Understanding Gradient Descent on Edge of Stability in Deep Learning

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Descent Lemma for Gradient Descent

Underpins most convergence proofs in Deep Learning

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If $\eta < \dfrac{2}{\lambda_{max}(\nabla^2 L)}$ then loss drops each iteration

Learning Rate (LR) → η

Sharpness (aka smoothness) → λ_{max}

Hessian of loss L → $\nabla^2 L$

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Learning Rate (LR)

Sharpness
(aka smoothness)

Hessian of loss L

Usual interpretation: $\lambda_{max}(\nabla^2 L)$ is globally bounded; trial and error is used to discover η that satisfies descent lemma.

Edge of Stability (EoS)

Cohen et al. [2021]

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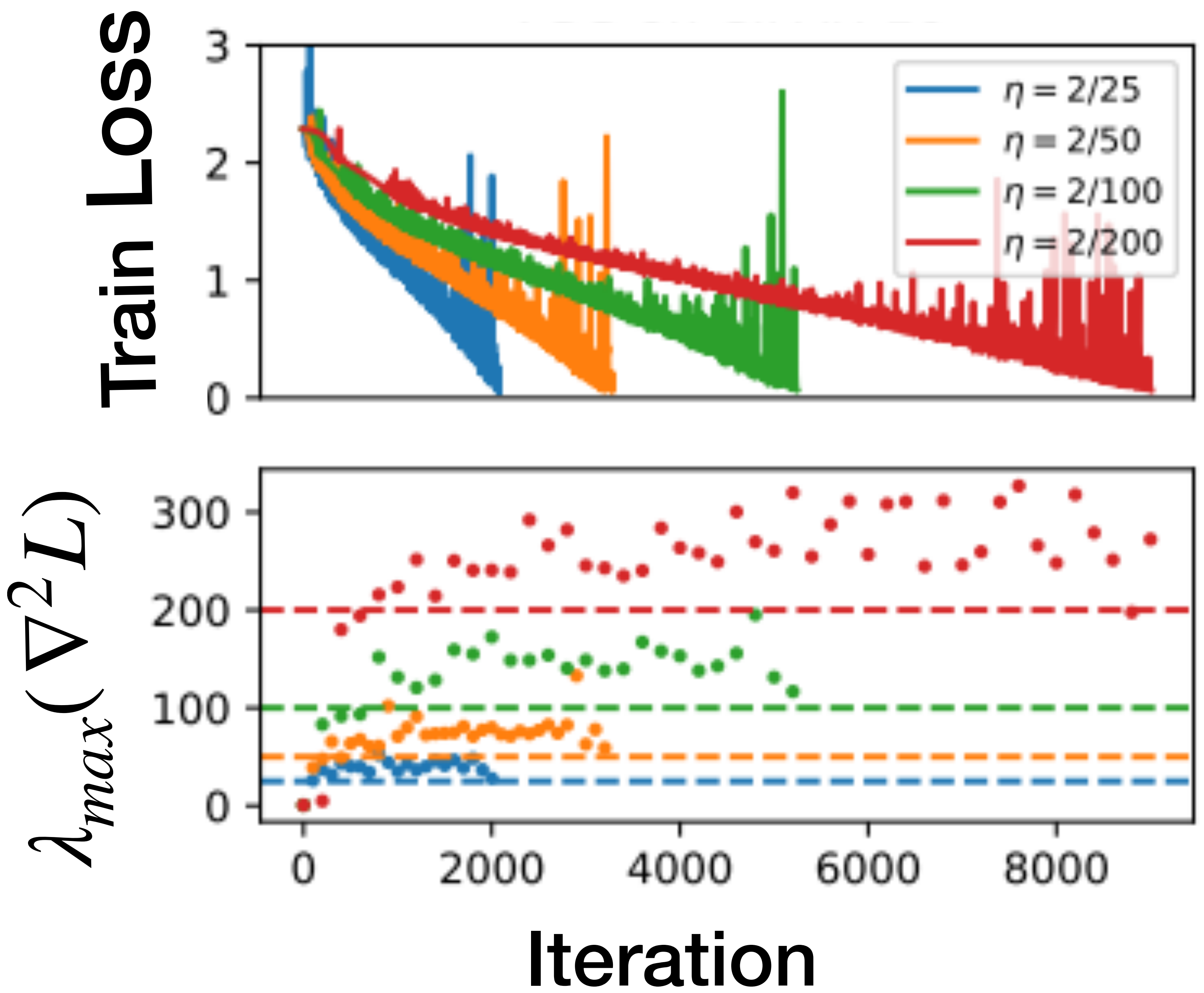
- Phenomenon appears for all finite η.

