The vanishing gradient problem revisited: Highway and residual connections

THE UNIVERSITY OF UTAH

Revisiting the vanishing gradient problem

Stems from the fact that the derivative of the activation is between zero and one…

… and as the number steps of gradient computation grows, these get multiplied

Not just applicable for LSTMs

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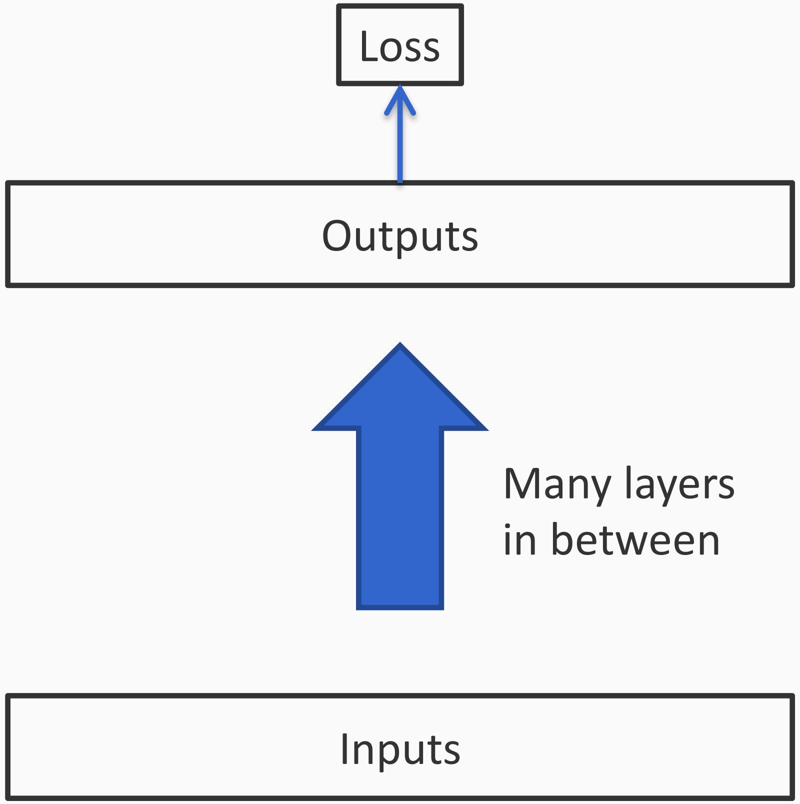

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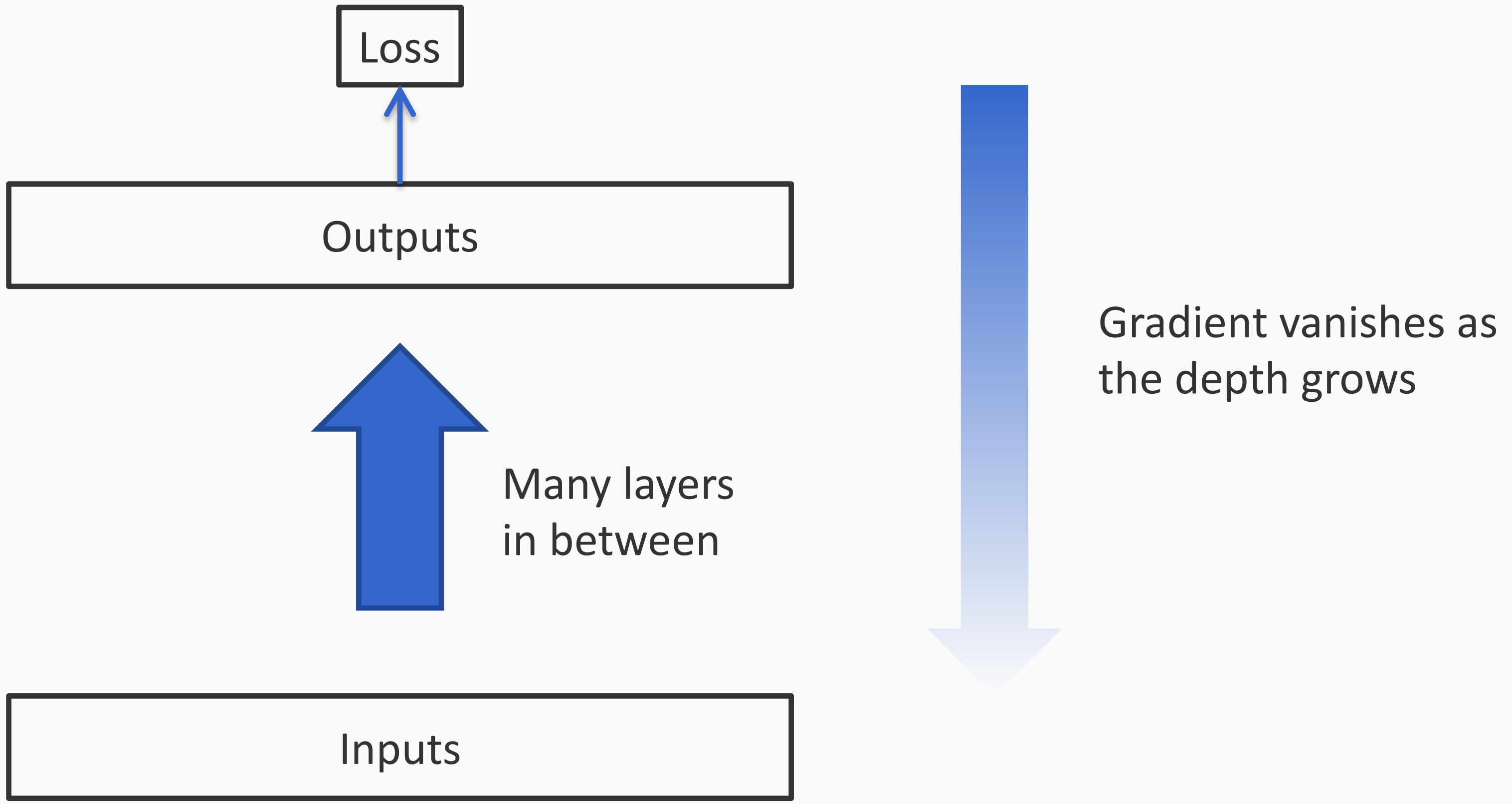

