

Gradient Descent Monotonically Decreases the Sharpness of Gradient Flow Solutions in Scalar Networks and Beyond

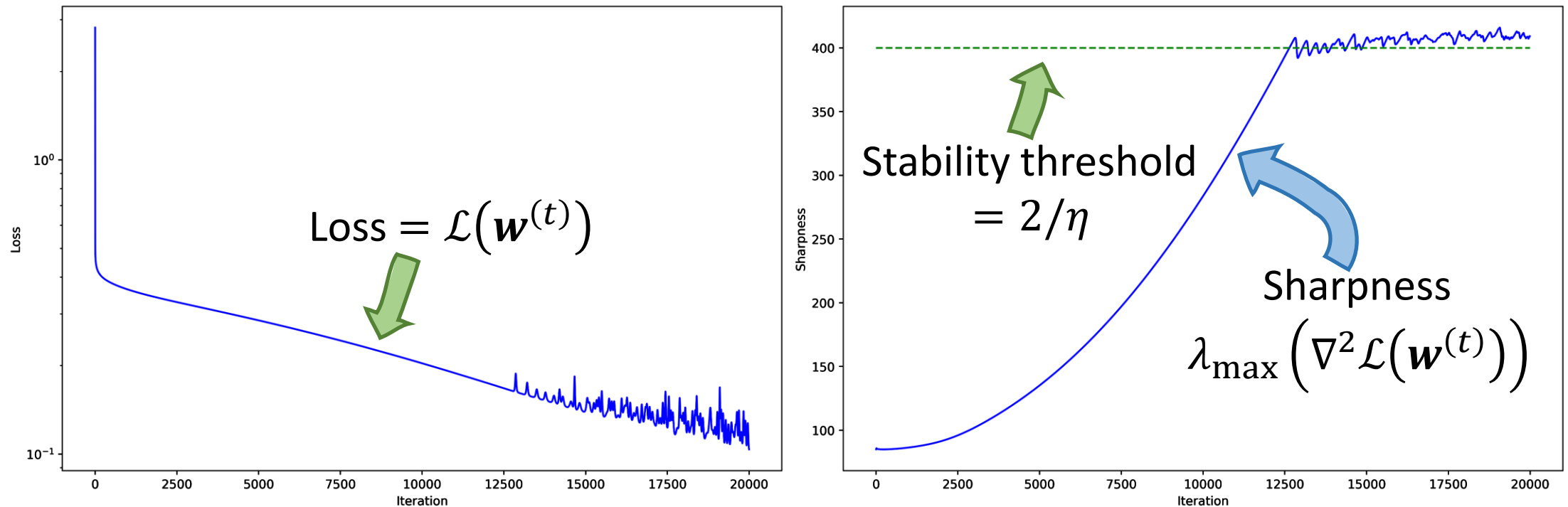
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Motivation: the edge of stability phenomenon



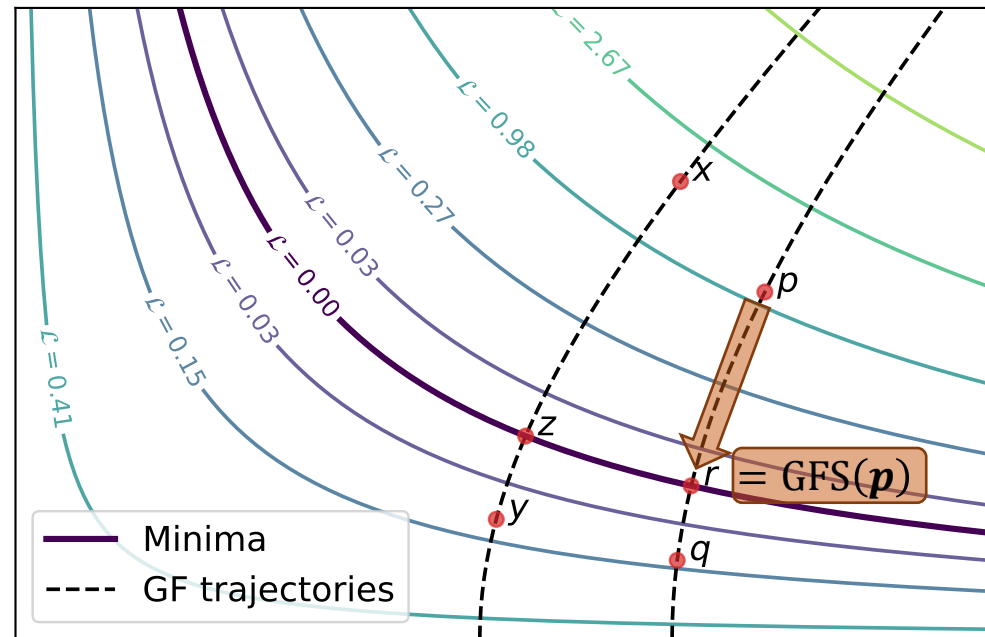
Cohen et al. (2021)