VGG-16 on CIFAR-10



(Also shown for other architectures)

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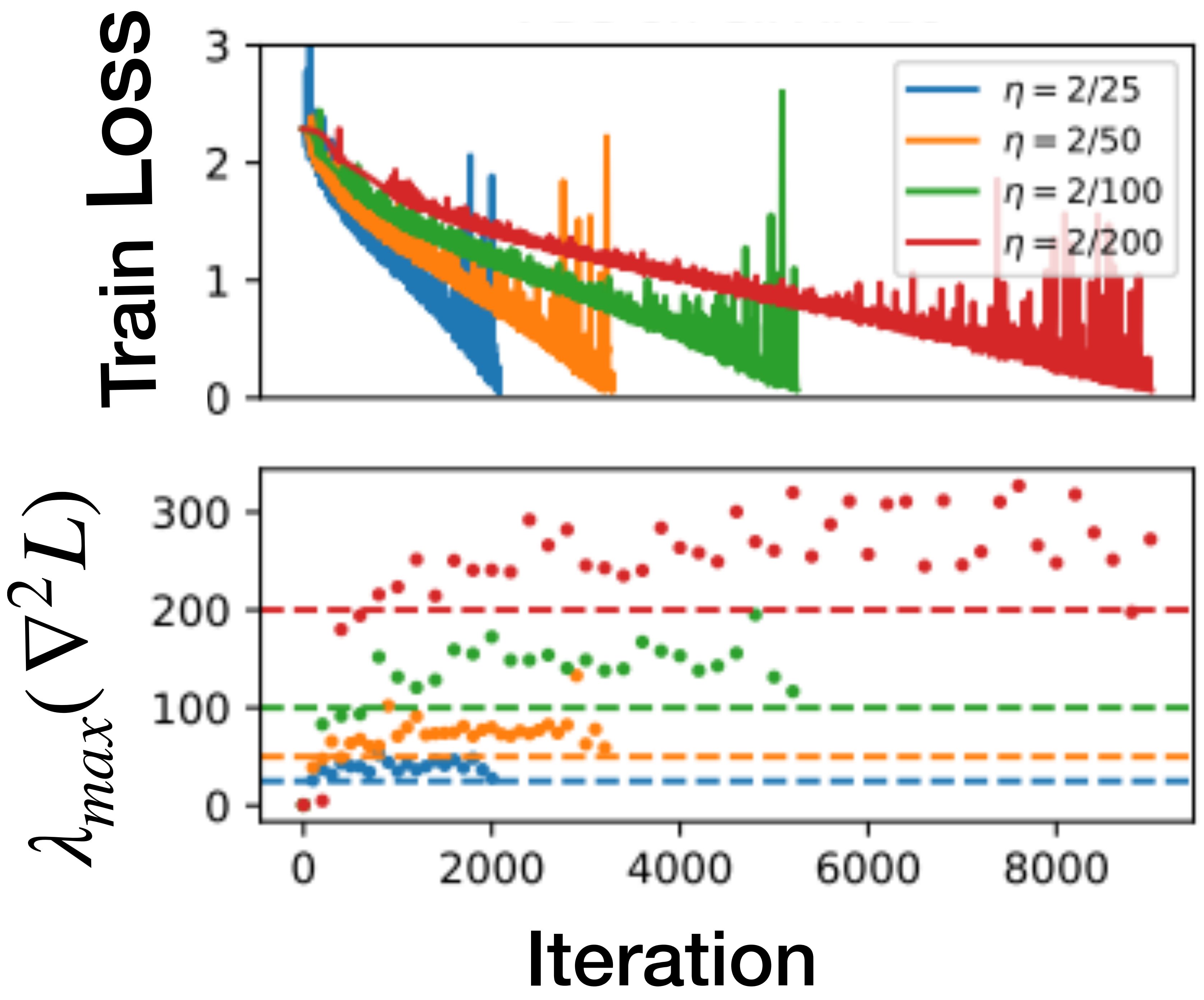

