Progressive Skeletonization: Trimming more fat from a network at initialization

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Philip Torr, Grégory Rogez and Puneet Dokania

Code: https://github.com/naver/force

ICLR 2021

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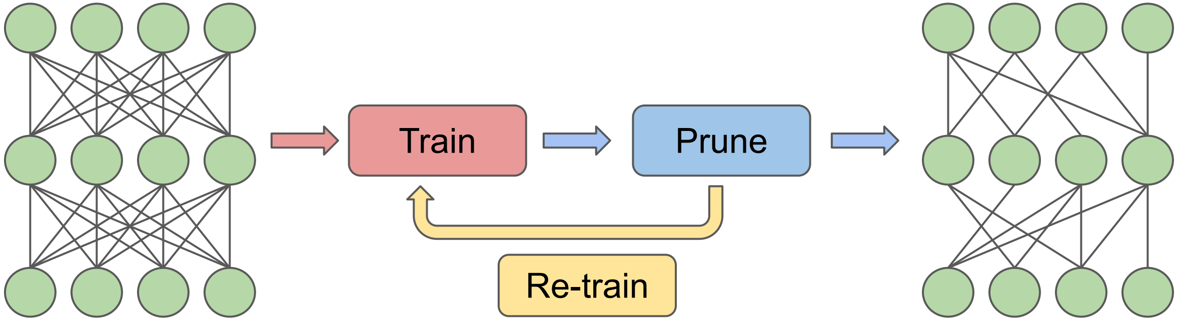
Network Pruning



Han *et al.* 2015
Renda *et al.* 2020

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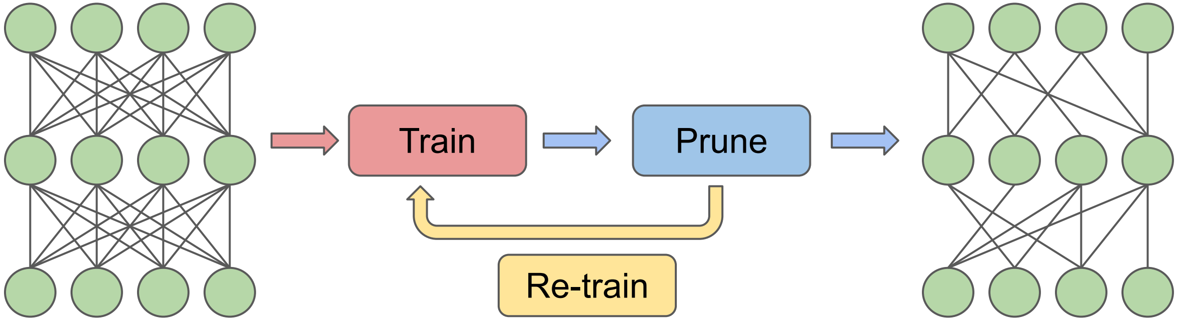

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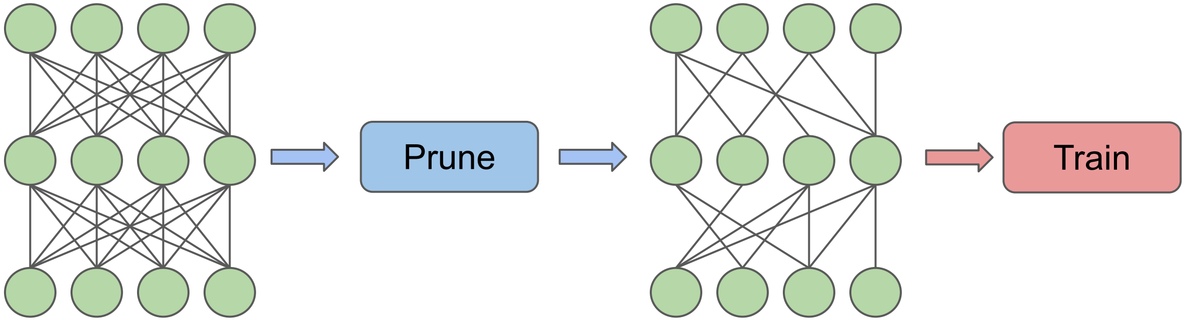

