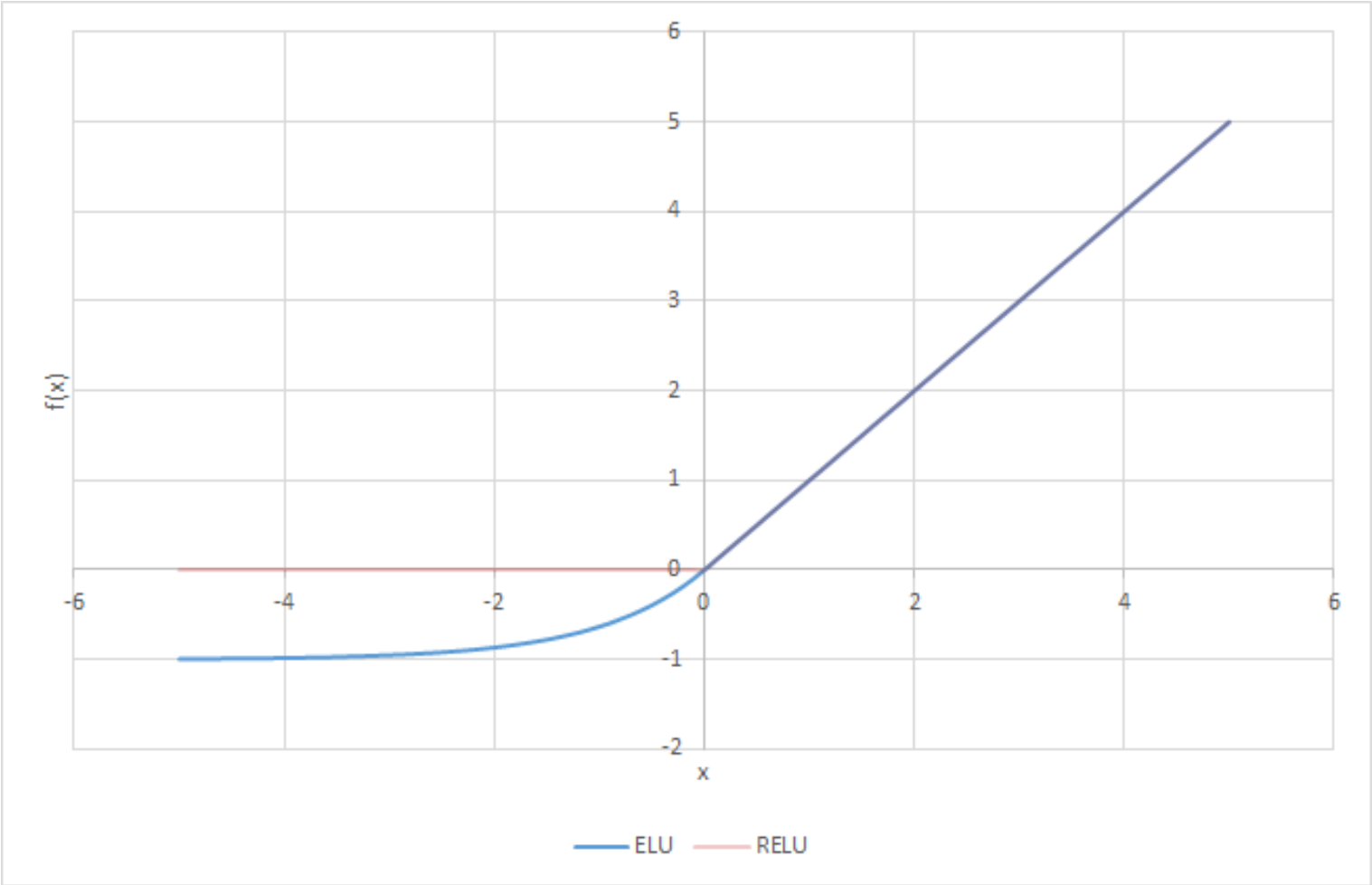

Activation functions

7. SoftPlus: $SP(x) = \log(1 + e^x)$

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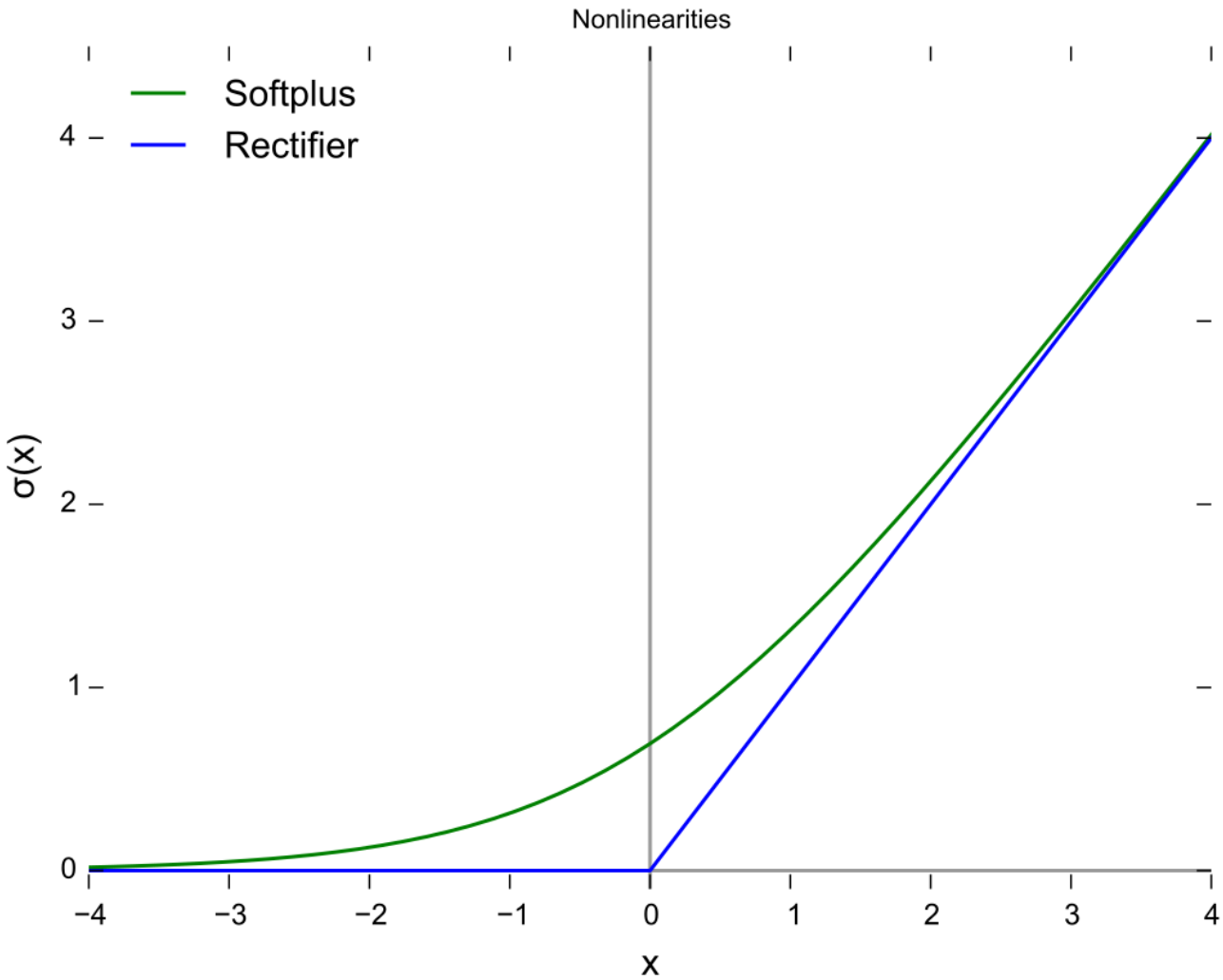

Activation functions

8. Softmax: $S\left(x_1, x_2, \ldots, x_n\right) = \left(\frac{e^{x_1}}{\sum_{i=1}^{n} e^{x_i}}, \frac{e^{x_2}}{\sum_{i=1}^{n} e^{x_i}}, \ldots, \frac{e^{x_n}}{\sum_{i=1}^{n} e^{x_i}} \right)$

Questions

1. Why do we need activation functions?

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2. How should we define activation functions, for a layer or for a neuron?

Outline

Gradient Descent

Let $f : \mathbb{R}^k \to \mathbb{R}$ be a convex function and we want to find its global minimum.

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Let $f : \mathbb{R}^k \to \mathbb{R}$ be a convex function and we want to find its global minimum. This optimization algorithm is based on the fact that the fastest decreasing direction of the function is the opposite direction of gradient:

$$x_{n+1} = x_n - \alpha \nabla f(x_n)$$

and $x_0 \in \mathbb{R}^k$ is a arbitrary point.

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Linear Regression

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We choose L^2 distance as our loss function:

$$\frac{1}{n} \sum_{l=1}^{n} \left(f(x_l) - y_l\right)^2.$$

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2. Can you represent this model as a neural network?