WEIGHT REPARAMETRIZATION FOR BUDGET-AWARE NETWORK PRUNING

ICIP 2021

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Machine Learning & Deep Learning for Information Access

Pruning and sparsity

Pruning - Overview

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Pruning

- Group of methods that aim to design **lightweight architectures** *(small memory footprint or fast inference time)*

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- Introduce **sparsity** by removing **redundant** or **unecessary weights** of the network

Pruning - Overview

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Pruning

- Group of methods that aim to design **lightweight architectures** *(small memory footprint or fast inference time)*
- Introduce **sparsity** by removing **redundant** or **unecessary weights** of the network
- Can by applied at **different granularity** *(fine-grained vs coarse-grained)*

Pruning - Coarse-grained

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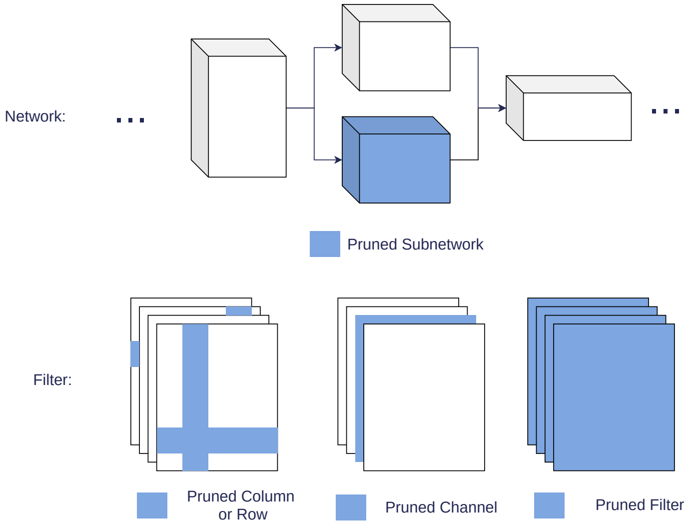

Pruning - Fine-grained

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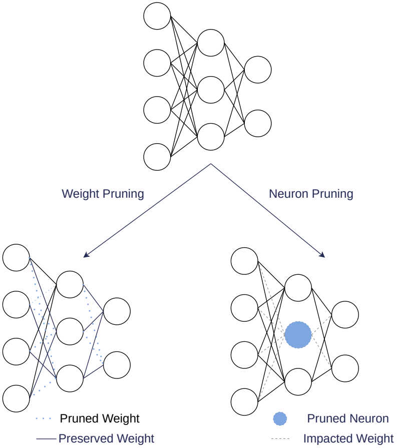

{*Optimal Brain Damage*, LeCun et al. 1989; *Optimal Brain Surgeon*, Hassibi et al. 1992; *Learning both weights and connections for efficient neural network*, Han et al. 2015}

Pruning - Fine-grained

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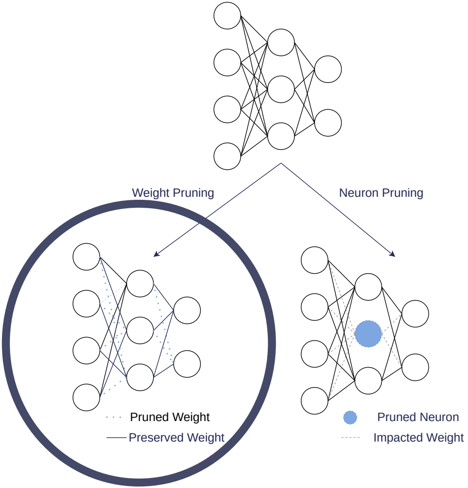

Our method belongs to the the **fine-grained weight pruning** category.

{*Optimal Brain Damage*, LeCun et al. 1989; *Optimal Brain Surgeon*, Hassibi et al. 1992; *Learning both weights and connections for efficient neural network*, Han et al. 2015}

Pipelines

Pruning Pipelines

Pruning - Standard Pipeline

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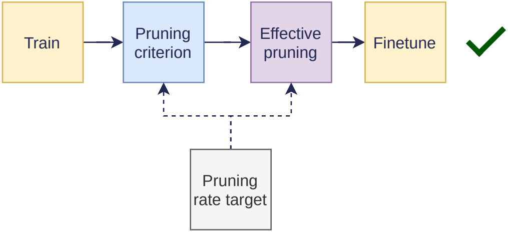
Standard Pruning Pipeline



Effective Pruning: Setting pruned weights to 0 and freezing them

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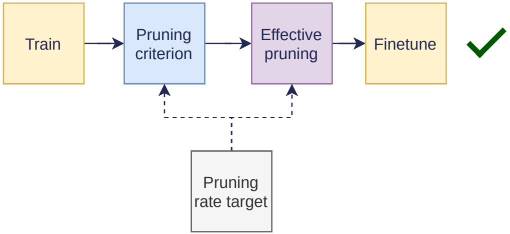

Standard pipelines requires the application of a **pruning criterion** to determine which weights will be **pruned**. This is done **after training**.