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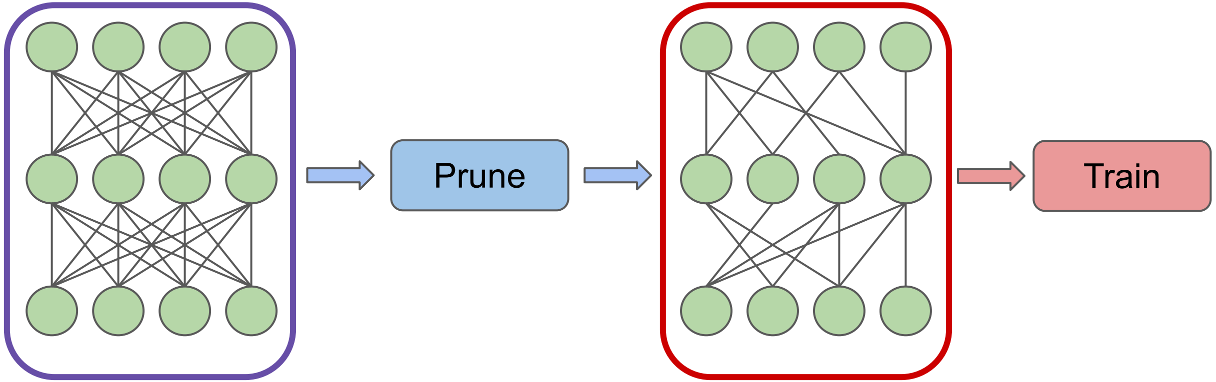
Pruning at initialization

Problem: Given a randomly initialized network and sparsity level, we want to find a sub-network such that, after training, we obtain maximum accuracy.



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Solving this optimization problem would require training all possible sub-networks!

Related work (SNIP)

SNIP (Lee *et al.* 2019) use the *Connection Sensitivity*:

$$\boldsymbol{g}(\boldsymbol{\theta}) := \left.\frac{\partial \mathcal{L}(\boldsymbol{\theta} \odot \boldsymbol{c})}{\partial \boldsymbol{c}}\right|_{\boldsymbol{c}=\mathbf{1}} = \frac{\partial \mathcal{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \odot \boldsymbol{\theta}$$

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GRASP (Wang *et al.* 2020) use the Gradient Norm:

$$\boxed{\Delta\mathcal{L}(\boldsymbol{\theta}) = \nabla\mathcal{L}(\boldsymbol{\theta})^T\nabla\mathcal{L}(\boldsymbol{\theta})}$$

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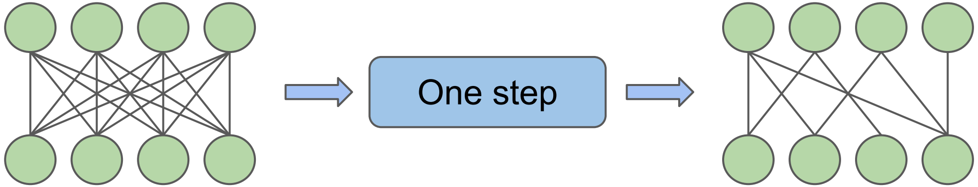
Motivation

SNIP and GRASP assume removing one weight is **independent** of other weights.



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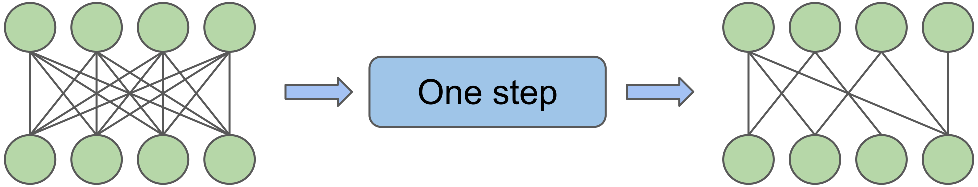
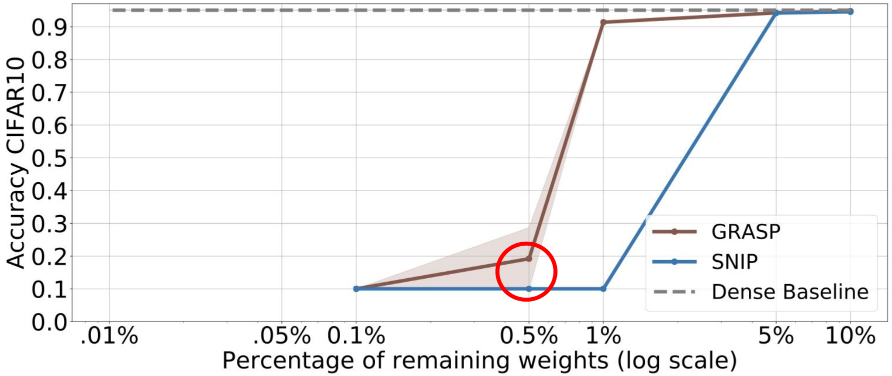