Gradient descent on neural networks typically occurs at the edge of stability

Explaining EoS convergence via gradient flow solution sharpness

$\text{GFS}(\mathbf{w})$ = the end of the gradient flow trajectory starting from \mathbf{w}

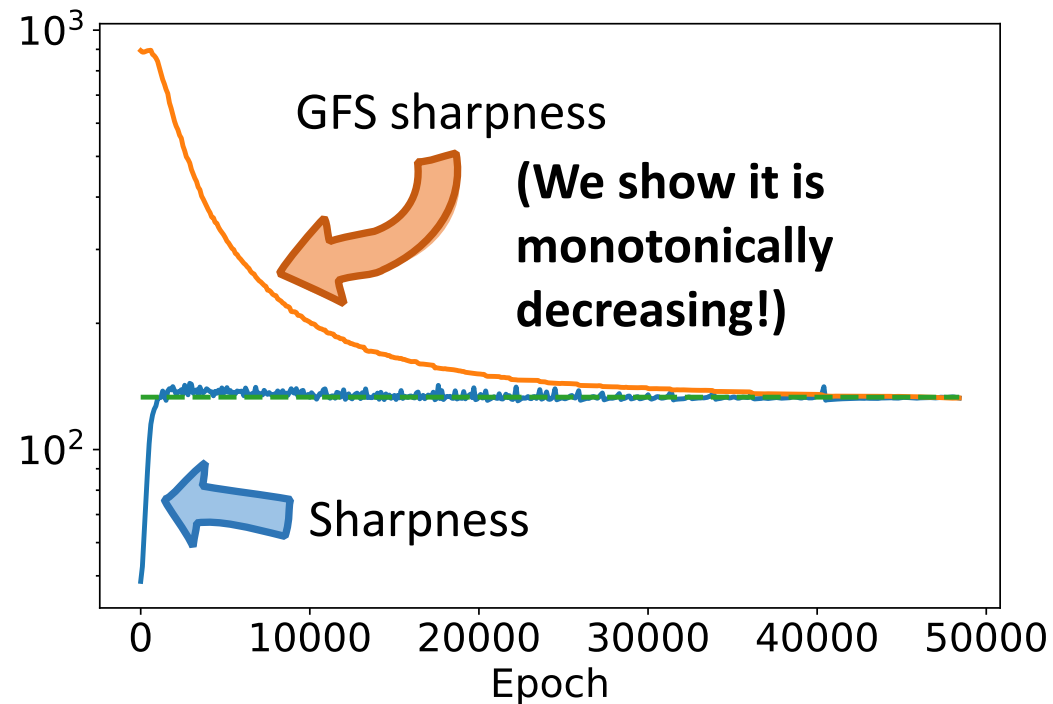
$\phi(\mathbf{w})$ = the GFS sharpness of $\mathbf{w} = \lambda_{\max}(\nabla^2 \mathcal{L}(\text{GFS}(\mathbf{w})))$



Explaining EoS convergence via gradient flow solution sharpness

$$\mathcal{L}(\mathbf{w}) \approx 0 \implies \phi(\mathbf{w}) \approx \lambda_{\max}(\nabla^2 \mathcal{L}(\mathbf{w}))$$

Understanding $\lim_{t \rightarrow \infty} \phi(\mathbf{w}^{(t)})$ allow us to understand EoS convergence