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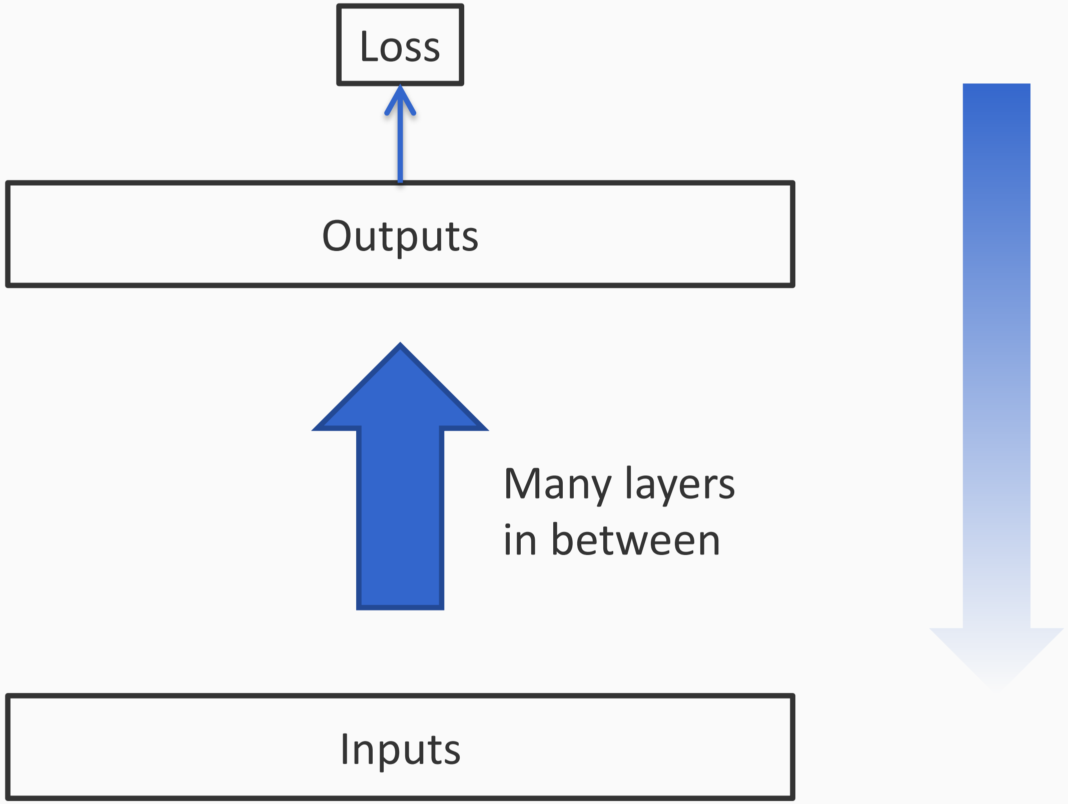

Gradient vanishes as the depth grows

The loss is no longer influenced by the inputs for very deep networks!

