




# Energy and Memory-Efficient AI for On-Device Learning

PhD Defense of Aël Quélennec

December 3, 2025

Supervisor: Van-Tam Nguyen
Co-Supervisors: Enzo Tartaglione and Pavlo Mozharovskyi
Reviewers: Dewey Yi and Ngoc-Son Vu
Examiners: Amel Bouzeghoub and Umut Şimşekli
Guest: Vito Paolo Pastore

# Outline

Introduction

Subnetwork Selection for Fine-Tuning

Activation Map Compression

Conclusion

# Motivations

**Three questions to begin with**

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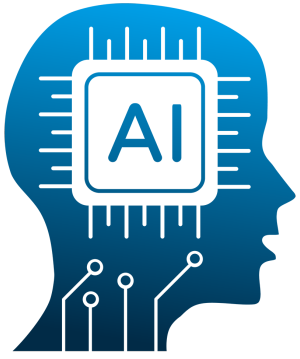

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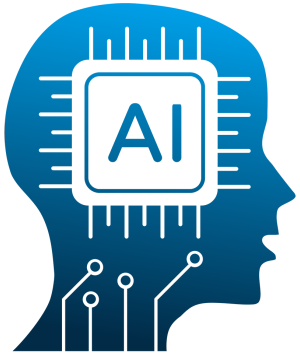


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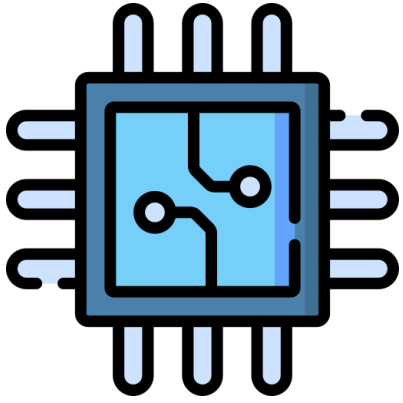

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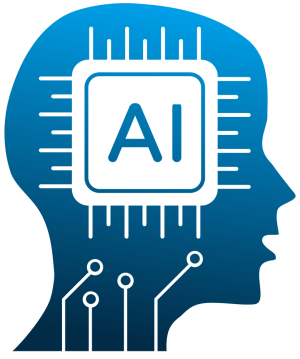


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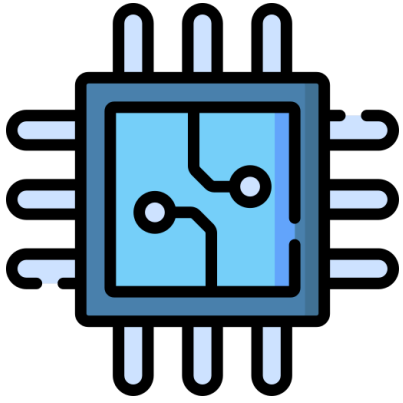

What Challenges?

# Uncovering Artificial Intelligence (AI)

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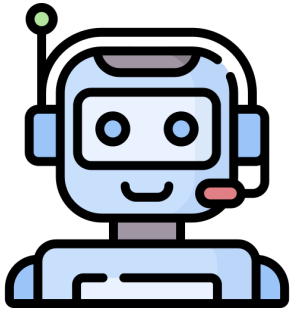
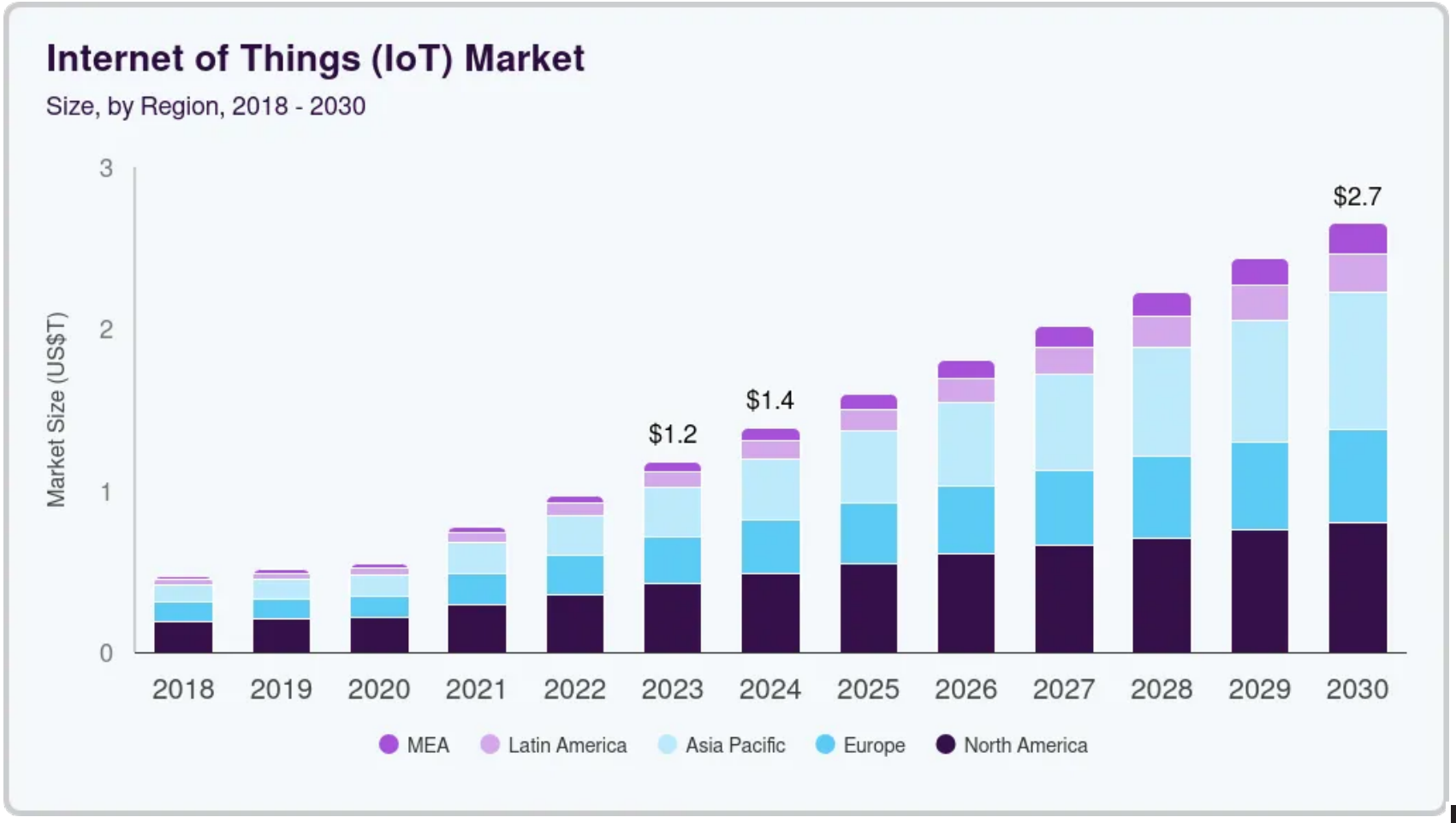


# Internet of Things

## A market in expansion




Source: Grand View Research - Internet of Things (IoT) Market (2024 - 2030)