Theory for scalar networks

$$\mathcal{L}(\mathbf{w}) = \frac{1}{2} (w_1 w_2 w_3 \cdots w_D - 1)^2$$

Theorem (Informal): Under a weak assumption on the initialization $\mathbf{w}^{(0)}$ then for all $t \geq 0$:

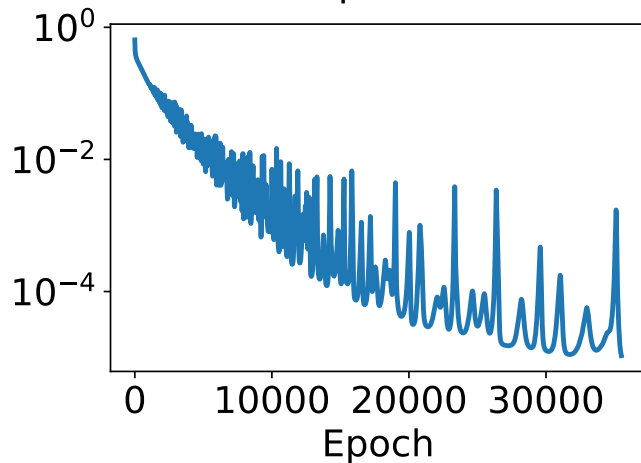
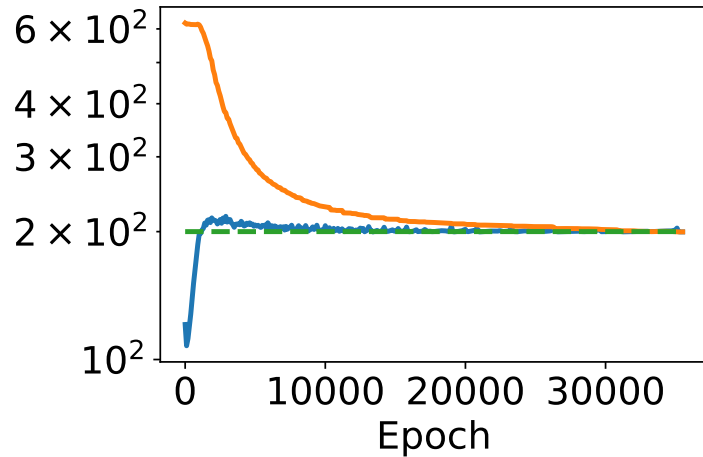
- The assumption hold for $\mathbf{w}^{(t)}$
- $\phi(\mathbf{w}^{(t+1)}) \leq \phi(\mathbf{w}^{(t)})$

Theorem (Informal): If for some $t \geq 0$ and $\delta \in (0, 0.4)$, the assumption hold for $\mathbf{w}^{(t)}$, $\phi(\mathbf{w}^{(t)}) = \frac{2-\delta}{\eta}$ and $\mathcal{L}(\mathbf{w}^{(t)}) = \mathcal{O}(\delta^2)$ then:

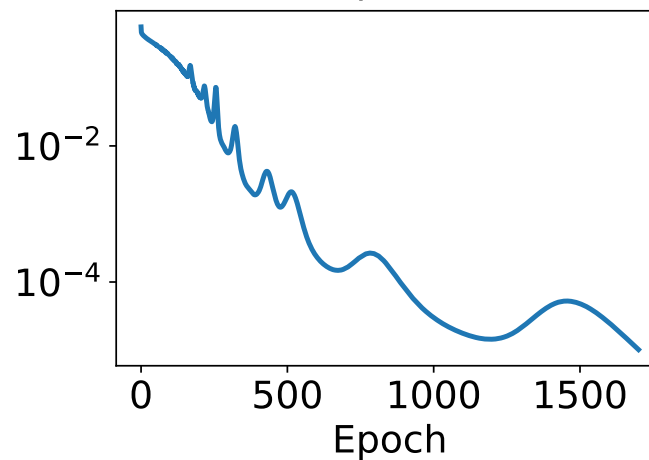
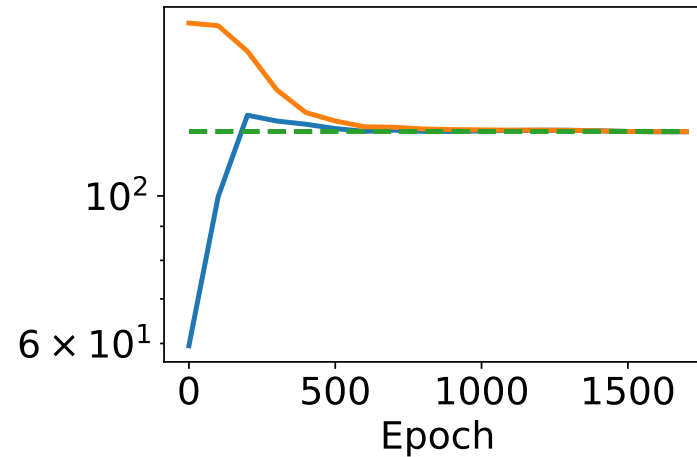
- $\lim_{k \rightarrow \infty} \phi(\mathbf{w}^{(k)}) \geq \frac{2(1-\delta)}{\eta}$
- The loss converges exponentially to 0