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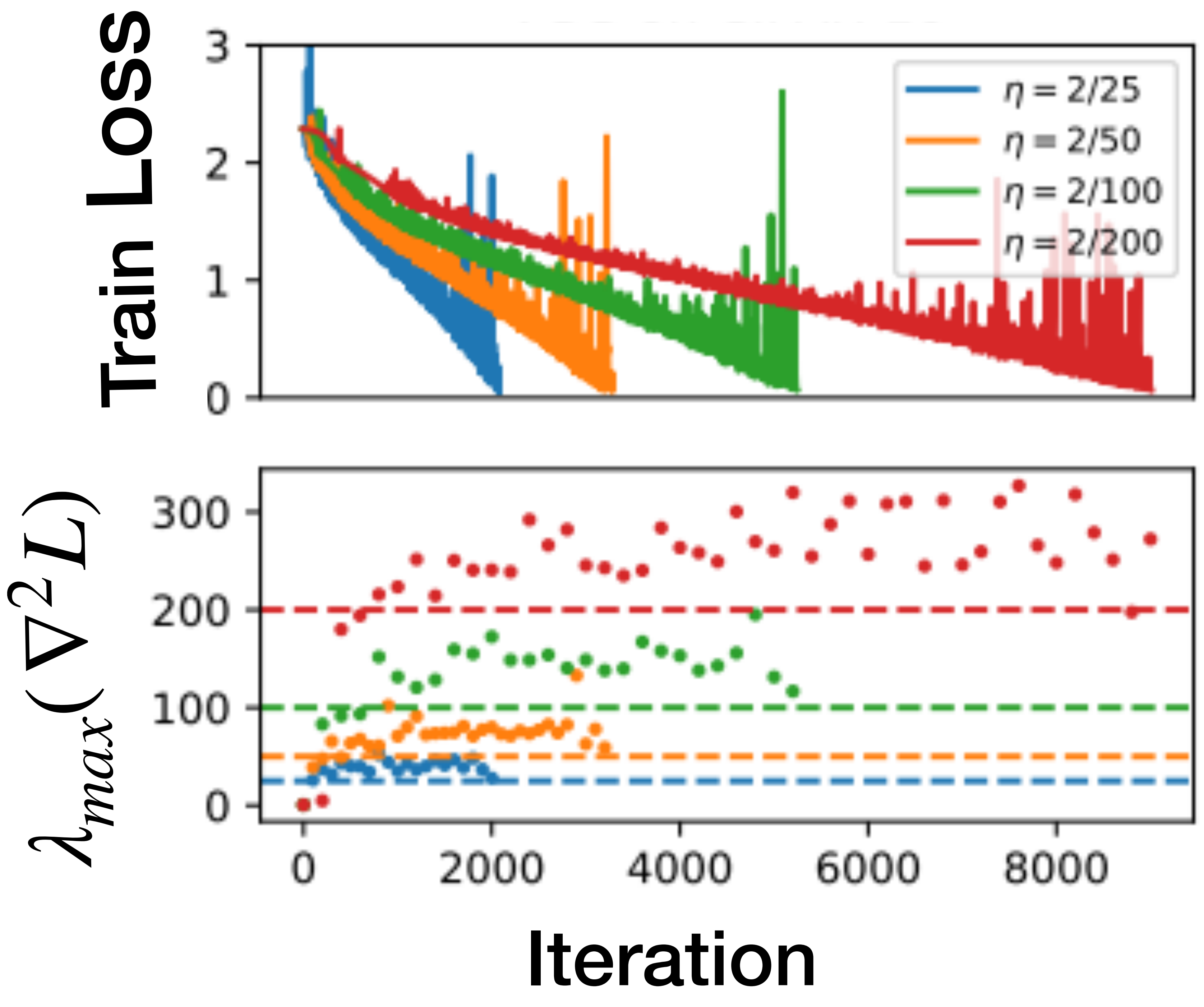

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1. How can we analyze optimization in EoS setting? (Given that descent lemma fails)

