



PERCEPTRONS AND MULTILAYER PERCEPTRONS

BE CAREFUL OF THE VANISHING GRADIENT !!

Vincent Barra

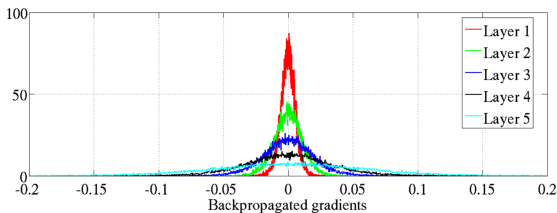
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Problem statement

When L increases, small gradients tend to disappear

- Blocking gradient descent
- Limited capacity of learning



Backpropagated gradients normalized histograms (source: Glorot & Bengio, 2010)

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Let consider a 3-layer MLP without bias

$$f_{\mathbf{w}}(x) = \sigma [w_3 \sigma (w_2 (\sigma(w_1 x)))]$$

To apply the chain rule, the MLP computes

$$u_1 = w_1 x, \quad u_2 = \sigma(u_1), \quad u_3 = w_2 u_2, \quad u_4 = \sigma(u_3), \quad u_5 = w_3 u_4$$

and thus

$$\begin{aligned} \frac{df_{\mathbf{w}}(x)}{dw_1} &= \frac{\partial f_{\mathbf{w}}(x)}{\partial u_5} \frac{\partial u_5}{\partial u_4} \frac{\partial u_4}{\partial u_3} \frac{\partial u_3}{\partial u_2} \frac{\partial u_2}{\partial u_1} \frac{\partial u_1}{\partial w_1} \\ &= \frac{\partial \sigma(u_5)}{\partial u_5} w_3 \frac{\partial \sigma(u_3)}{\partial u_3} w_2 \frac{\partial \sigma(u_1)}{\partial u_1} x \end{aligned}$$

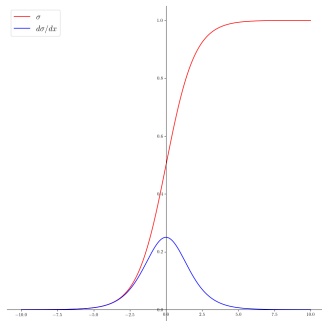
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$$\frac{df_{\mathbf{w}}(x)}{dw_1} = \frac{d\sigma(u_5)}{du_5} w_3 \frac{d\sigma(u_3)}{du_3} w_2 \frac{d\sigma(u_1)}{du_1} x$$

$$\text{But } 0 \leq \frac{d\sigma(z)}{dz} = \sigma(z)(1 - \sigma(z)) \leq \frac{1}{4}$$

So if $w_i \sim \mathcal{N}(0, \Sigma)$, $\Sigma < 1$ then with high probability $w_i \leq 1$ and

$$0 \leq \frac{df_{\mathbf{w}}(x)}{dw_1} \leq \frac{1}{4^3} x$$



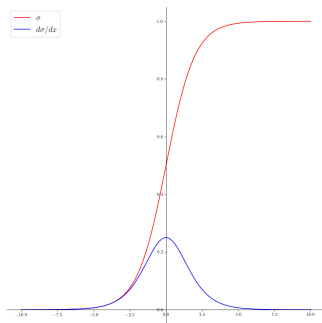
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→ $\frac{df_{\mathbf{w}}(x)}{dw_1} \rightarrow 0$ as L increases

→ True for almost all bounded activation functions (σ, \tanh, \dots)

→ Proper initialization scheme needed for the w_i