Experiments: neural networks

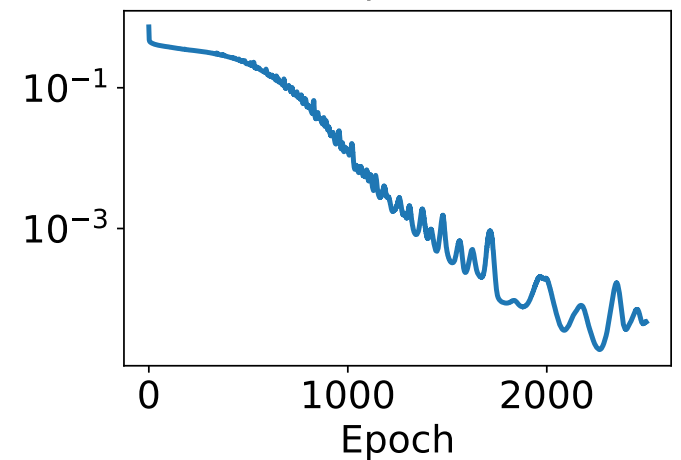
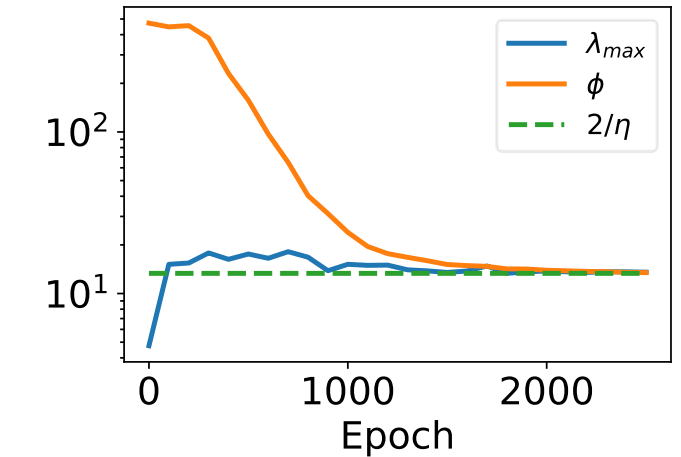
Cifar10: FC-hardtanh