We argue this leads to collapse in performance for high sparsities



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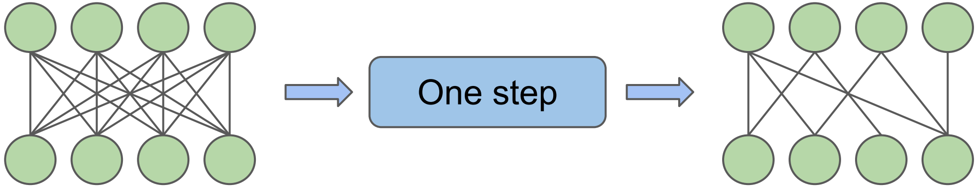

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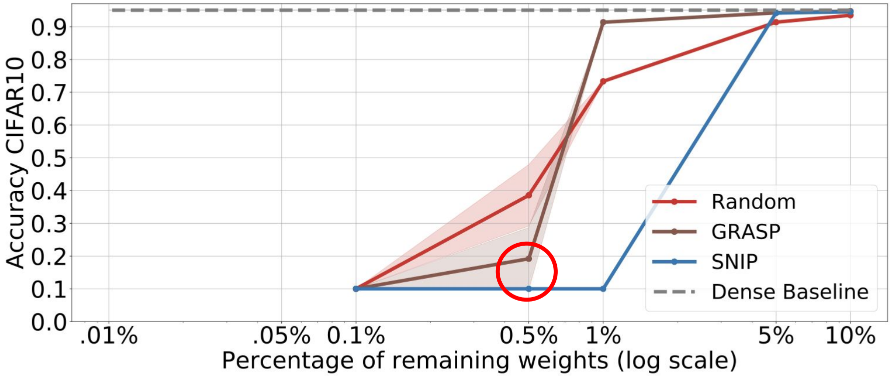

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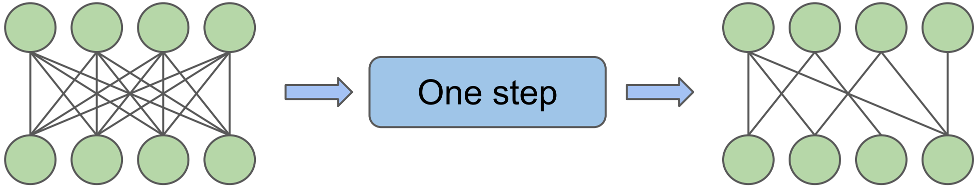

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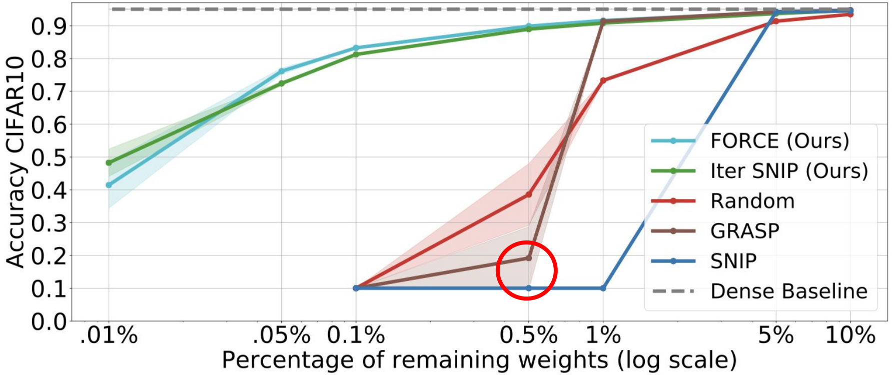

Method

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FOResight Connection sEnsitivity (FORCE) evaluates connections *after* pruning.

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$$\boldsymbol{g}(\boldsymbol{\theta}) := \left.\frac{\partial \mathcal{L}(\boldsymbol{\theta} \odot \boldsymbol{c})}{\partial \boldsymbol{c}}\right|_{\boldsymbol{c}=\mathbf{1}} = \frac{\partial \mathcal{L}(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \odot \boldsymbol{\theta}$$

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In order to optimize FORCE, we compute the pruning mask iteratively.