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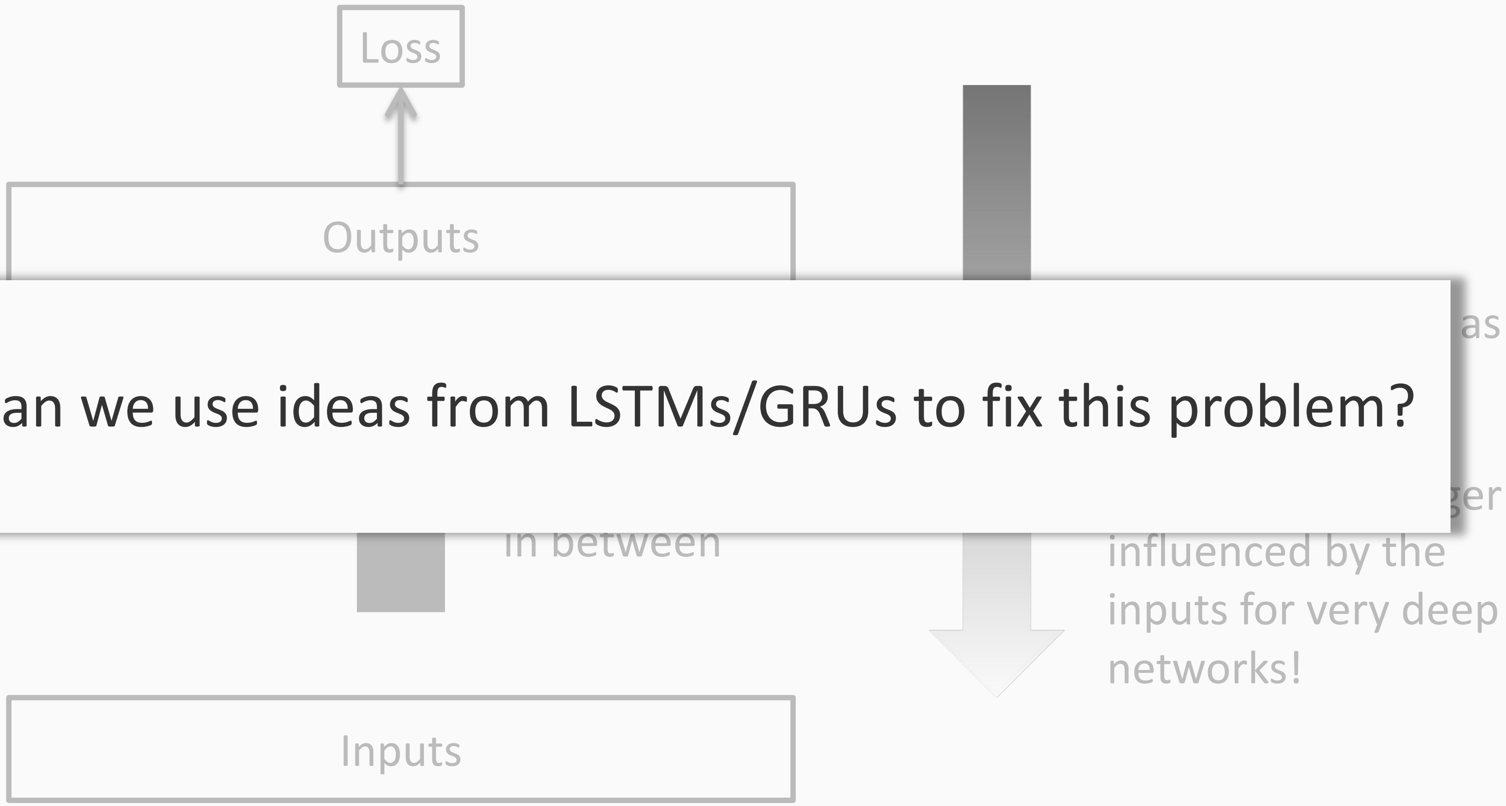

Can we use ideas from LSTMs/GRUs to fix this problem?

Revisiting the vanishing gradient problem

Intuition: Consider a single layer

$$\boldsymbol{l}^t = g(\boldsymbol{l}^{t-1}\mathbf{W} + \boldsymbol{b}^{t-1})$$

The t-1th layer is used to calculate the value of the tth layer

Revisiting the vanishing gradient problem

Intuition: Consider a single layer

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Instead of a non-linear update that directly
calculates the next layer, let us try a linear update

$$\boldsymbol{l}^t = \boldsymbol{l}^{t-1} + g(\boldsymbol{l}^{t-1}\mathbf{W} + \boldsymbol{b}^{t-1})$$

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The gradients can be propagated all the way to the input without attenuation

Residual networks

[He et al 2015]