2. What mechanism controls $\lambda_{max}(\nabla^2 L)$ in the EoS phase? 🤔

This paper (* setting 1): GD on $\sqrt{L}$

($\min_x L(x) = 0$, **with smooth** L)

(*Setting 2: Normalized GD; see paper)

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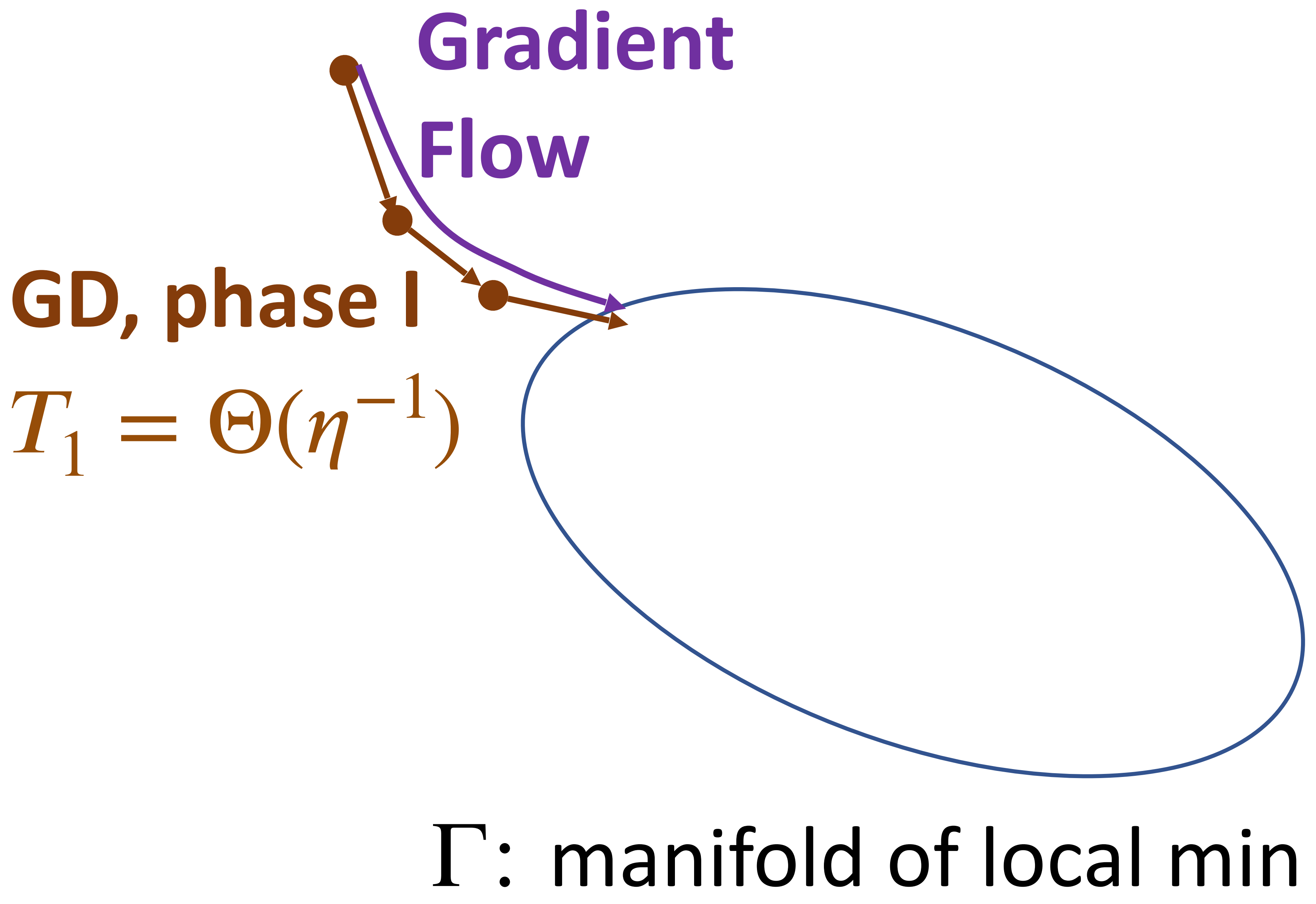
Phase 1:

Loss monotonically decreases till it becomes $\mathcal{O}(\eta)$ in $\Theta(1/\eta)$ steps.