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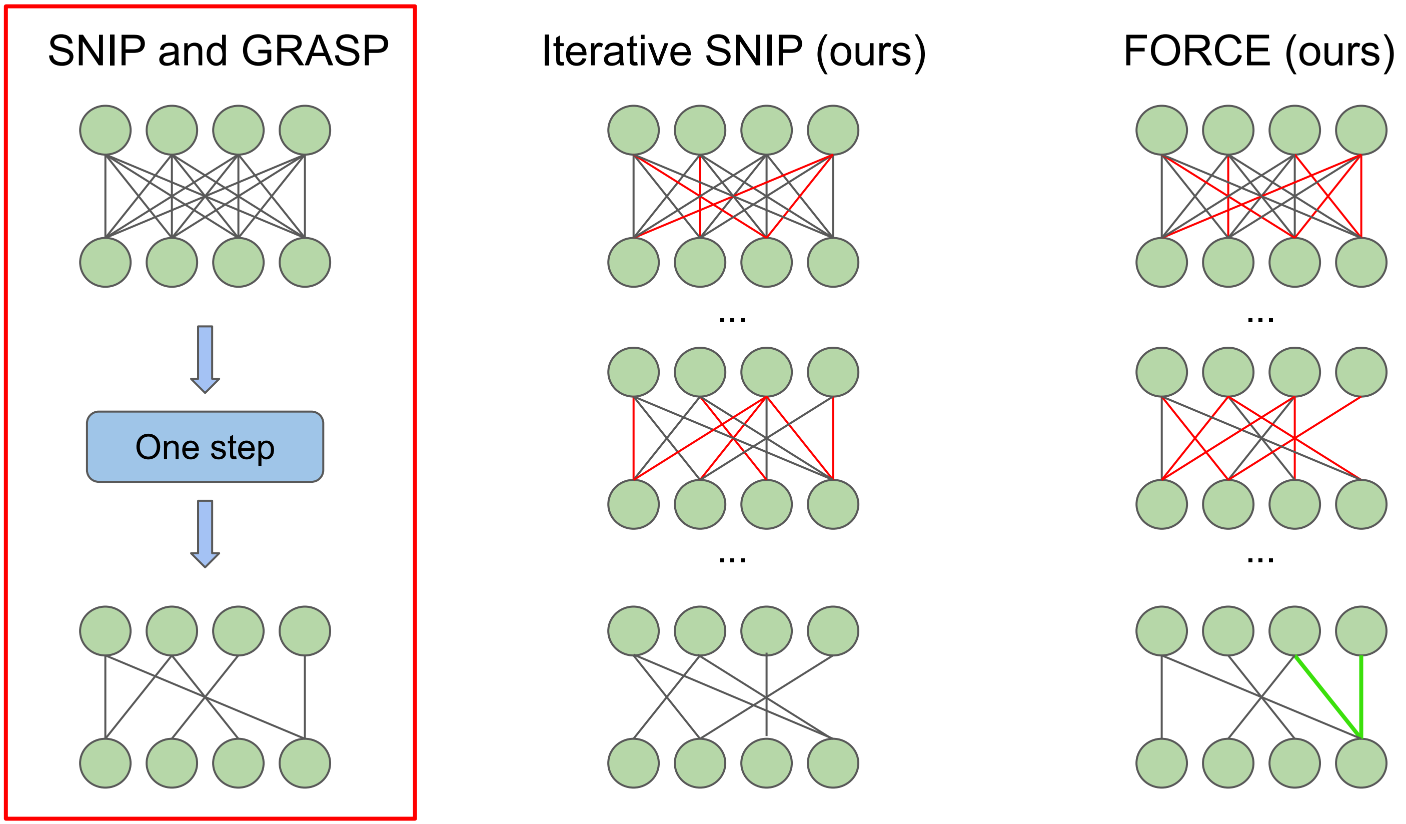