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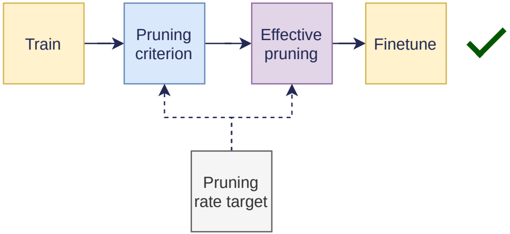

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Initial training does **not take into account final weight budget**.

Effective Pruning: Setting pruned weights to 0 and freezing them

Pruning - Our Pipeline

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Our Pipeline

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Our Pipeline

Our pipeline takes the **final pruning rate** as an input **during initial training**.

Effective Pruning: Setting pruned weights to 0 and freezing them

Pruning - Our Pipeline

Our Pipeline

Our pipeline takes the **final pruning rate** as an input **during initial training**.

Topology is optimized with the budget constraint **from the start.** This helps **preventing disconnections** in the network.

Effective Pruning: Setting pruned weights to 0 and freezing them

Our Method

Weight Reparametrization

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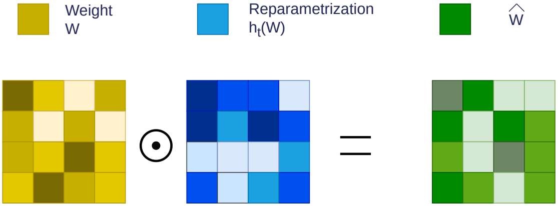
Weight Reparametrization



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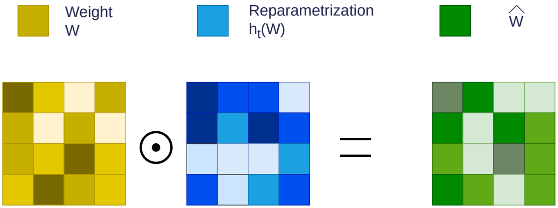

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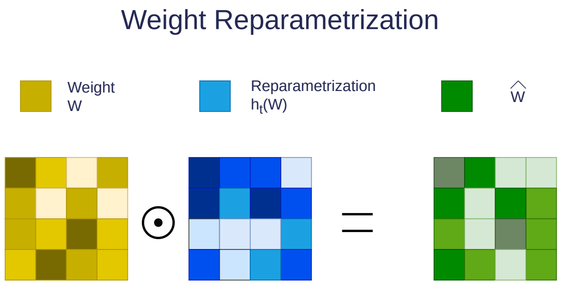
Weight Reparametrization



- New weights $\hat{w}$ are defined by $\hat{w} = w \odot h_t(w)$.
- w are the standard neural network weights.

Reparametrization Function

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Reparametrization function

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C_1 and ***C_2*** ensure
$0 \le h_t(x) \le 1$

$$h_t(x) = C_1\left(\exp\left\{-\frac{1}{(tx)^n + 1}\right\} - C_2\right)$$

t controls the
bandwidth of the pit.
It is a learnt parameter

n controls the
sharpness of the falling
and raising edges

+1 to numerically
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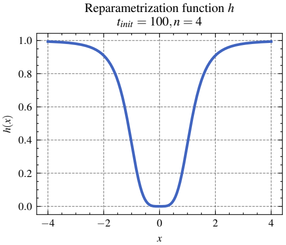

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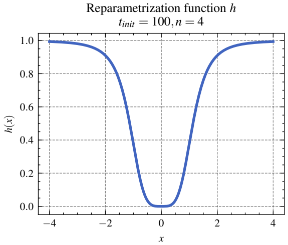

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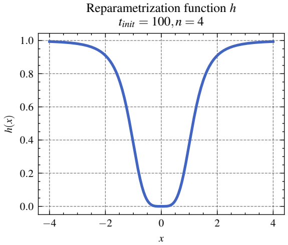

- t is a **learnt parameter**, optimized with SGD. t is initialized to 100.
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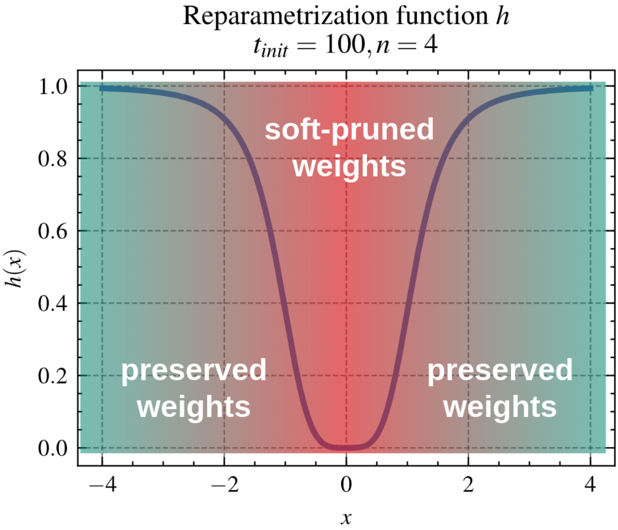
Reparametrization function



Budget Loss

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(sum of weight reparametrizations)

$$C(\{\mathbf{w}_1, \ldots, \mathbf{w}_L\}) = \sum_{i=1}^{L} h(\mathbf{w}_i)$$

Target cost

$$\mathcal{L}_{\text{budget}} = \left(\frac{C(\{\mathbf{w}_1, \ldots, \mathbf{w}_L\}) - C_{\text{target}}}{C_{\text{initial}}} \right)^2$$

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- **Current cost** is computed at **each step**.

