Phase Collapse in Neural Networks

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Neural collapse



CNN classifiers simultaneously move spatial information into channels and increase linear separation

Can we define a non-linear operator with these properties?

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- Soft-thresholding: preserves the sign, thresholds the amplitude

Concentration with soft-thresholding



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Comparison between sparsity and phase collapse

Concentration with soft-thresholding



Odd part of ReLU Collapses small amplitudes



Concentrates additive variability Does not separate class means



Performs denoising Cannot be further sparsified

Separation with complex modulus



Even part of ReLU Collapses complex phases



Concentrates multiplicative variability Separates class means



Computes support Can be further sparsified

Phase collapse versus sparsity: numerical results



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Phase collapse is sufficient to achieve good performance, while any non-linearity which preserves the phase is not. Phase collapse is thus also necessary.

How far can we further constrain the network?

Diagonalizing local translations

Known source of within-class variability: local translations

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Small translations τ of an image x become phase shifts:

$$(\tau \cdot x) * \psi \approx e^{-i\xi \cdot \tau} (x * \psi)$$

with a relative error bounded by $\sigma |\tau|$: approximate diagonalization!

Constrain the spatial filters with the phase collapse operator:

$$\rho Px(u) = \left(x * \phi(2u), (|x * \psi_{\theta}(2u)|)_{\theta}\right)$$



- Mathematical definition: no learning
- Combines linear and non-linear invariants to local translations
- All the desired properties!
- What accuracy can we achieve with this?

Learned scattering network



- Simplified architecture with phase collapses and minimal learning
- No learned spatial filters nor biases
- Only one learned component: channel matrices at every layer
- Reaches ResNet-18 accuracy with only 11 layers

Zarka, G, and Mallat. Separation and concentration in deep networks. *ICLR*, 2021. G, Zarka, and Mallat. Phase collapse in neural networks. *ICLR*, 2022.

- Paper: arxiv.org/pdf/2110.05283.pdf
- Code: github.com/FlorentinGuth/PhaseCollapse
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Code



Email