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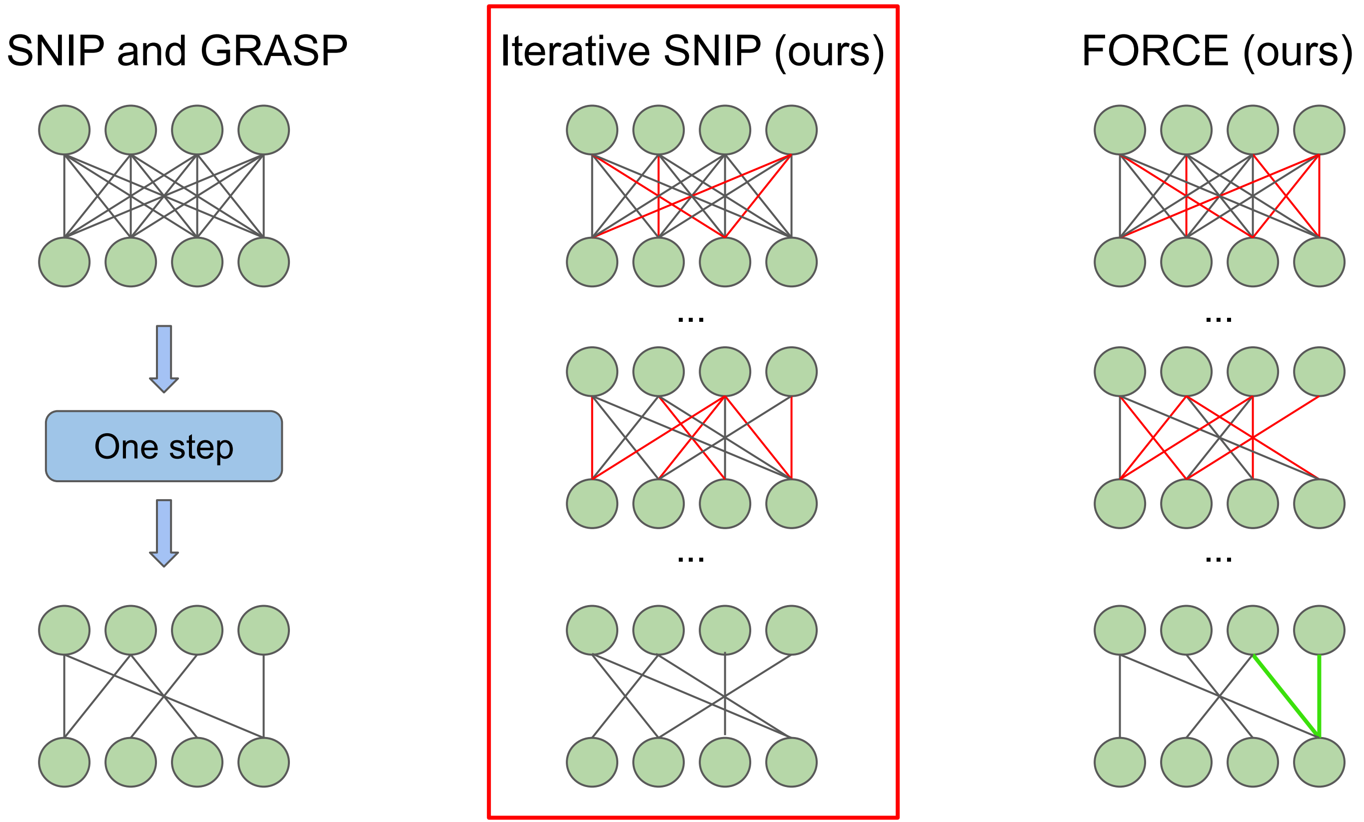

