Xavier and Kaiming initialization

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Xavier and Kaiming initialization

• Strategy to set variance σ^2 of Normal initialization

 $\mathbf{W}_1 \sim \mathcal{N}(\mu_1, \sigma_1^2 \mathbf{I})$

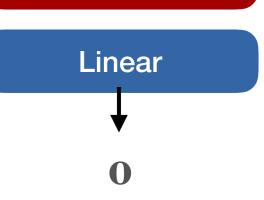
Linear

ReLU

X

 All activations are of similar scale

$$\mathbf{W}_3 \sim \mathcal{N}(\mu_3, \sigma_3^2 \mathbf{I})$$



Random matrix multiplication

$$\mathbf{a}^{\mathsf{T}}\mathbf{x} \sim \mathcal{N}(\mu_a \sum_i \mathbf{x}_i, \|\mathbf{x}\|^2 \sigma_a^2)$$
 for $\mathbf{a} \sim \mathcal{N}(\mu_a, \sigma_a^2 \mathbf{I})$

Random matrix multiplication

$$\mathbf{z}_i = \mathbf{W}_{i-1} \mathbf{z}_{i-1} \sim \mathcal{N}(0, \|\mathbf{z}_{i-1}\|^2 \sigma_{W_{i-1}}^2 \mathbf{I})$$
 for $\mathbf{W}_{i-1} \sim \mathcal{N}(0, \sigma_{W_{i-1}}^2 \mathbf{I})$

Random ReLU

$$\mathbf{z}_{i+1} = \max(\mathbf{z}_i, 0)$$
 for $\mathbf{z}_i \sim \mathcal{N}(0, \sigma_i^2 \mathbf{I})$

$$\mathbb{E}[\|\mathbf{z}_{i+1}\|^2] = \frac{1}{2}n_{\mathbf{z}_i}\sigma_i^2$$

Putting things together

$$\mathbf{z}_i \sim \mathcal{N}(0, \, \sigma_i^2 \mathbf{I})$$

$$\|\mathbf{z}_{i+1}\|^2 \approx \mathbb{E}[\|\mathbf{z}_{i+1}\|^2] = \frac{1}{2} n_{\mathbf{z}_i} \sigma_i^2 \qquad \mathbf{z}_{i+2} \sim \mathcal{N}(0, \|\mathbf{z}_{i+1}\|^2 \sigma_{W_{i+1}}^2 \mathbf{I})$$

$$\mathbf{z}_{i+2} \sim \mathcal{N}(0, \|\mathbf{z}_{i+1}\|^2 \sigma_{W_{i+1}}^2 \mathbf{I})$$

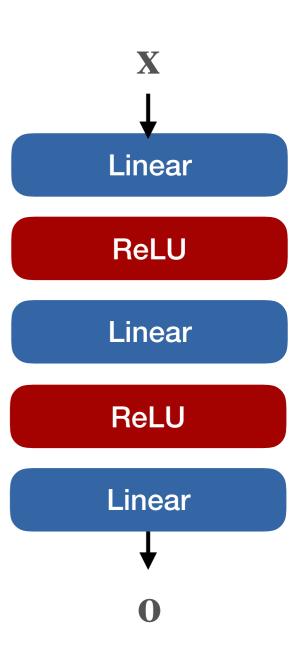
$$\underbrace{\phantom{\mathbf{z}_{i+2}}}_{\sigma_{i+2}^2}$$

$$\sigma_{i+2} = \frac{1}{\sqrt{2}} \sigma_{W_{i+1}} \sigma_i \sqrt{n_{\mathbf{z}_i}}$$

$$\sigma_{i} = \prod_{k=0}^{(i-1)/2} \left(\frac{1}{\sqrt{2}} \sigma_{W_{2k+1}} \sqrt{n_{\mathbf{z}_{2k}}} \right) \sigma_{x}$$

Randomly initialized network

$$\sigma_{i} = \prod_{k=0}^{(i-1)/2} \left(\frac{1}{\sqrt{2}} \sigma_{W_{2k+1}} \sqrt{n_{\mathbf{z}_{2k}}} \right) \sigma_{x}$$



Variance of back-propagation graph

$$\hat{\sigma}_i = \prod_{k=i/2}^{(N-1)/2} \left(\frac{1}{\sqrt{2}} \sigma_{W_{2k+1}} \sqrt{n_{\mathbf{Z}_{2k+2}}}\right) \hat{\sigma}_N \qquad \begin{array}{c} \mathbf{X} \\ \mathbf{Linear} \\ \mathbf{ReLU} \\ \mathbf{ReLU} \\ \mathbf{ReLU} \\ \mathbf{ReLU} \\ \mathbf{ReLU} \\ \mathbf{ReLU} \\ \mathbf{Cinear} \\ \mathbf{ReLU} \\ \mathbf{Cinear} \\ \mathbf{Cin$$

Xavier initialization

$$\sigma_{i} = \prod_{k=0}^{(i-1)/2} \left(\frac{1}{\sqrt{2}} \sigma_{W_{2k+1}} \sqrt{n_{\mathbf{z}_{2k}}} \right) \sigma_{x}$$

 Try to keep both activations and gradient magnitude constant

$$\bullet \quad \sigma_W = \sqrt{2} \sqrt{\frac{2}{n_{\mathbf{z}_i} + n_{\mathbf{z}_{i+1}}}}$$

$$\hat{\sigma}_{i} = \prod_{k=i/2}^{(N-1)/2} \left(\frac{1}{\sqrt{2}} \sigma_{W_{2k+1}} \sqrt{n_{\mathbf{z}_{2k+2}}} \right) \hat{\sigma}_{N}$$

Kaiming initialization

 Try to keep either activation or gradient magnitude constant

$$\sigma_{i} = \prod_{k=0}^{(i-1)/2} \left(\frac{1}{\sqrt{2}} \sigma_{W_{2k+1}} \sqrt{n_{\mathbf{z}_{2k}}} \right) \sigma_{x}$$

$$\boldsymbol{\sigma}_W = \sqrt{2} \frac{1}{\sqrt{n_{\mathbf{z}_i}}}$$

$$\hat{\sigma}_{i} = \prod_{k=i/2}^{(N-1)/2} \left(\frac{1}{\sqrt{2}} \sigma_{W_{2k+1}} \sqrt{n_{\mathbf{z}_{2k+2}}} \right) \hat{\sigma}_{N}$$

$$\sigma_W = \sqrt{2} \frac{1}{\sqrt{n_{\mathbf{z}_{i+1}}}}$$

Initialization in practice

- Xavier (default) is often good enough
- Initialize last layer to zero