Deep Learning

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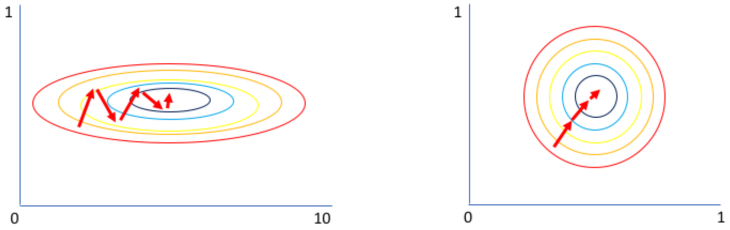
Outline

1. Data Normalization

2. Random Initialization

Data Normalization

Why normalize?



Gradient of larger parameter dominates the update

Both parameters can be updated in equal proportions

Standard Normalization

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Denote $\mu^j = \dfrac{1}{n}\sum_{i=1}^n x_i^j$, $\sigma^j = \sqrt{\dfrac{1}{n}\sum_{i=1}^n \left(x_i^j - \mu^j\right)^2}$

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Our new data will be $(z_i, y_i)_{i=1}^n$, $z_i \in \mathbb{R}^k$, $y_i \in \mathbb{R}^m$.

Min-Max Normalization

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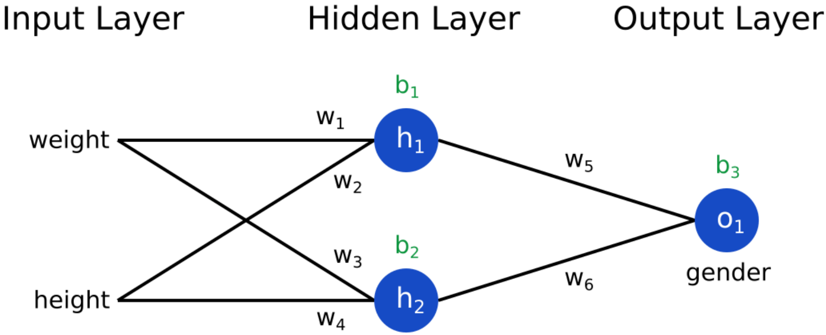

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So we see that $w_1^1 = w_3^1 = const$, $w_2^1 = w_4^1 = const$. In the same way we can prove that $b_1^1 = b_2^1 = const$.

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- If the weights in a network start too small, then the signal shrinks as it passes through each layer until it's too tiny to be useful.
- If the weights in a network start too large, then the signal grows as it passes through each layer until it's too massive to be useful.

What's Xavier initialization?

Initializing the weights in your network by drawing them from a distribution with zero mean and a specific variance

$$\text{Var}(W) = \frac{1}{n_{in}},$$

where W is the initialization distribution for the neuron in question, and n_{in} is the number of neurons feeding into it. The distribution used is typically Gaussian or uniform.

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$$\mathrm{Var}(W) = \frac{2}{n_{in} + n_{out}},$$

where n_{out} is the number of neurons the result is fed to.

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$$\operatorname{Var}(W_iX_i) = E(X_i)^2 \operatorname{Var}(W_i) + E(W_i)^2 \operatorname{Var}(X_i) + \operatorname{Var}(W_i)\operatorname{Var}(X_i)$$

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to keep the variance of the input gradient the output gradient the same. These two constraints can only be satisfied simultaneously if $n_{in} = n_{out}$, so as a compromise, Glorot & Bengio take the average of the two:

$$\mathrm{Var}\left(W_1\right) = \frac{2}{n_{in} + n_{out}}$$

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for rectifying activation functions. Which makes sense: a rectifying linear unit is zero for half of its input, so you need to double the size of weight variance to keep the signal's variance constant. But Xavier Glorot initialization is still okay.