Generalization and Memorization in Sparse Neural Network

Ziyu Ye Chaoqi Wang Zixin Ding Yuxin Chen

University of Chicago

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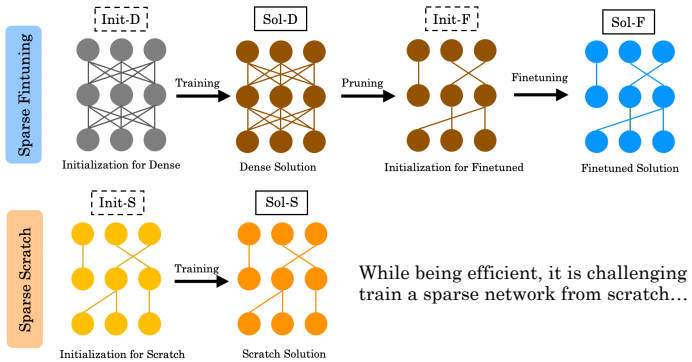
1 *Motivation*: Future is Sparse Training from Scratch

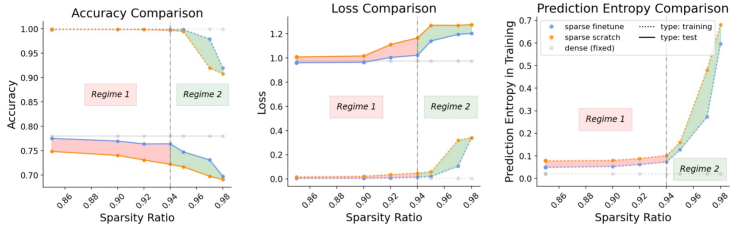
[Backgrounds] True Efficiency by Sparse Training from Scratch



While being efficient, it is challenging to train a sparse network from scratch…

[Challenges] Performance Gap: A Tale of Two Regimes

Performance gap (i.e., *generalization discrepancy*) exists between sparse scratch and sparse finetuning.



[Research Questions] Closing the Gap Requires Understanding

- What is the *root cause* for the *performance gap* (between sparse scratch and sparse finetuning)?
- How may we *close* the *performance gap*?

[Preliminaries] Hessian, Jacobian, Fisher Info and Memorization

Hessian and the Loss Curvature

$$\mathbf{H}(\boldsymbol{\theta}) = \nabla^2_{\boldsymbol{\theta}}\, \mathcal{L}(\boldsymbol{\theta}).$$

Jacobian and Network Sensitivity

$$\mathbf{J}(\mathbf{x}) = \nabla_{\mathbf{x}^T} f(\mathbf{x}; \boldsymbol{\theta}).$$

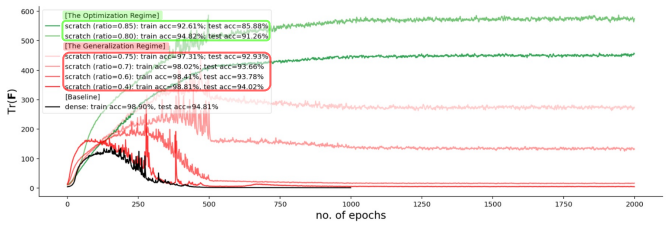
Fisher Information

$$\mathbf{F}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{x}\sim\mathcal{D}, \hat{y}\sim p_{\boldsymbol{\theta}}(y|\mathbf{x})}\left[\nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\hat{y} \mid \mathbf{x}) \nabla_{\boldsymbol{\theta}} \log p_{\boldsymbol{\theta}}(\hat{y} \mid \mathbf{x})^T\right].$$

Long-Tail Hypothesis of Memorization

Memorization of data labels is necessary to achieve good generalization on long-tailed data distribution (Feldman, 2020).

2 *Experiments*: Underlying Mechanisms



	Training Error	Trend of Fisher Information	Reasons for the Generalization Discrepancy
Generalization Regime	near optimal	increases first, then decreases, yet ends up with a higher level compared to sparse finetuning's	sharper minima, higher sensitivity
Optimization regime	far worse than the optimal	increases and hardly decreases	weaker memorization on training data

Table 1: Summary of the underlying mechanisms for sparse training from scratch.