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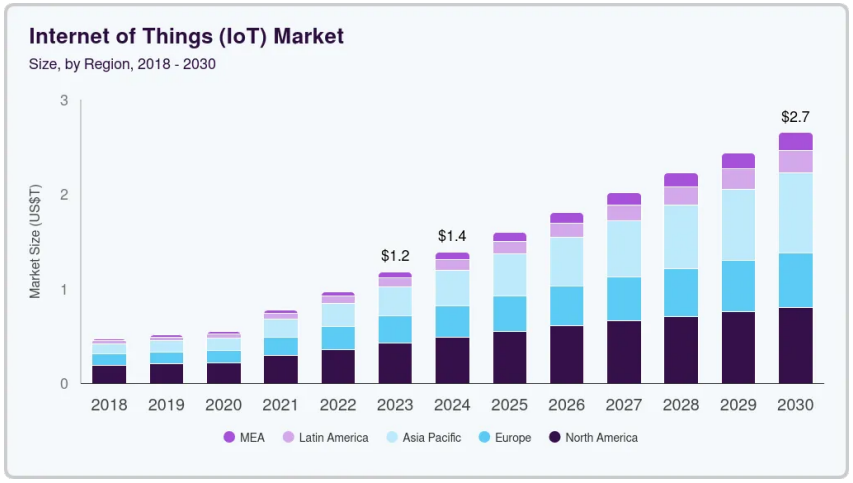
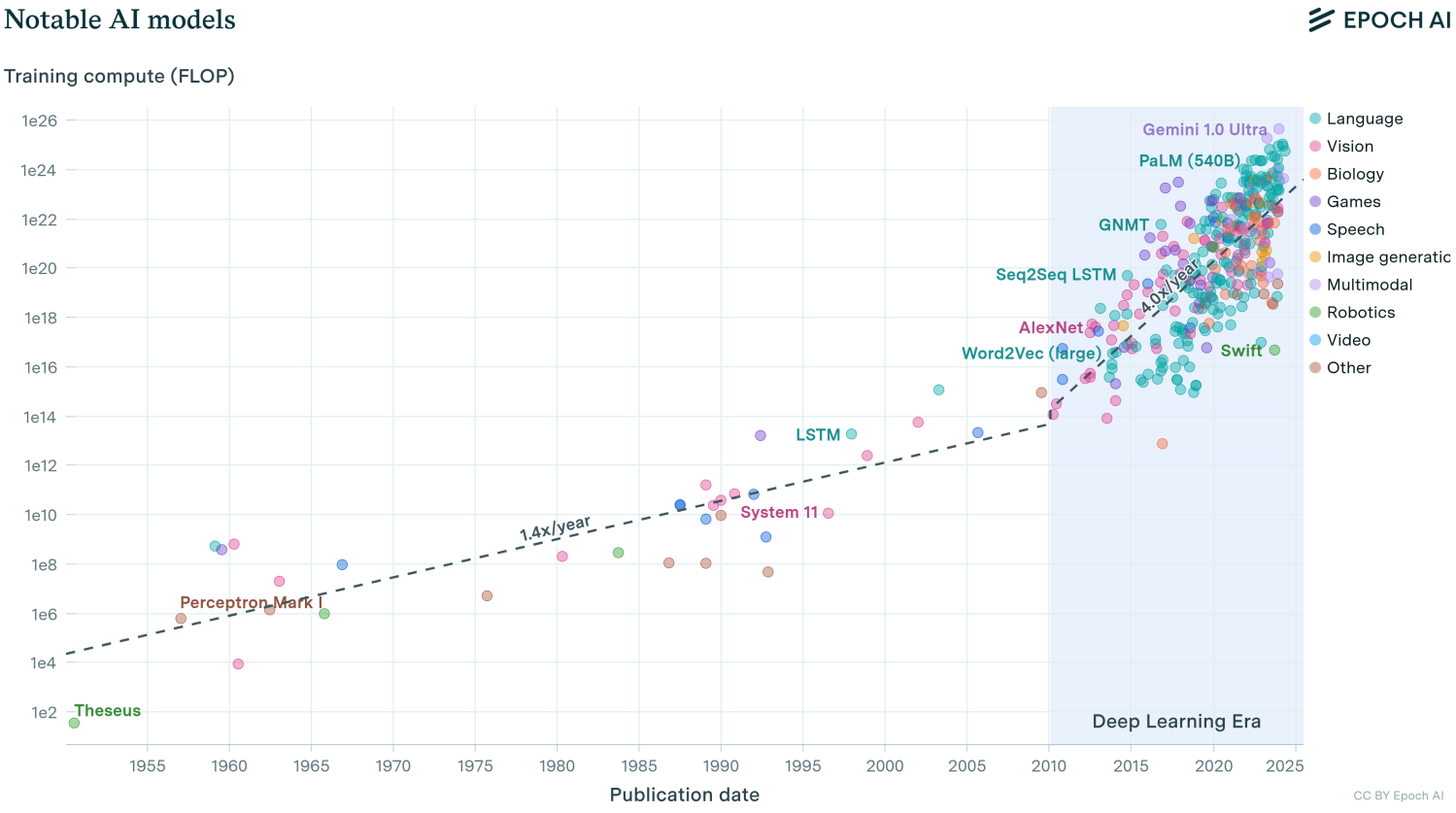



On-device AI has several benefits, among which:

1. Enhanced privacy and security
2. Adaptive user personalization
3. Reduced energy consumption
4. Network independence

# Challenges of Embedded AI

## Computational trend in deep learning



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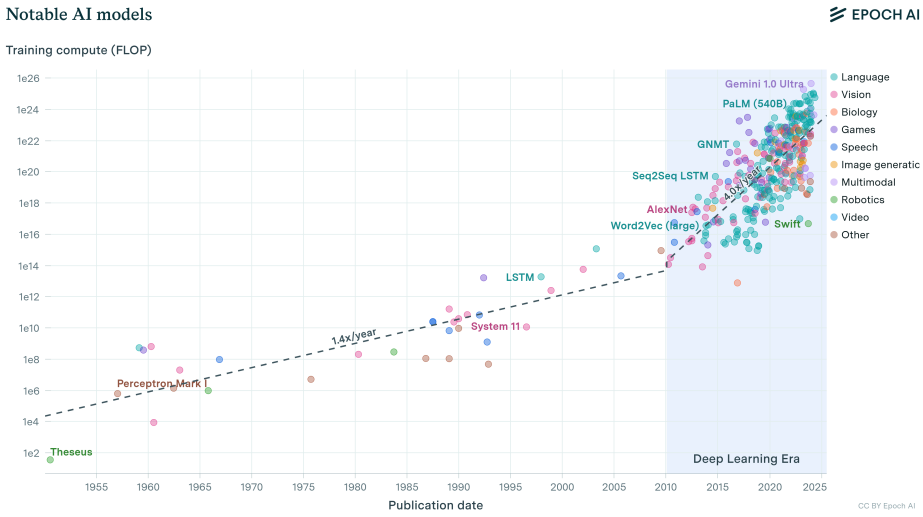


Source: Epoch AI - Compute trends across three eras of machine learning

- GPT-4: 1.76 trillion parameters, 25,000 Nvidia A100 GPUs for 90–100 day to train and cost $100 M
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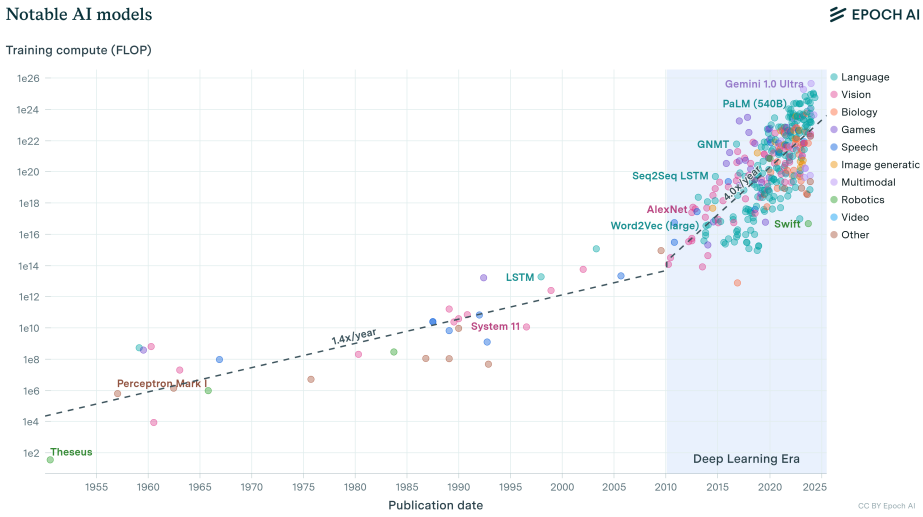


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VS 

| | | |
|---|---|---|
| RAM: | GB/TB | 256kB |
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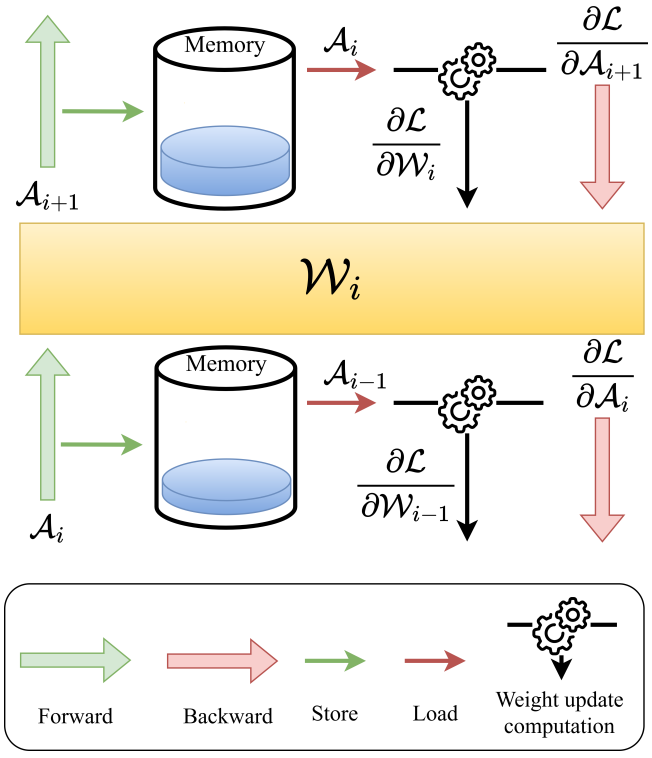

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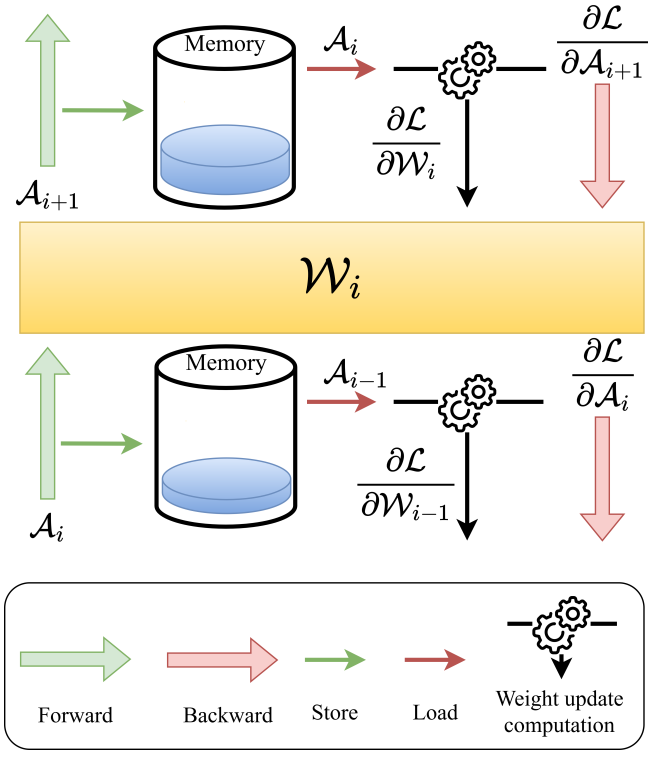


