Deep Learning for Computer Vision

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So far in the class..

- Brief introduction to ML

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- MLP, CNNs and different families of architecture
- (today) Some of the important training aspects of CNNs

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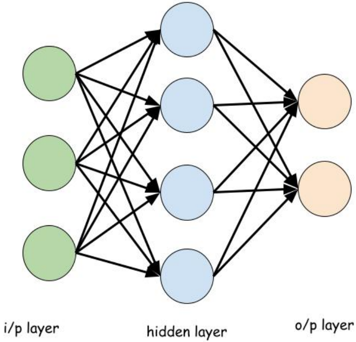
- PCA or whitening are not common

Weight Initialization



- What if all the parameters are initialized to zero?

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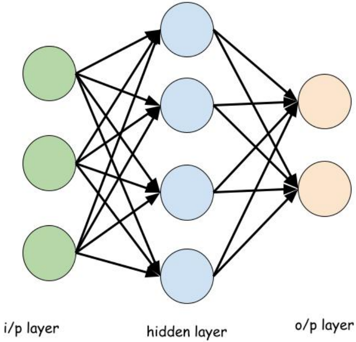

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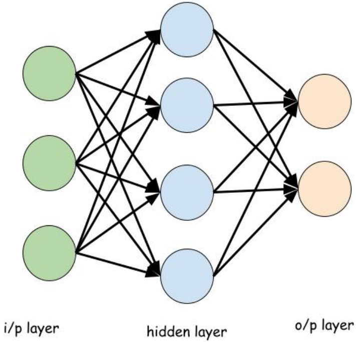

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- Leads to a failure mode (often known as the 'symmetry' problem)

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Figure credits: Dr Justin Johnson, U Michigan

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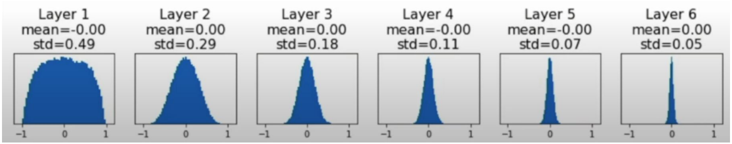

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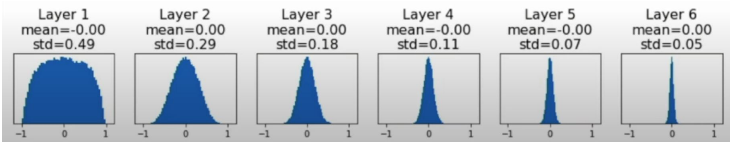

- All zero gradients, no learning!

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Xavier Initialization

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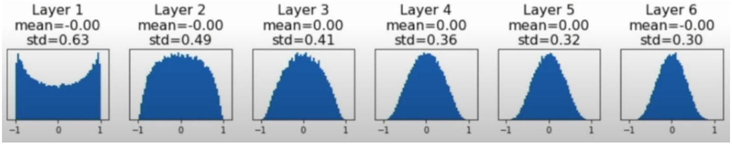
- 

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- $\rightarrow$ var$(w_i) = \frac{1}{d_{l-1}}$

Weight Initialization with ReLU activations

- Kaiming or MSRA initialization

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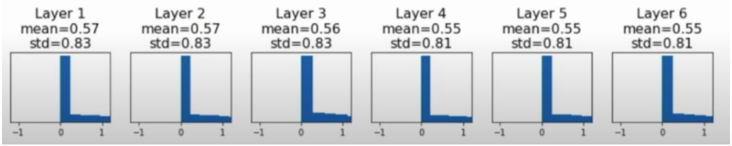
- std=sqrt$(2/d_{l-1})$



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