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- **Current cost** is computed at **each step**.
- **Target cost** is the **number of parameters** that will be **kept**.
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- Total loss is $\mathcal{L} = \mathcal{L}_{\text{task}} + \lambda \mathcal{L}_{\text{budget}}$, with $\lambda > 0$

Results

CIFAR 10

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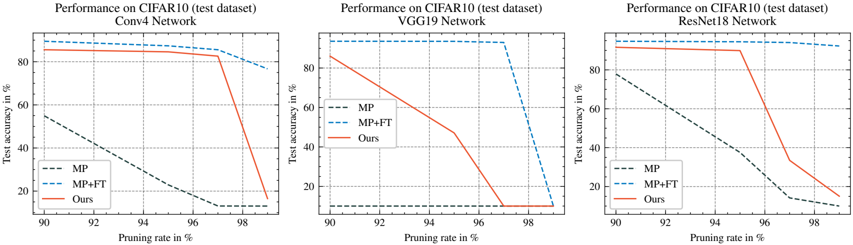
Results on CIFAR 10 for **Conv4**, **VGG19** and **ResNet18** networks



MP: Magnitude Pruning, MP+FT: Finetuned Magnitude Pruning

{Frankle et al. 2019; Simonyan at al. 2015; He et al. 2016}

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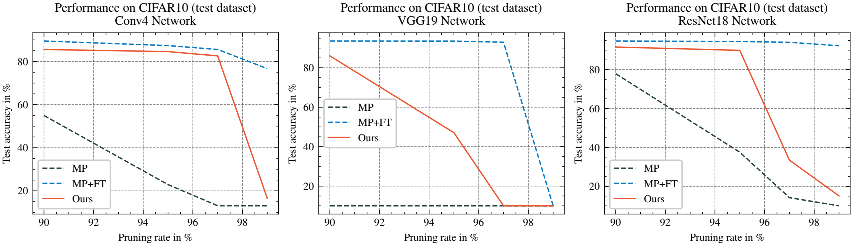

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TinyImageNet

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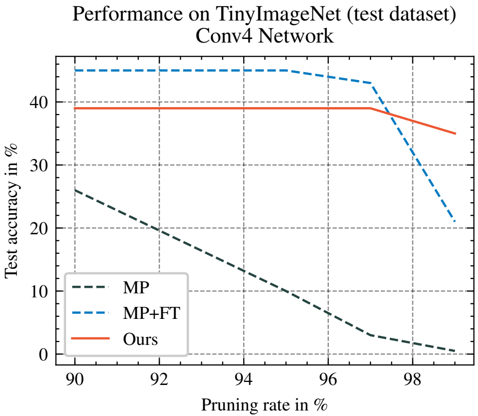
Results on TinyImageNet for **Conv4** network



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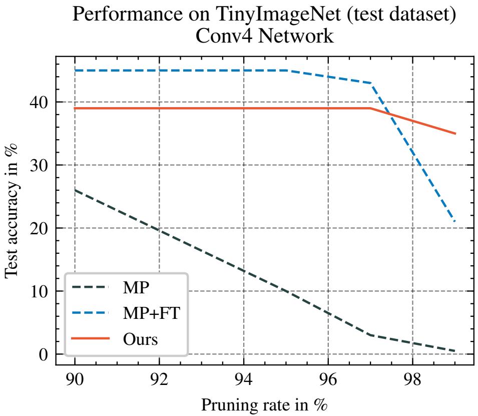

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SUM UP

Key points

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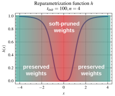

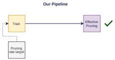

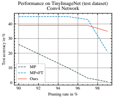

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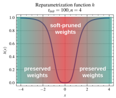
Key points



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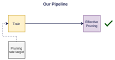
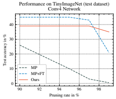


- It allows to optimize **both topology and weights** under **bugdet constraints**.



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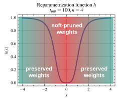

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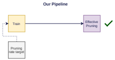

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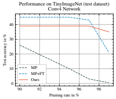

- Our method significantly **overperforms magnitude pruning without finetuning**, and performs better than finetuned magnitude pruning for **very high pruning rates** on more complex datasets.

Budget Loss

Perspectives

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- Evaluate our method on **larger** and **more complex datasets.**

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- Evaluate our method on **larger** and **more complex datasets.**
- Improve performances to outperform **finetuned** magnitude pruning more consistently.
- Assess the **impact of the reparametrization** function and test other functions.

Thank you! 👍

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