## Forward pass

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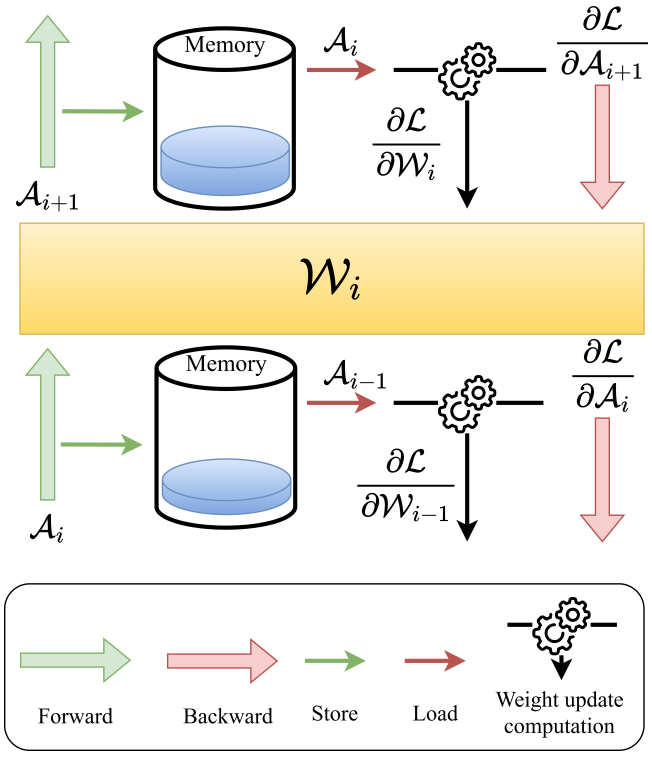


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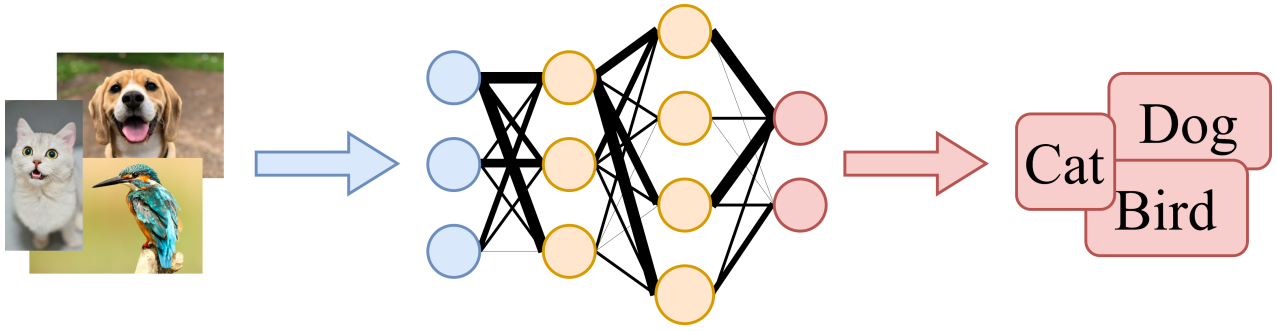
## Backward pass

$$\frac{\partial \mathcal{L}}{\partial \mathcal{W}_i} = f_1\left(\mathcal{A}_i, \frac{\partial \mathcal{L}}{\partial \mathcal{A}_{i+1}}\right)$$

$$\frac{\partial \mathcal{L}}{\partial \mathcal{A}_i} = f_2\left(\frac{\partial \mathcal{L}}{\partial \mathcal{A}_{i+1}}, \mathcal{W}_i\right)$$

# Fine-Tuning Pipeline

## Stage 1 - Learning general features



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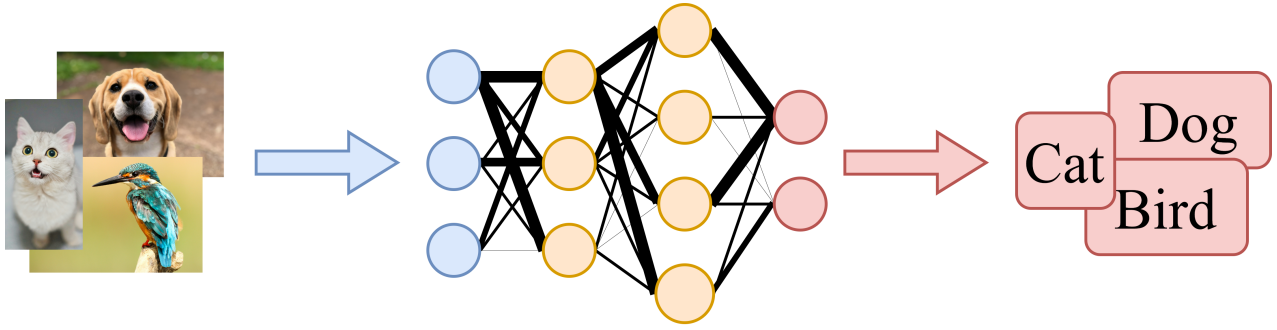
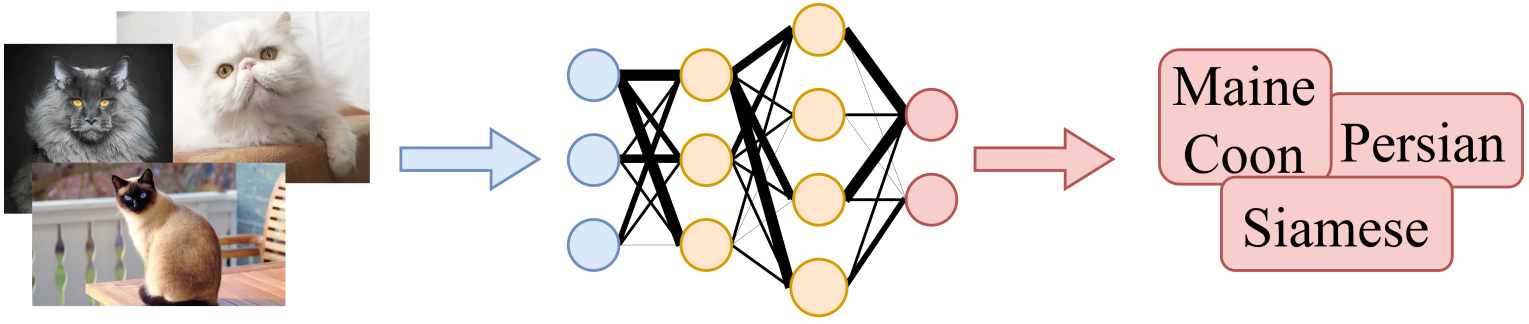



## Stage 2 - Specializing on a downstream task



# Sparse Fine-Tuning

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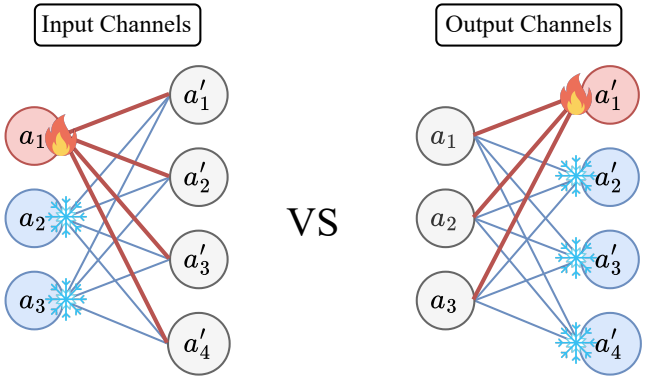
### Channel level



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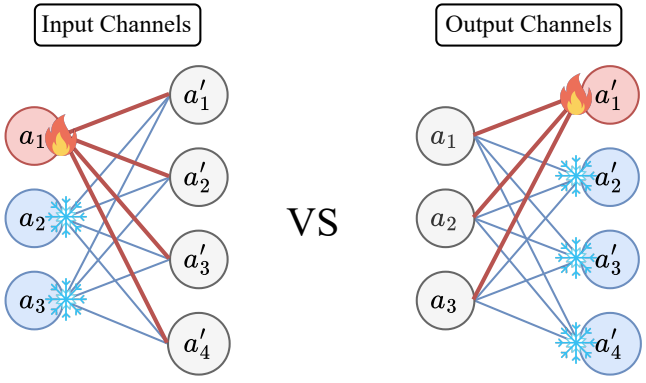
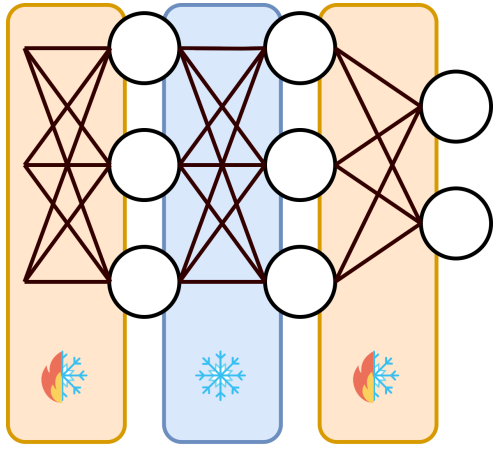
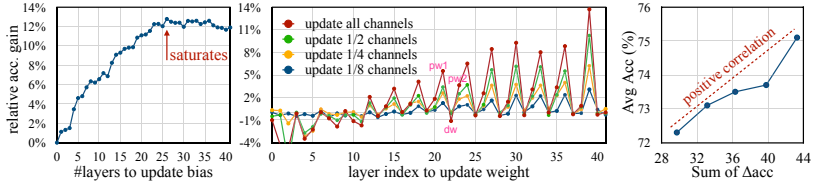