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Phase 2:

For $\Theta(1/\eta^2)$ steps,

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$$= \eta \lambda_{\max}(\nabla^2 L(x(t))) + \mathcal{O}(\eta^2)$$

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$\sqrt{L}$ decreases over time overall.

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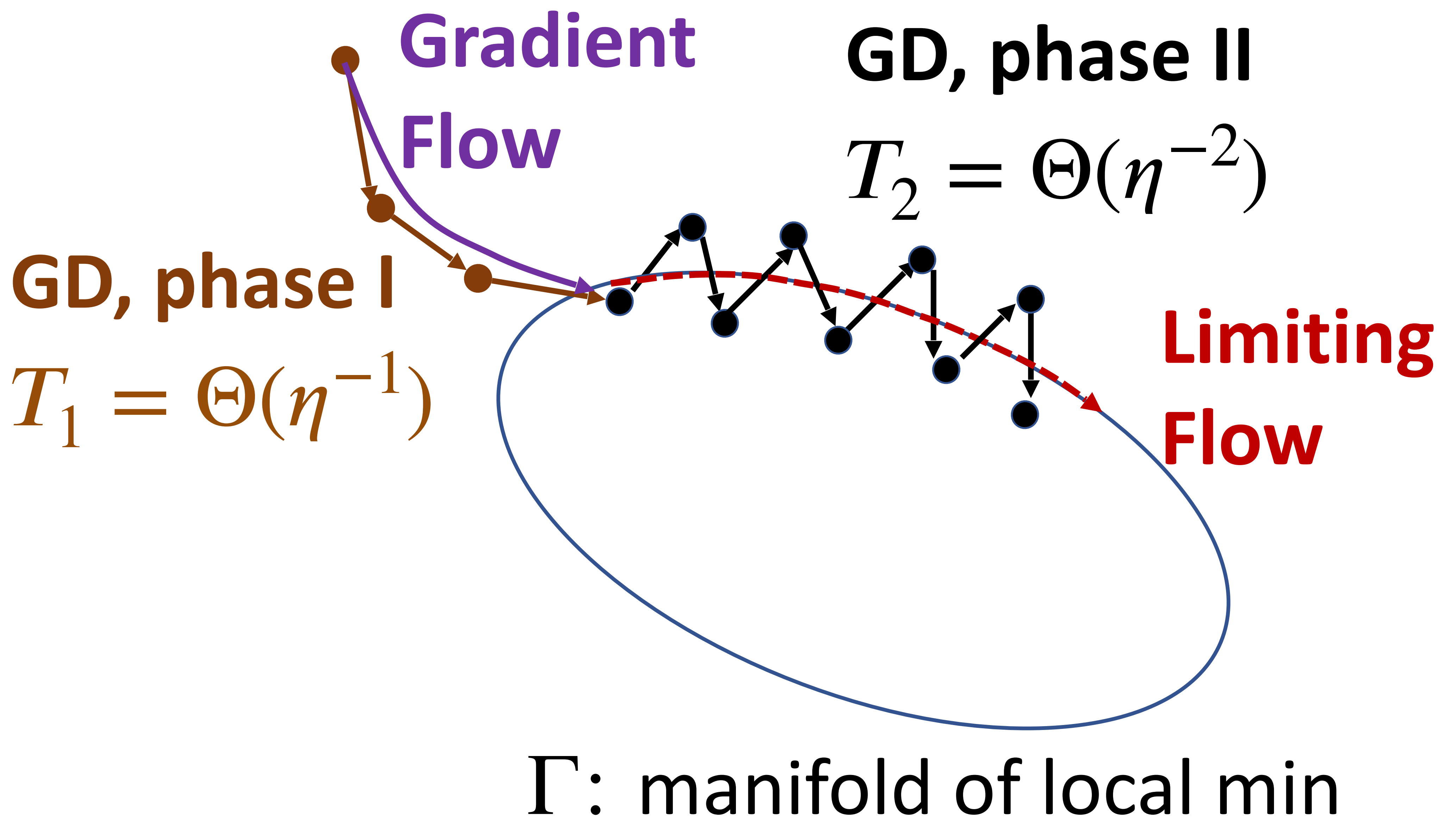
