Deep Learning

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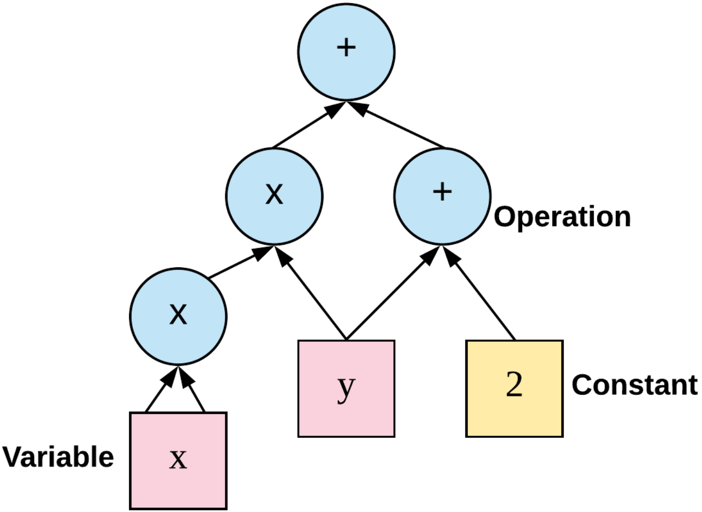
Computational Graphs



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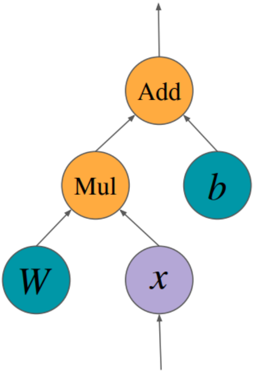
- Ops are functions on tensors.

Computational Graphs

$$\hat{y} = Wx + b$$

variable ops placeholder variable



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- Upon op execution, only the subgraph (required for calculating its value) is evaluated

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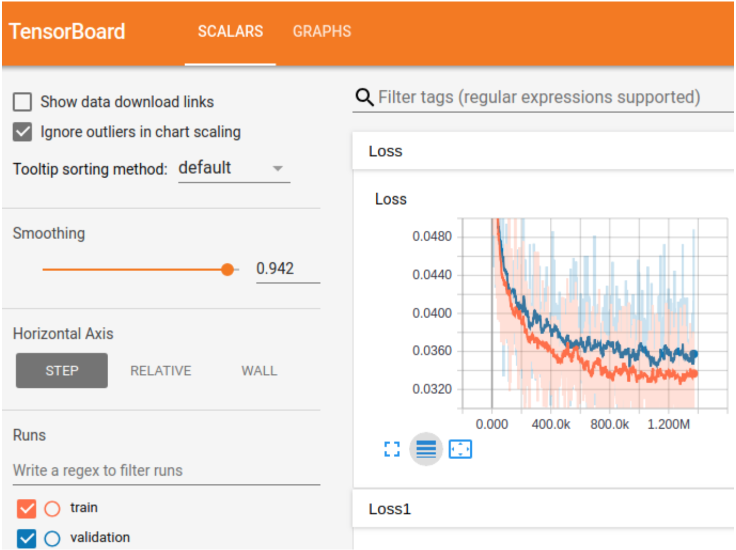
    - Run the optimizer over batches.

Tensorboard



Outline

1 Back-Propagation

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Theorem 1

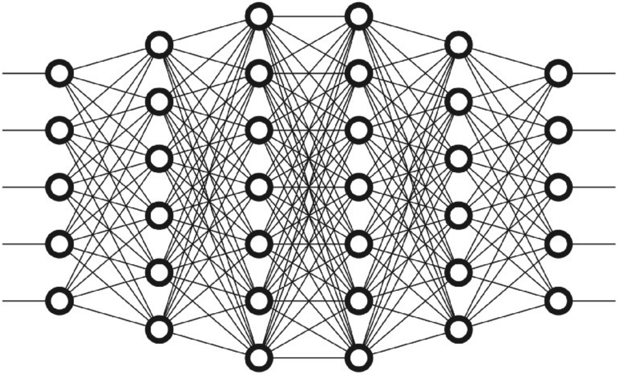
Given n functions $f_1, \dots, f_n$ with the composite function

$$f = f_1 \circ (f_2 \circ \cdots (f_{n-1} \circ f_n)),$$

if each function f_i is differentiable at its immediate input, then the composite function is also differentiable by the repeated application of Chain Rule, where the derivative is

$$\frac{df}{dx} = \frac{df_1}{df_2} \frac{df_2}{df_3} \cdots \frac{df_n}{dx}.$$

Back-Propagation



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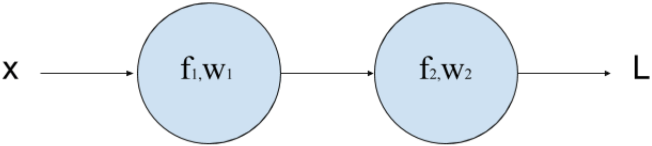

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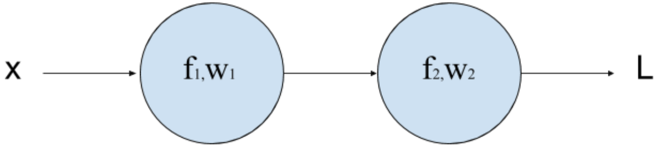
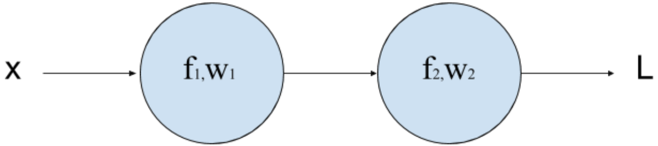


In this case we have the following function

$$L(w_1, w_2) = \left(f_2\left(w_2 f_1\left(w_1 x\right)\right) - y\right)^2$$



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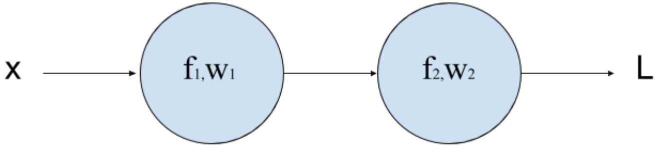

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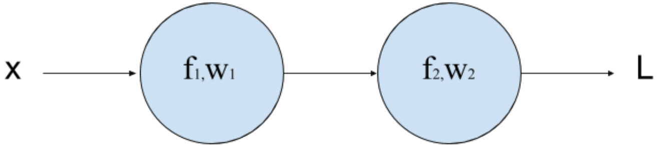

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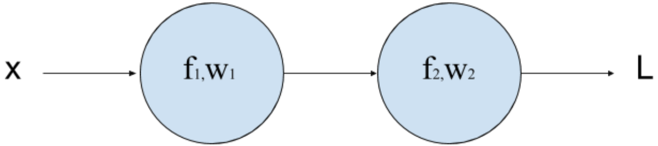

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