### Layer level



# Existing Approaches

Lin et al. (2022)'s **Sparse Update** (SU):




(a) Contribution of last $k$ biases $\Delta acc_{b[:k]}$ (b) Contribution of a certain weight $\Delta acc_{W_{i,r}}$ (c) Effectiveness of search

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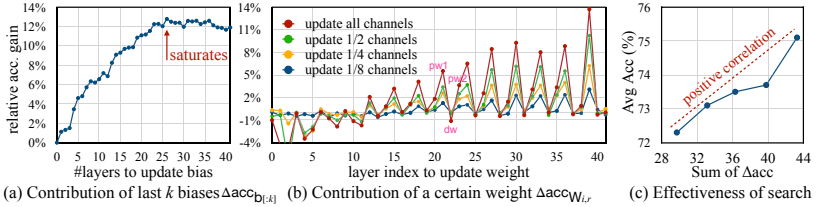


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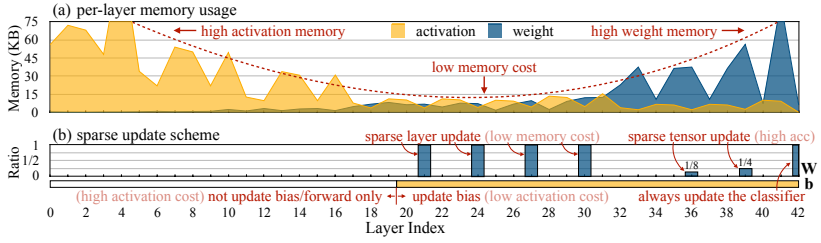

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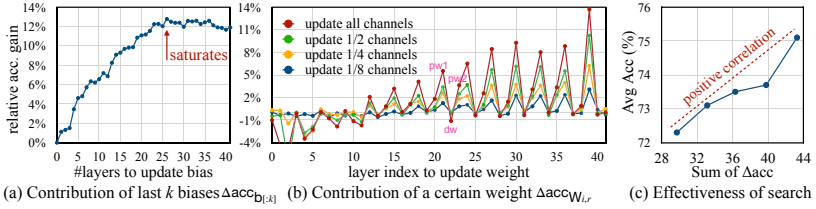


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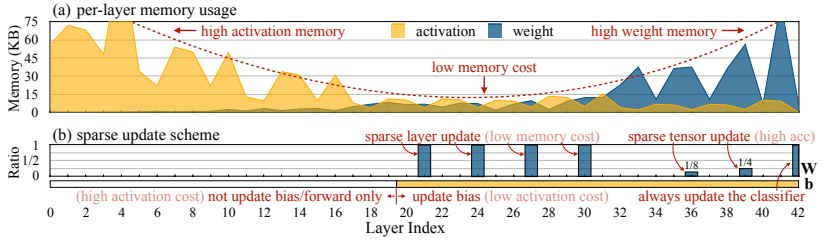


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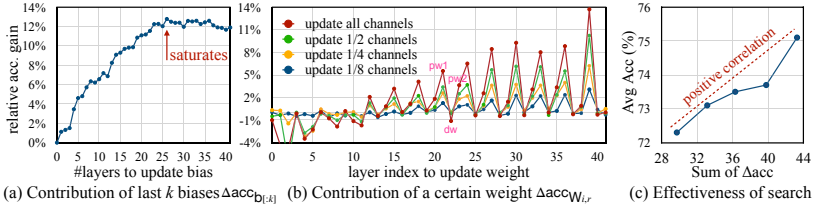


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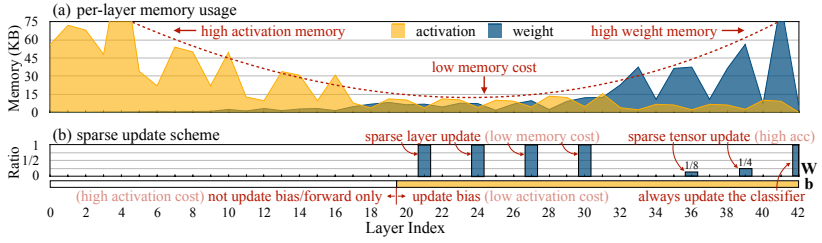


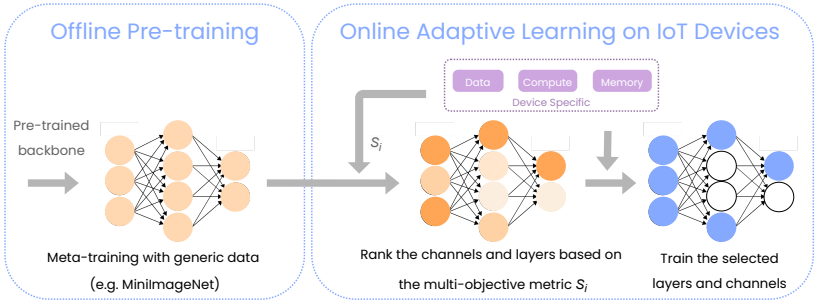


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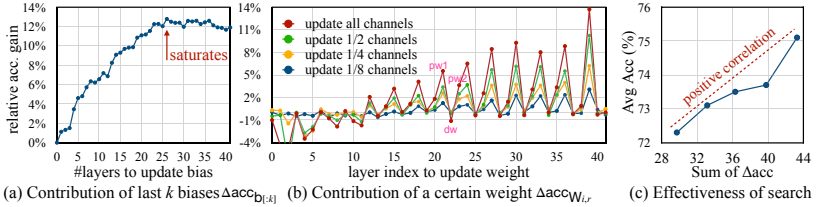


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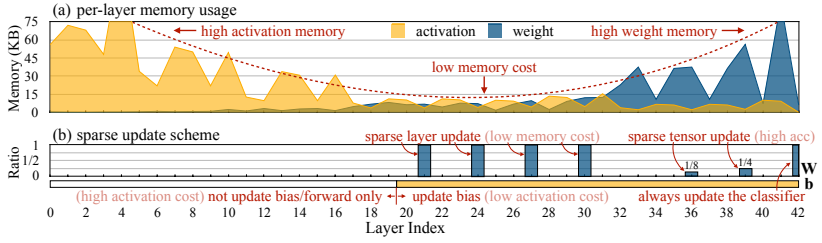


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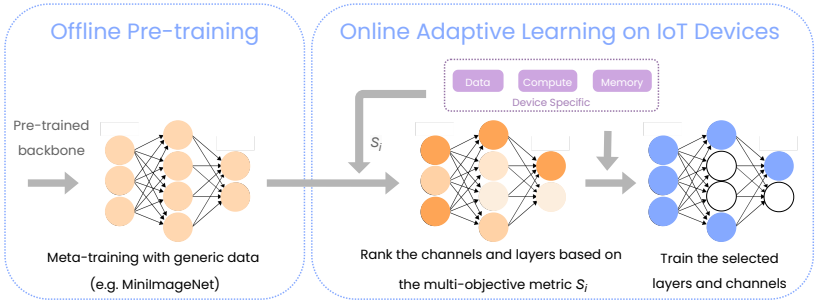


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**How to predict this in advance?**

# Introducing Heavy-Tailed Theory

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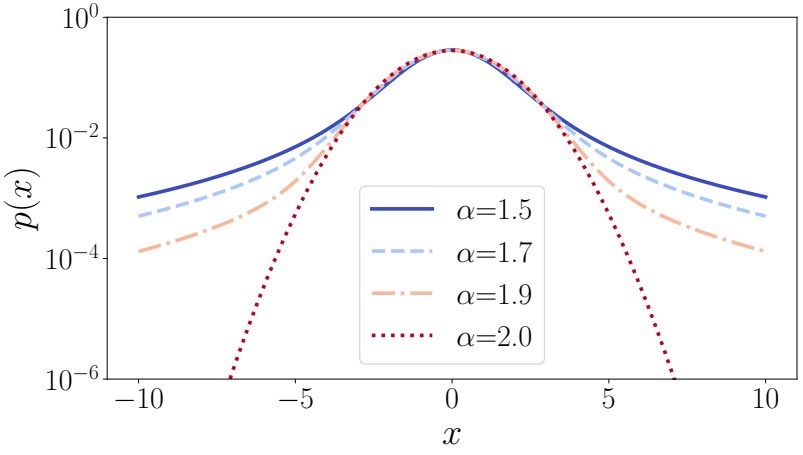
$$U_k(\mathcal{W}) = \Delta\tilde{\mathcal{W}}_k - \Delta\mathcal{W},$$