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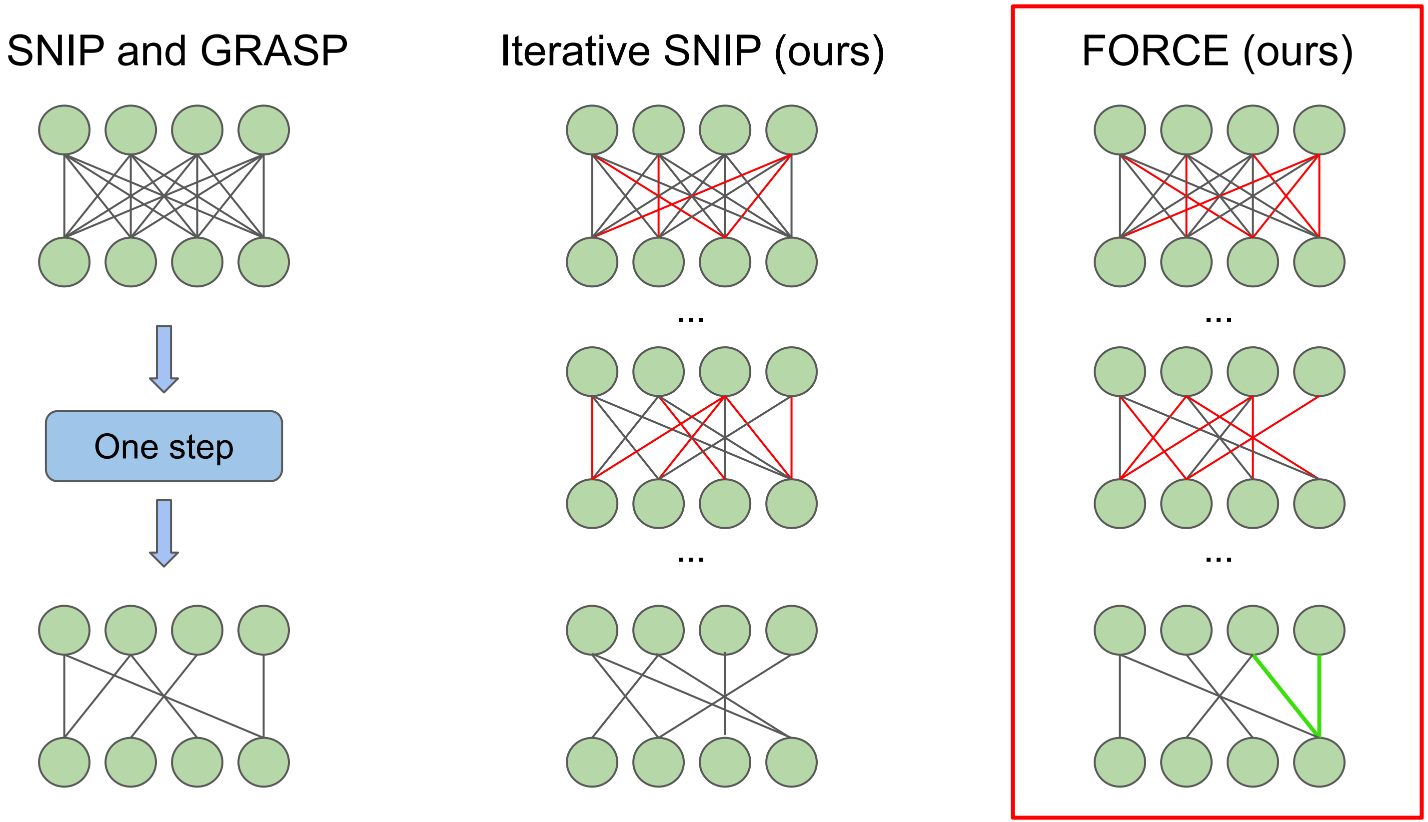

Results

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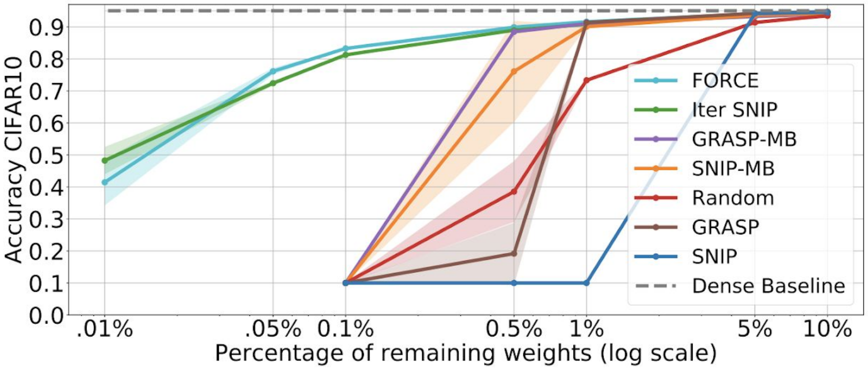