Each layer is reformulated as

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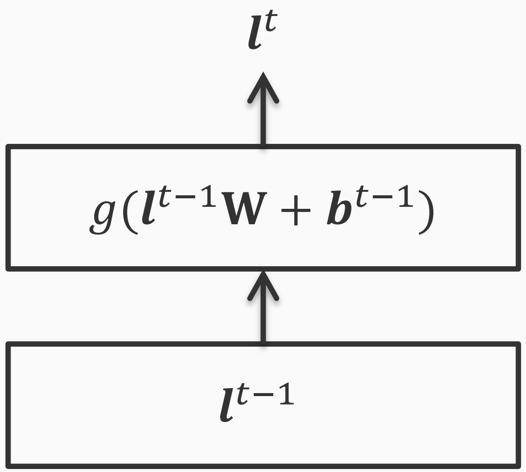

Original layer

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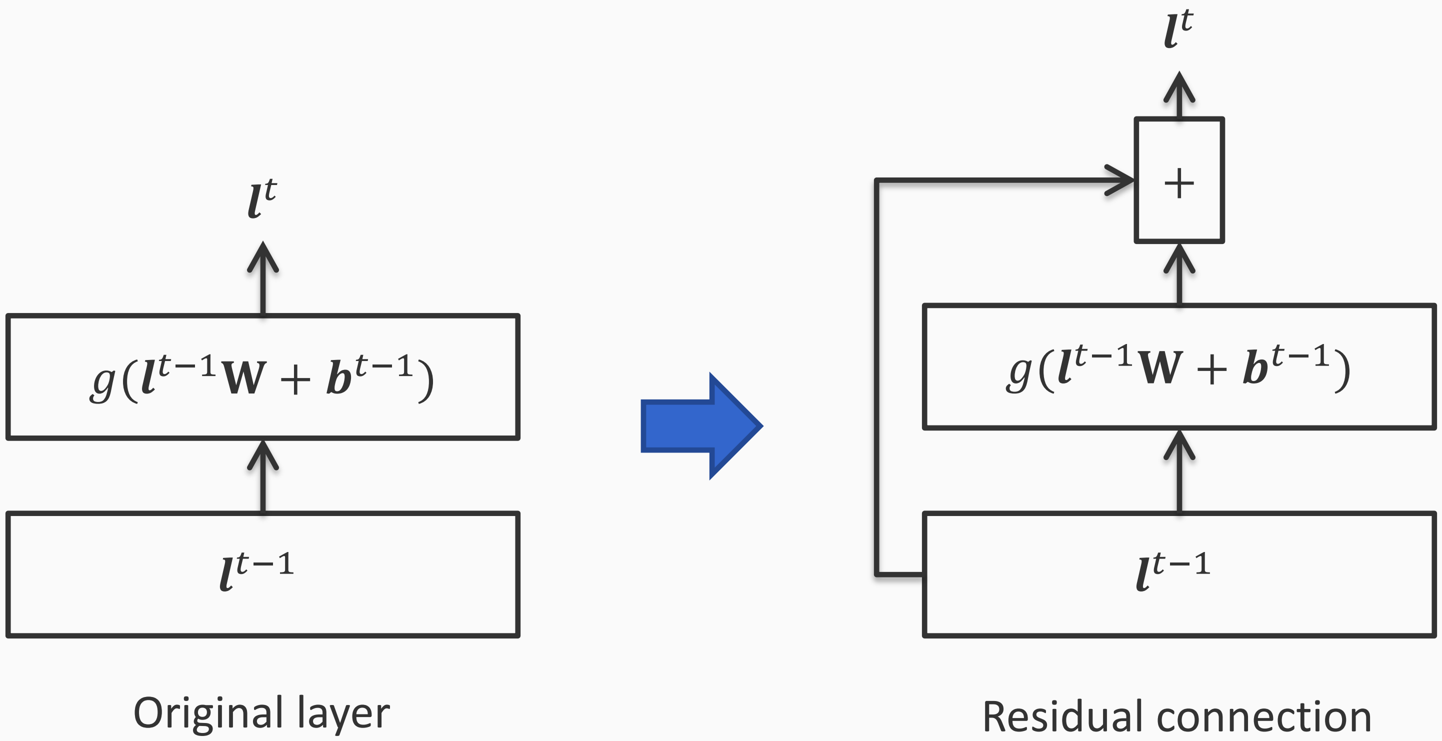

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The computation graph g is not trained to predict the next layer

It predicts an *update to* the current layer value instead

That is, it can be seen as a residual function (that is the difference between the layers)

Highway connections

[Srivastava et al 2015]

Extend the idea, using gates to stabilize learning

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- Finally, compute the actual value of the next layer

$$\boldsymbol{l}^t = (1 - \mathbf{T}) \odot \boldsymbol{l}^{t-1} + \mathbf{T} \odot \mathbf{C}$$

Why residual/highway connections?

- As networks become deeper, or as sequences get larger, we can no longer hope for gradients to be carried through the network

- If we want to capture long-range dependencies with the input, we need this mechanism

- More generally, a blueprint of an idea that can be combined with your neural network model if it gets too deep