VGG11-BN



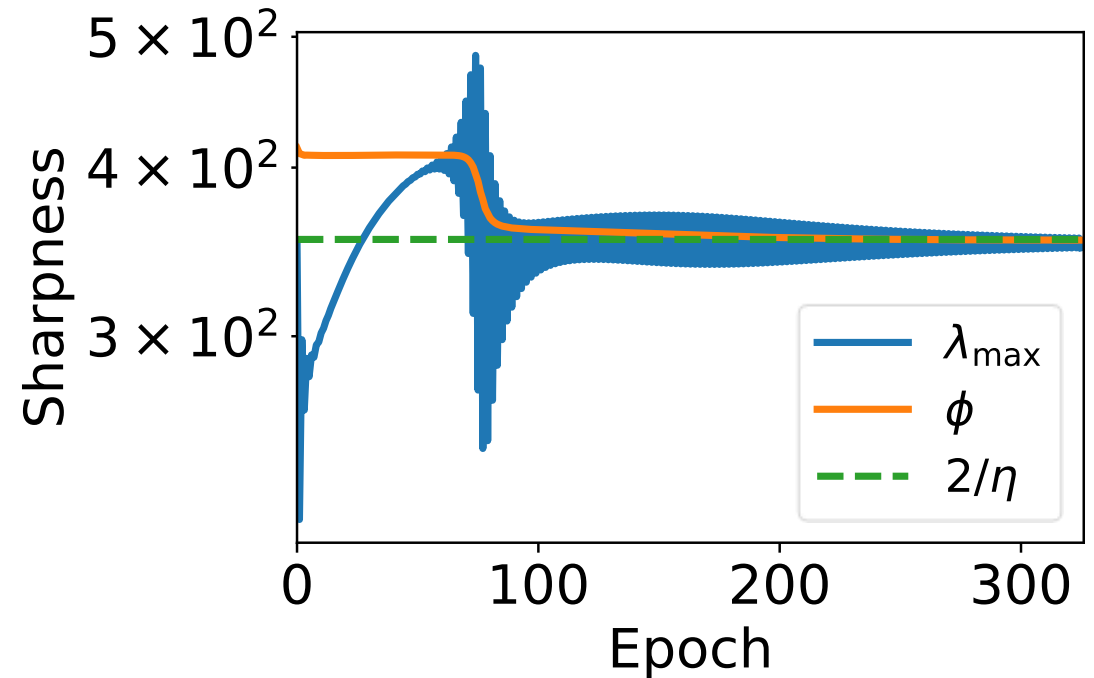
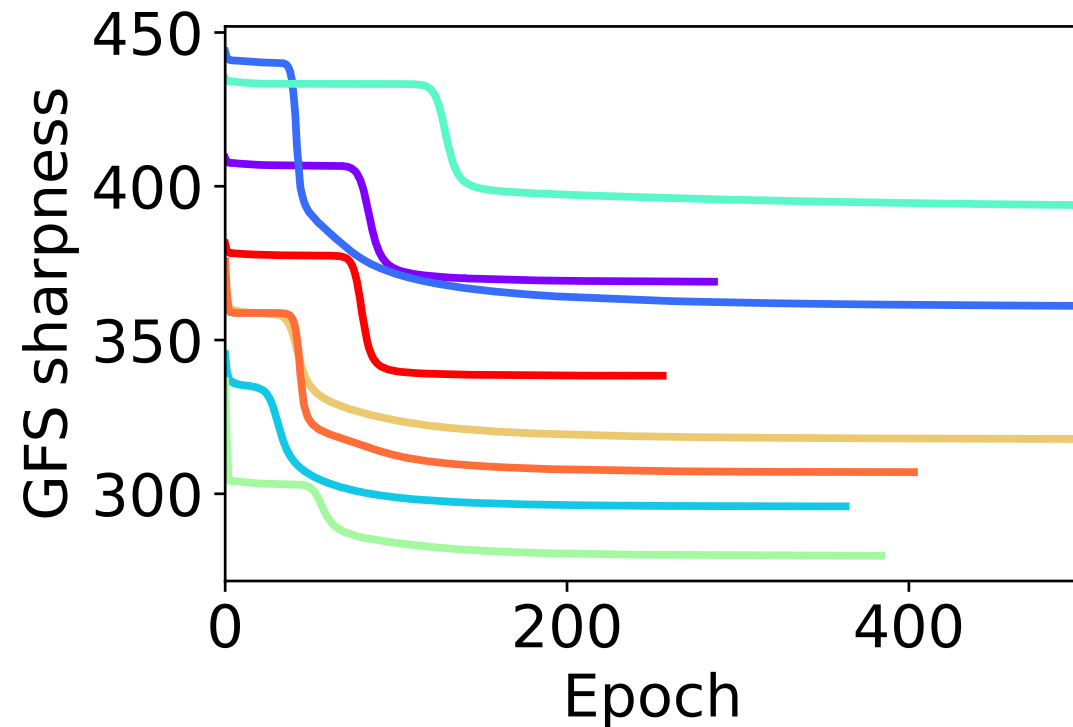
Resnet20



Experiments: squared regression model

$$f_{\theta}(x) = \langle u_+^2 - u_-^2, x \rangle$$

The GFS can be efficiently calculated



Thanks!