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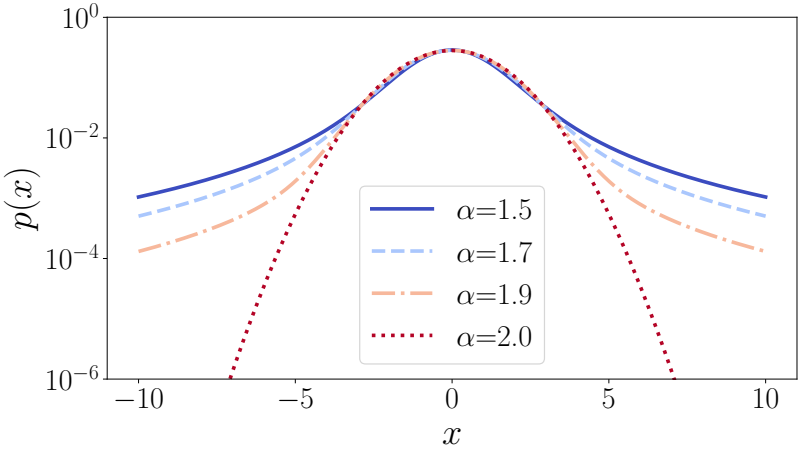


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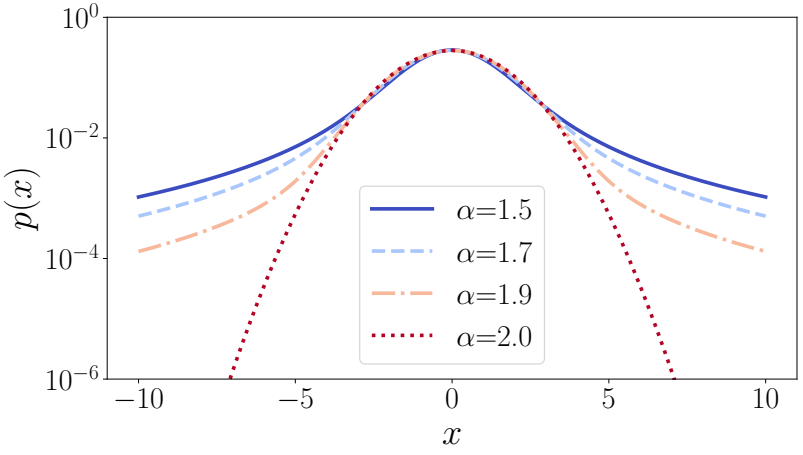


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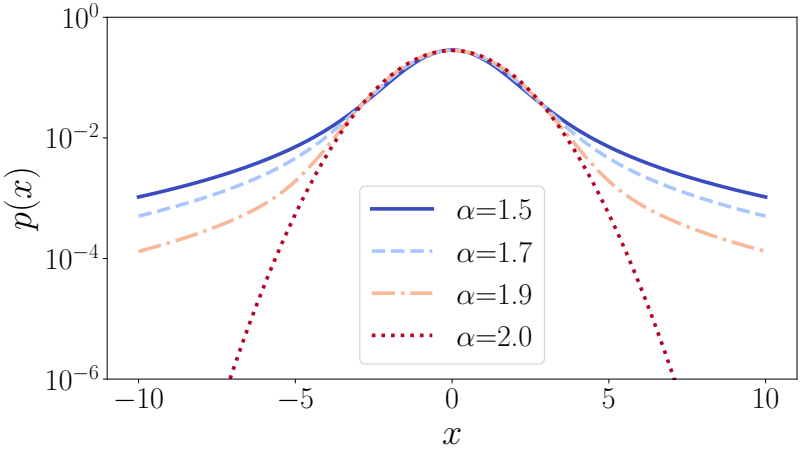


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Gradient = stochastic gradient + heavy-tailed noise → **gradient is prunable with respect to norm**

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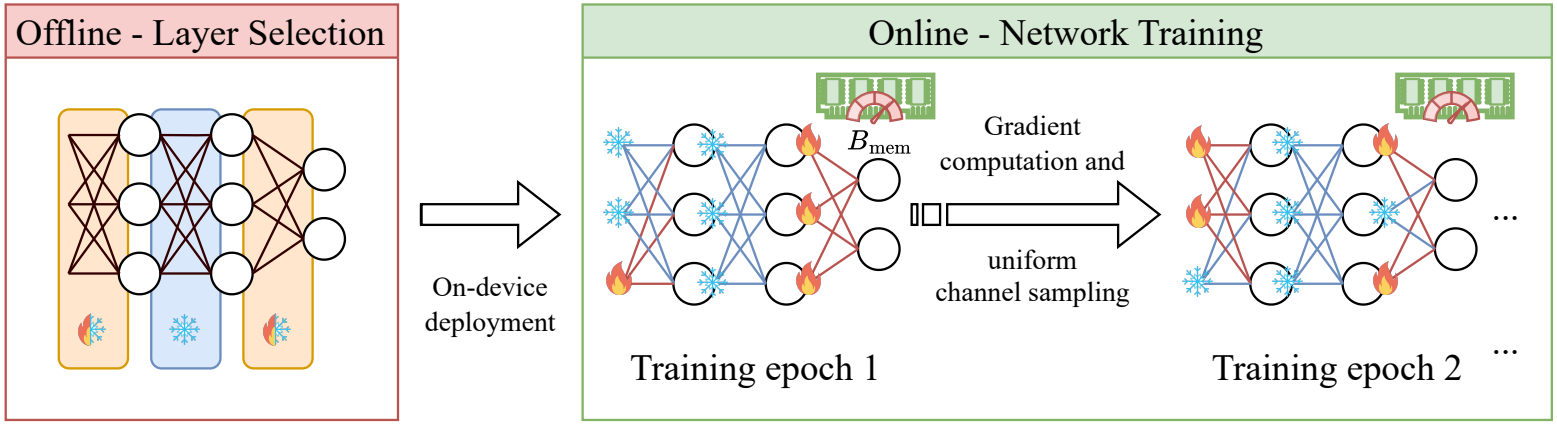
# Our Proposed Algorithm

## **Tra**ining **Dy**namics (TraDy)



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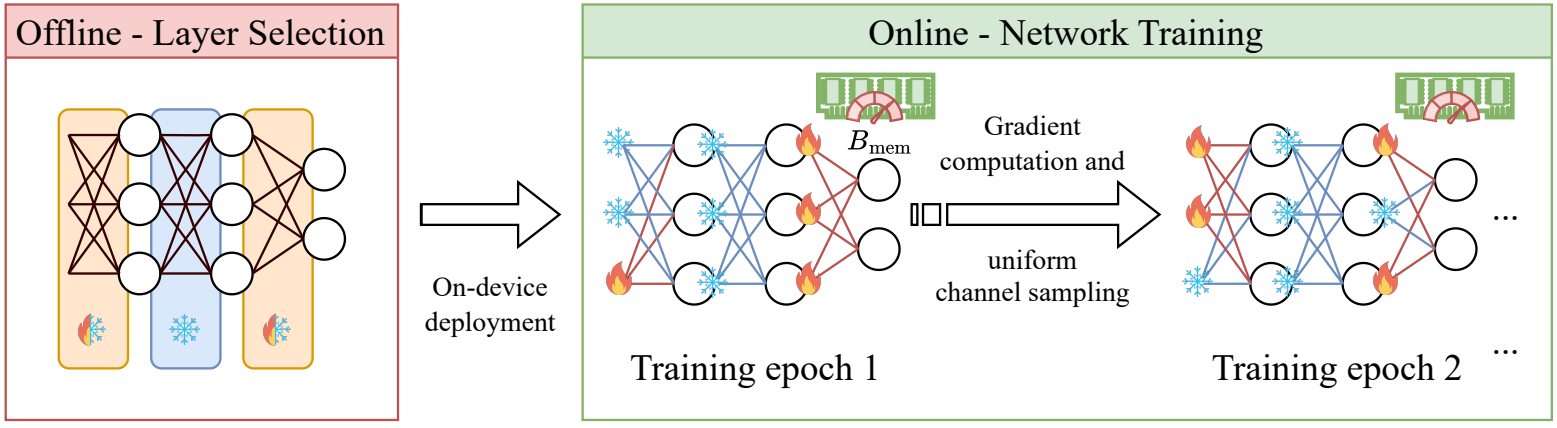
## Training Dynamics (TraDy)