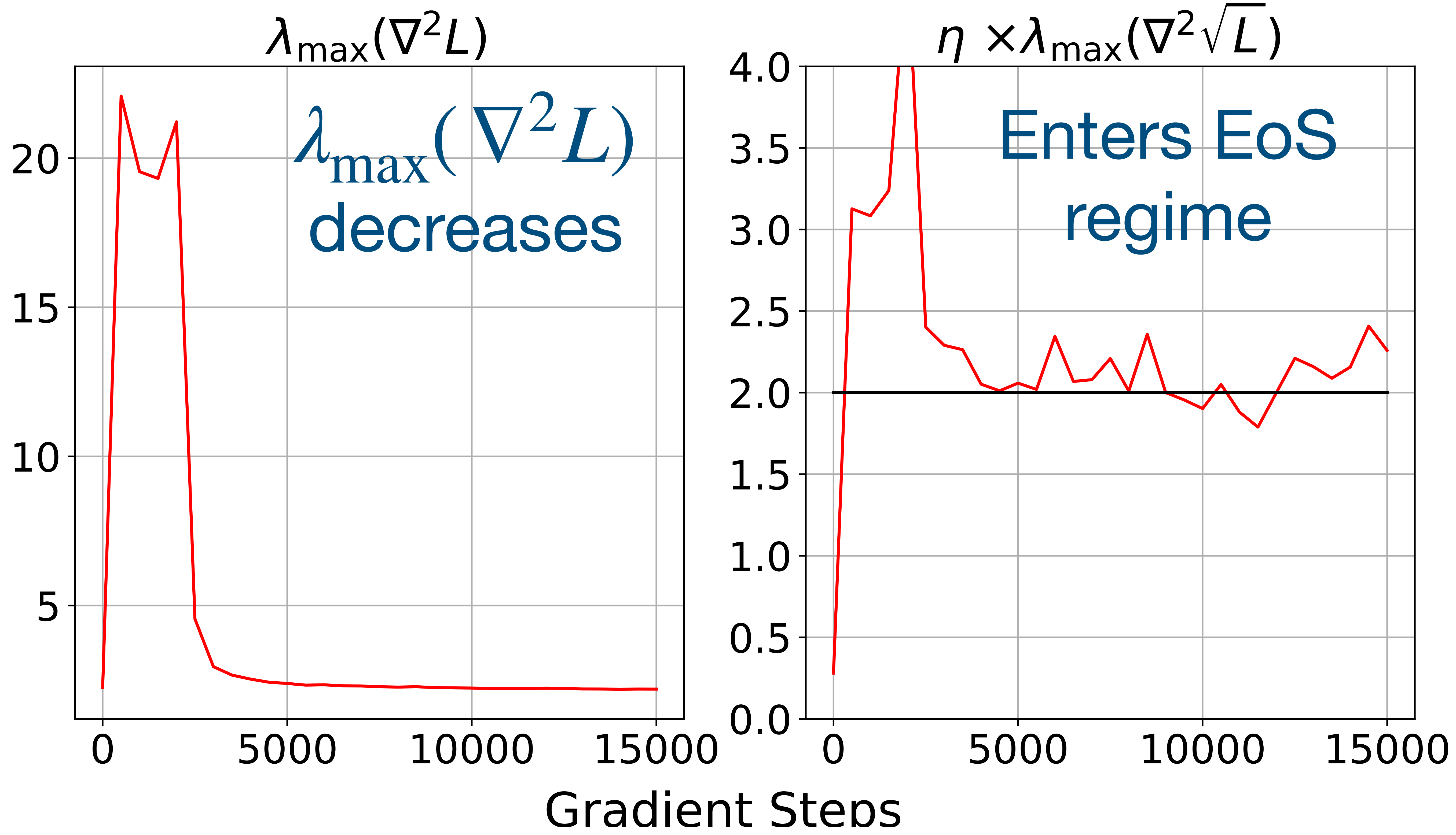


"Implicit bias for Sharpness Minimization": $\lambda_{max}(\nabla^2 L)$ decreases over time.

Experiments: GD trajectory consistent with theory



VGG-16 on CIFAR-10 dataset with Mean Square Loss

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Poster at Hall E #1219

Wed 6.30 pm - 8.30 pm EDT