(a) Resnet50

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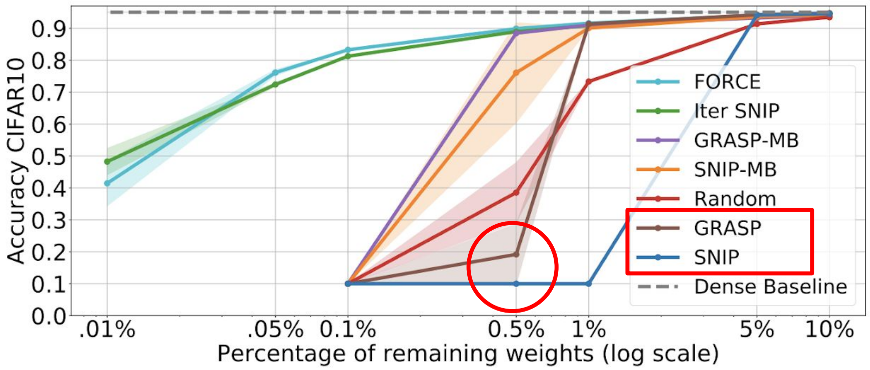

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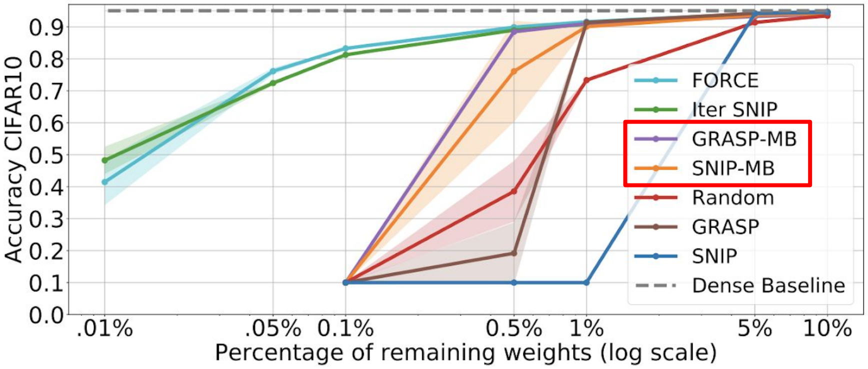

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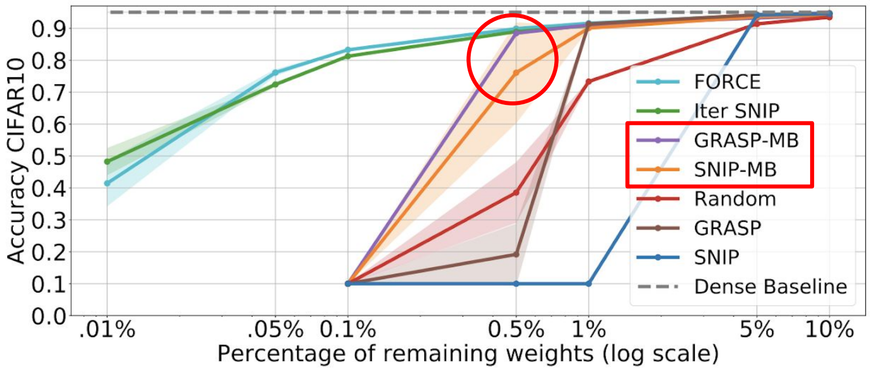

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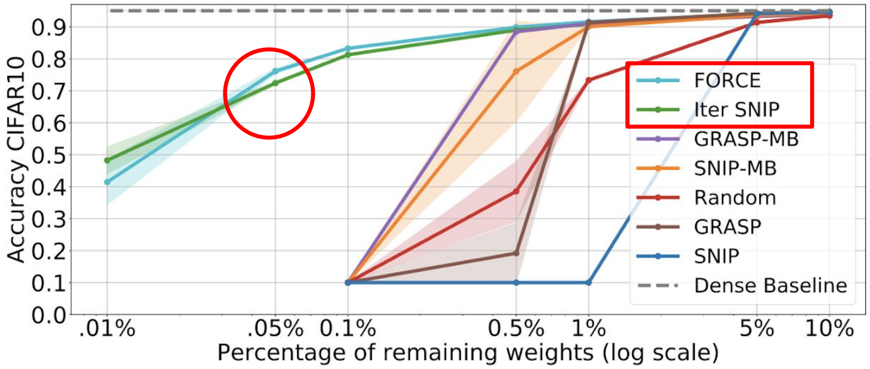

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- SNIP-MB and GRASP-MB use as many batches as FORCE and Iter-SNIP.

- Using multiple batches to compute the saliency improves SNIP and GRASP dramatically.