## Design choices

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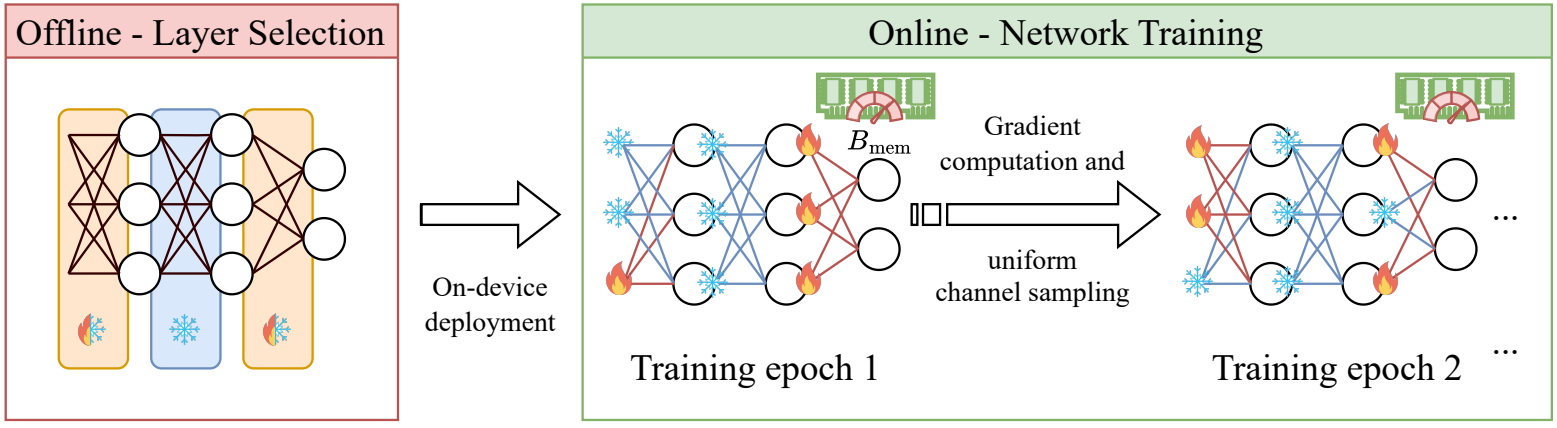


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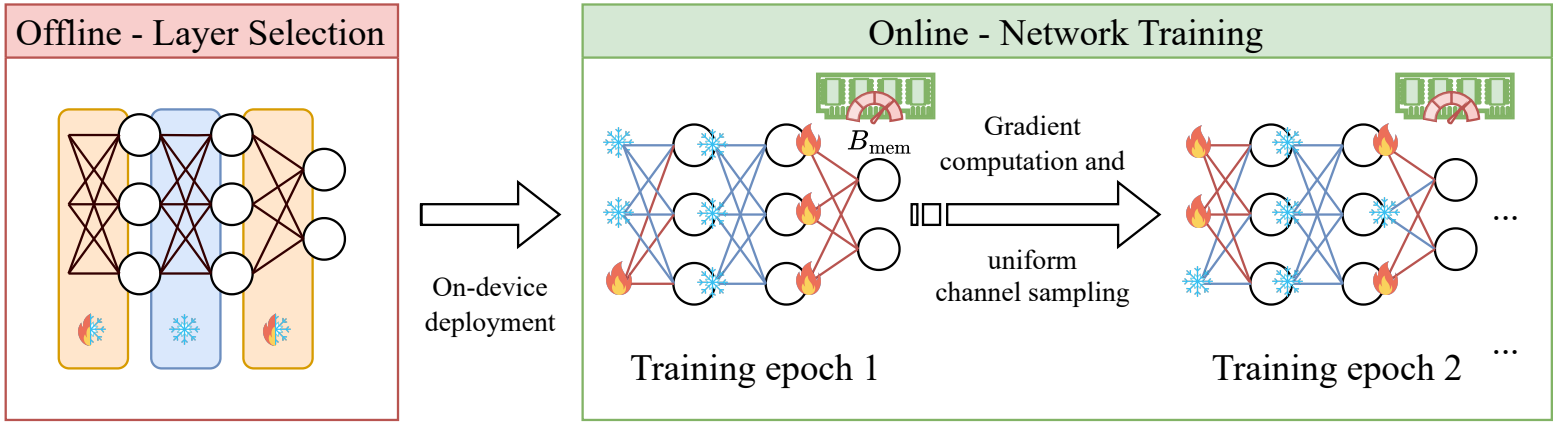


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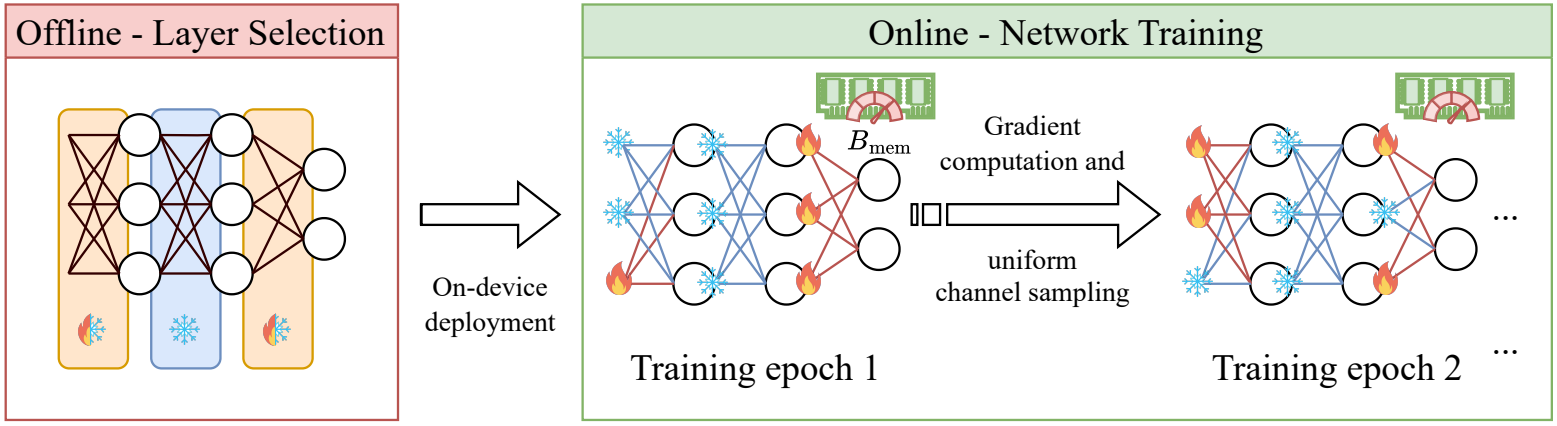


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- Layer selection: retain layers capturing 97% of cumulative RGN $\rightarrow$ reduces from 52 to 35 layers in MobileNetV2
- Dynamic random channel selection $\rightarrow$ maintains non-null gradient expectation: $\mathbb{E}_t \left[ \Delta \tilde{\mathcal{W}}_t \right] \simeq \mathbb{E}_t \left[ \Delta \mathcal{W}_{\{C^t\}} \right]$

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**Setup:** 3 architectures, 7 datasets, 3 memory budgets, 3 seeds

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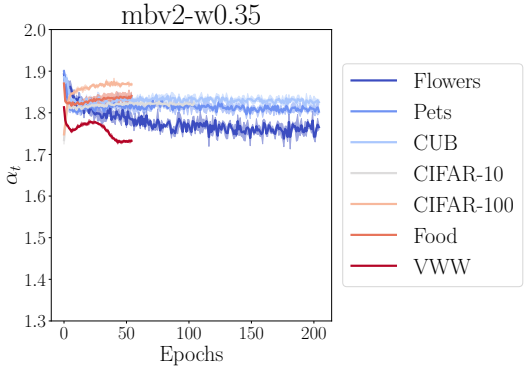


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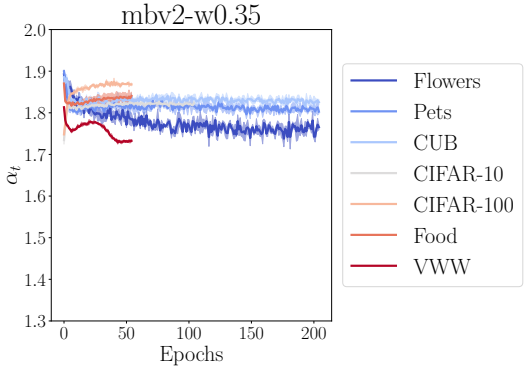
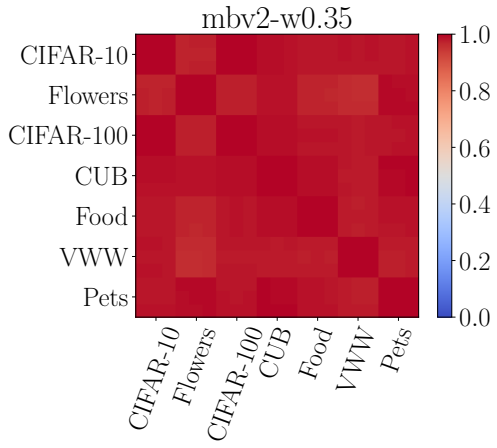



Layer proposition:

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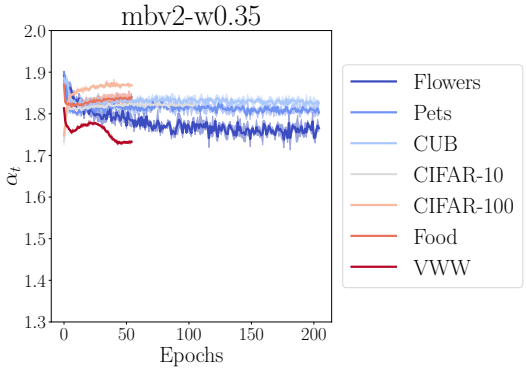