[Generalization Regime] Curse of Information

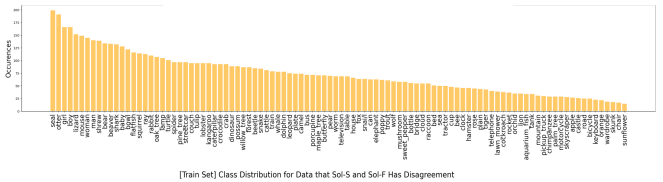
The Curse of Information for Sparse Training:
Sparse scratch requires *more information* in learning, hurting its generalization.

	Sparsity Ratio	Tr(F)	Tr(H)	Jacobian Norm
Sol-D	0.00	53.81	66.32	35.60
Sol-F	0.90	543.27	720.49	43.27
	0.94	2573.51	4198.26	52.25
	0.96	4376.32	9618.40	67.92
Sol-S	0.90	2701.68 ↑	10452.93 ↑	63.74 ↑
	0.94	9840.60 ↑	12905.88 ↑	66.36 ↑
	0.96	15818.65 ↑	20715.41 ↑	70.10 ↑

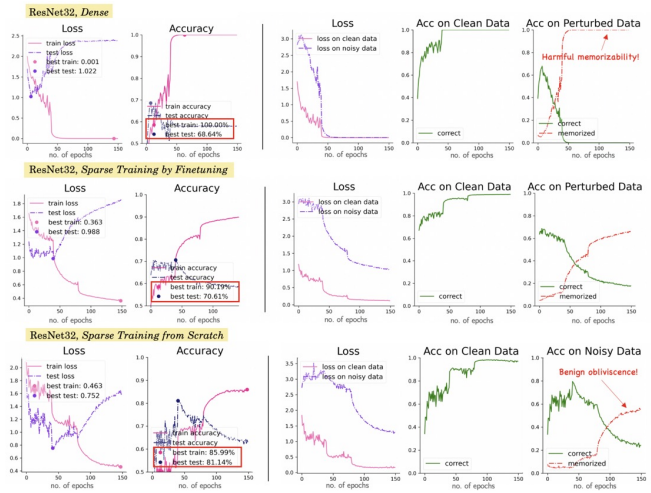
[Optimization Regime] The Memorization Hypothesis

Memorization Hypothesis for Sparse Training:
Sparse scratch is *weaker at memorization* than sparse finetuning.

(CIFAR100) It is hard for sparse scratch to distinguish data needs memorization, e.g., that has *hard/low-level/class-specialized features*.



[Optimization Regime] Robustness by Memorization



Sparse training from scratch is more robust to label noise. This experiment is conducted on CIFAR-10 with ResNet32. The training set contains 30% perturbed data whose labels are uniformly randomly flipped. The sparsity ratio is 0.95 for sparse training. The learning rate is 0.02 and decay by 0.1 at the 40th and 80th epoch. The left two columns show the performance on the training set (noisy) and test set (clean), and the right two columns show the performance on the clean and noisy data in the training set; the notation correct means predicted label equals to true label, while memorized means predicted label equals to noisy label.

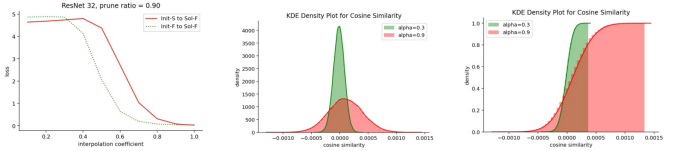
3 *Insights*: Closing the Gap

Regularized Sparse Training from Scratch

A naïve approach is to adaptively apply *Fisher information regularization*.

Data-Efficient Sparse Training from Scratch

Scheduling data (e.g., iteratively constructing training data subsets) may be effective.



Cosine similarity distribution of per sample gradient to the linear interpolation direction from Init-S to Sol-F (α is the interpolation coefficient).

4 Takeaways

- Sparse scratch is weaker at memorization and requires more information in learning.
- Next steps: closing the gap for sparse scratch by regularization or data scheduling.