- Our “Progressive Skeletonization” methods find trainable models at much higher sparsity levels.

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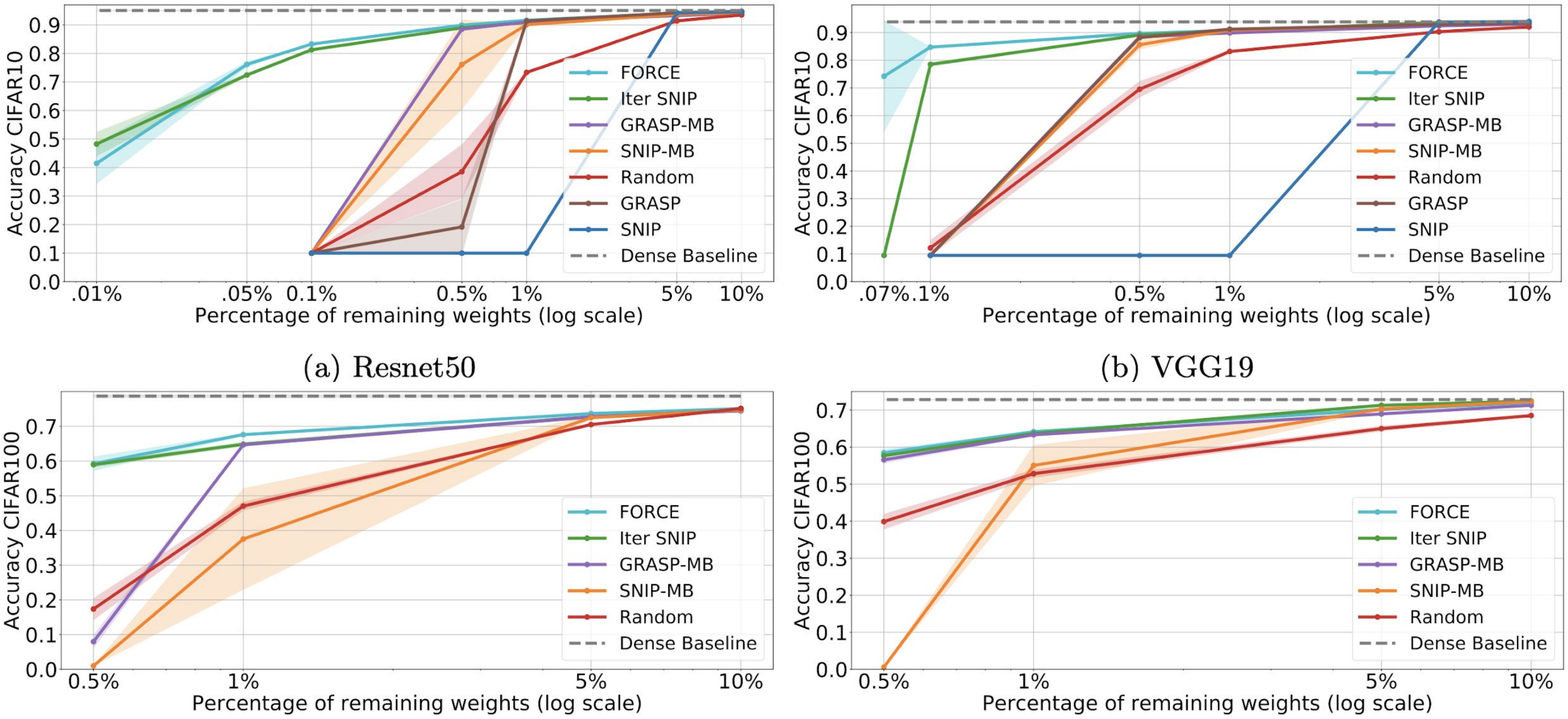

(a) Resnet50

(b) VGG19

Future directions

- We observe that for Imagenet, the difference between pruning methods and random pruning is much larger for VGG than for Resnet.
- Understanding the trade-off between the complexity of the task and network capacity
- Improving the pruning baselines at moderate sparsities.
- Taking into account bias and batch norm layers for pruning.

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Summary

- SNIP and GRASP collapse at high sparsities.
- We argue interactions between weights should be taken into account.
- We suggest two methods to optimize FORCE: With and without recovery of weights.
- We validate empirically iterative pruning is crucial at high sparsities.

Code: https://github.com/naver/force