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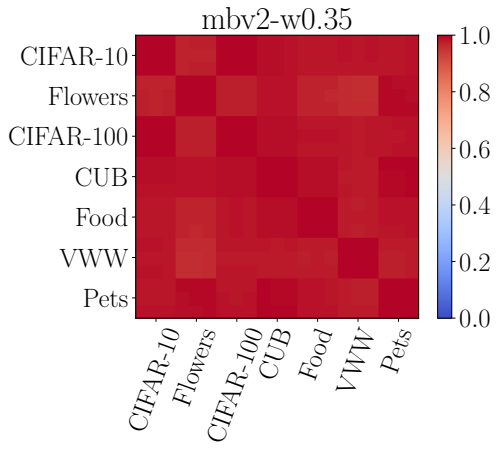
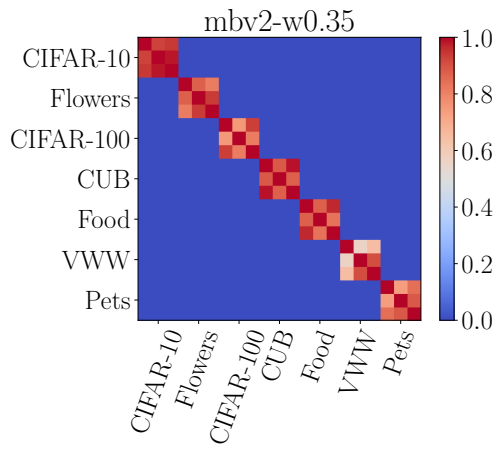
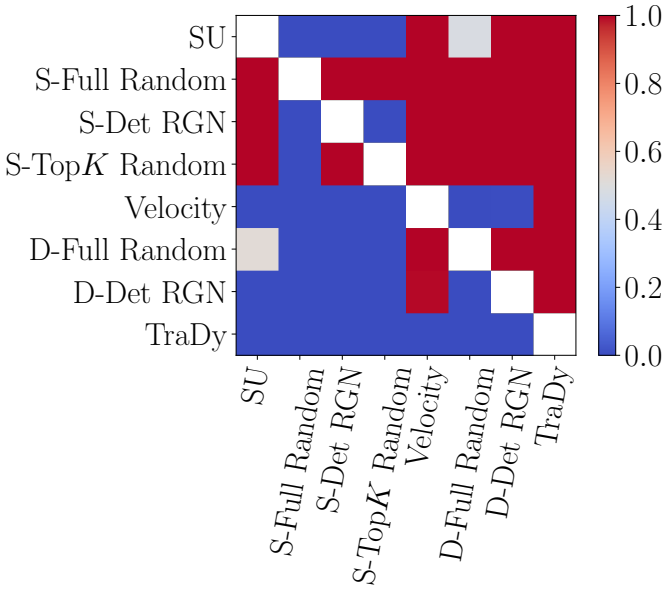



Channel proposition:




1. Stochastic gradients exhibit heavy-tailed behavior
2. Layer rankings show high Spearman correlation across tasks
3. T-test confirms channel gradient norms vary significantly between tasks

# Performance Analysis



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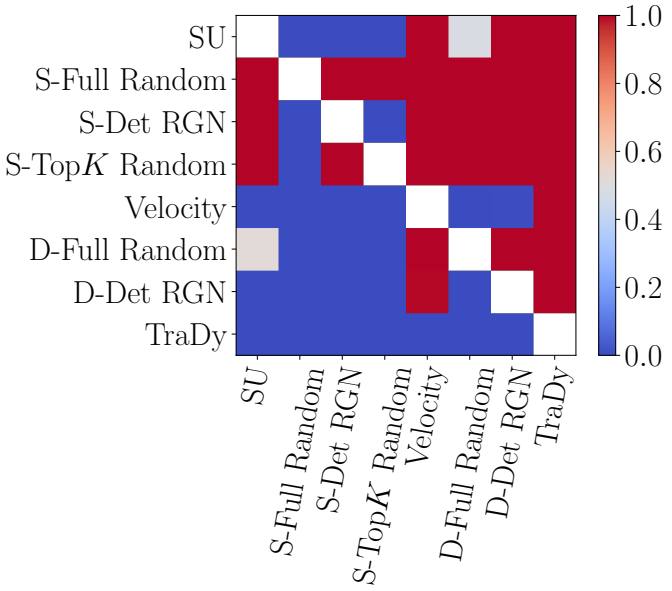


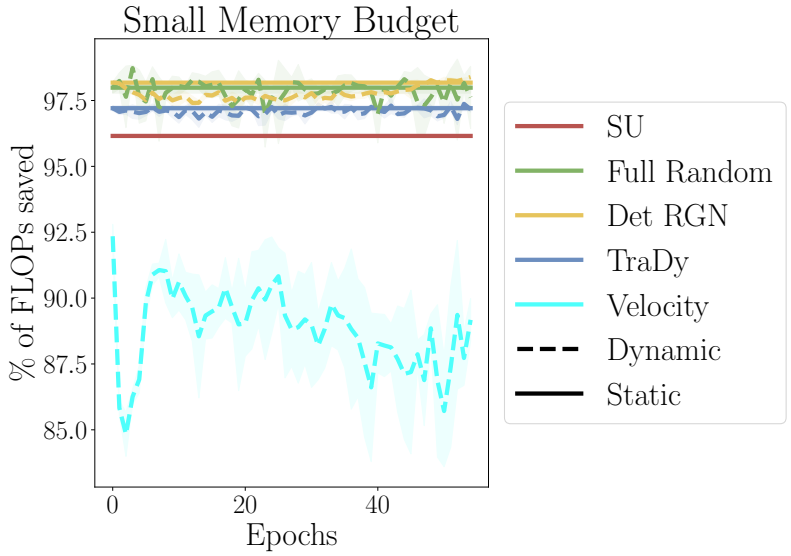


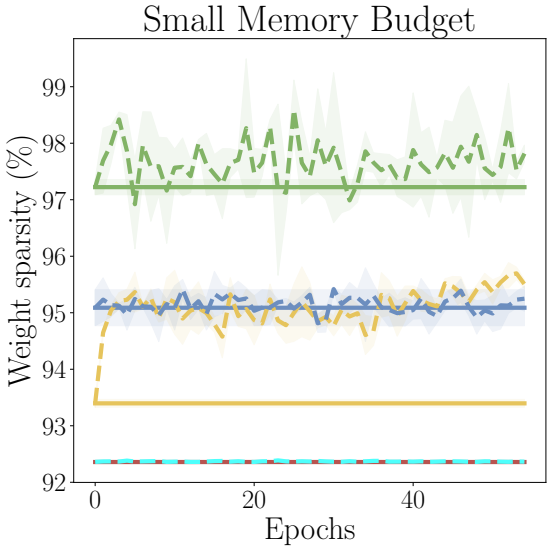


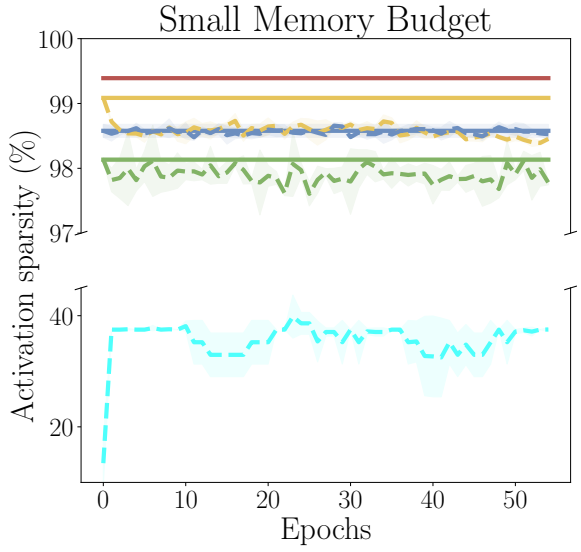

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   → Leverage channel stability for probabilistic sampling

# Key Innovations

**Layer importance metric**

From $\text{RGN}_i$:

$$\frac{1}{(\Theta_{\text{space}})_i} \sum_{c=1}^{C} \left\| \left( \frac{\partial \mathcal{L}}{\partial \mathcal{W}_i} \right)_c \right\|_2$$

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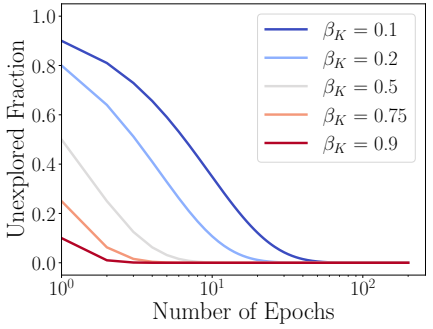
## Budget-adaptive layer selection

Introduction of $\beta_K = \frac{B_{\text{mem}}}{M_K}$:



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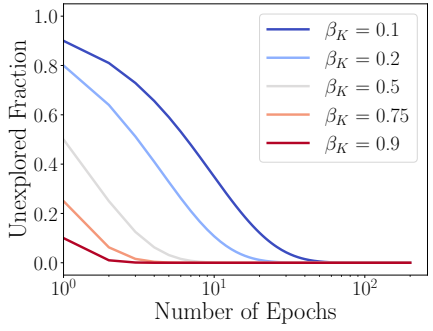
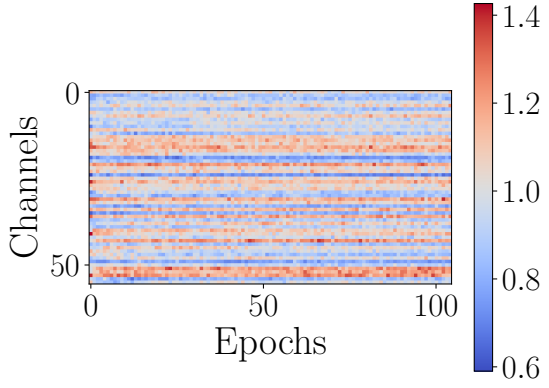
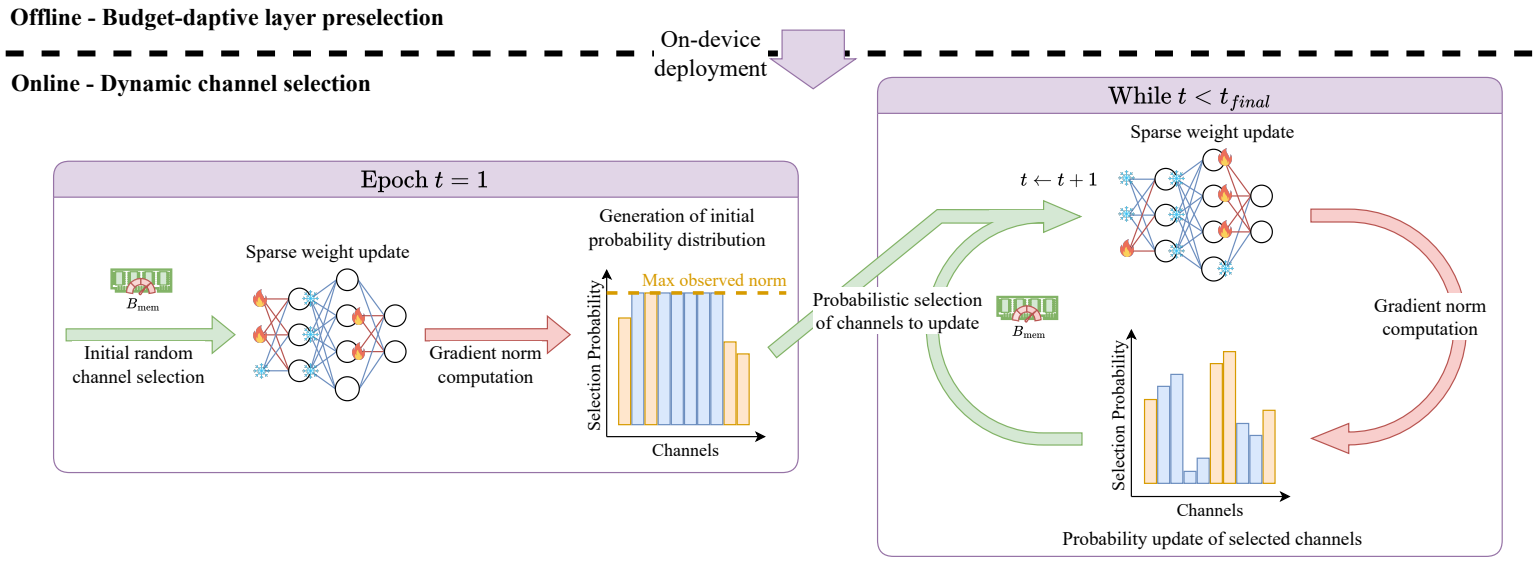



## Channel importance stability



# Unpacking our Improved Algorithm

## Memory-constrained **Dy**namic subnetwork upd**ate** (MeDyate)



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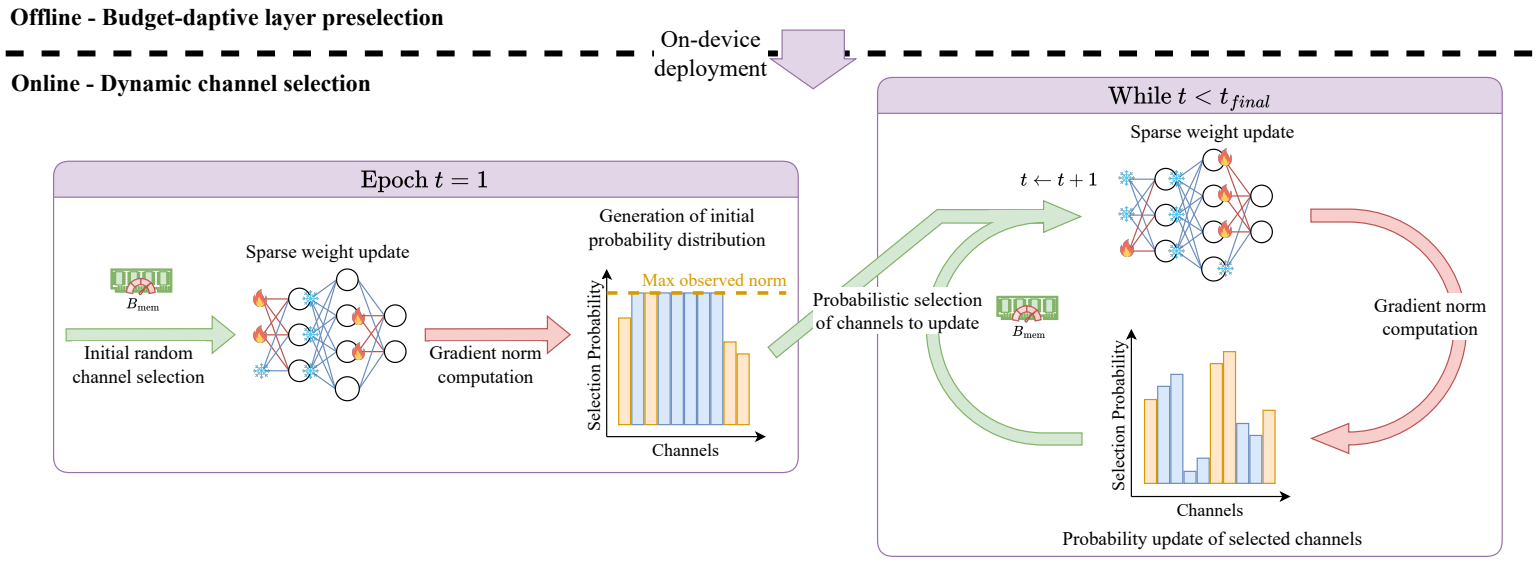
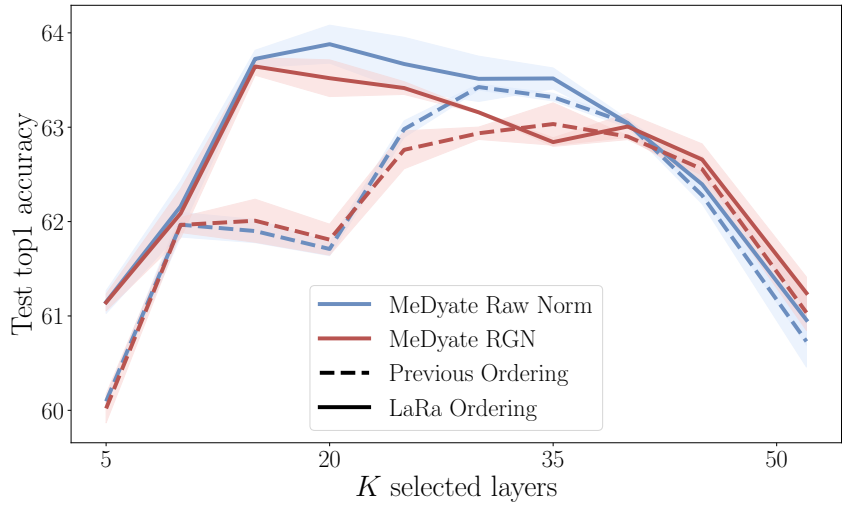



- Budget-adaptive layer selection → synergizes with exploration strategy
- Probabilistic sampling → enables importance-based selection

# Experimental Results



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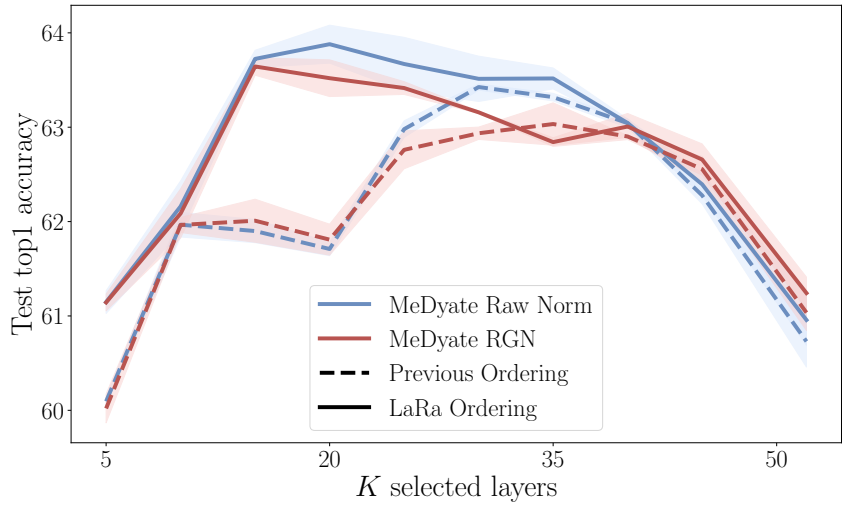


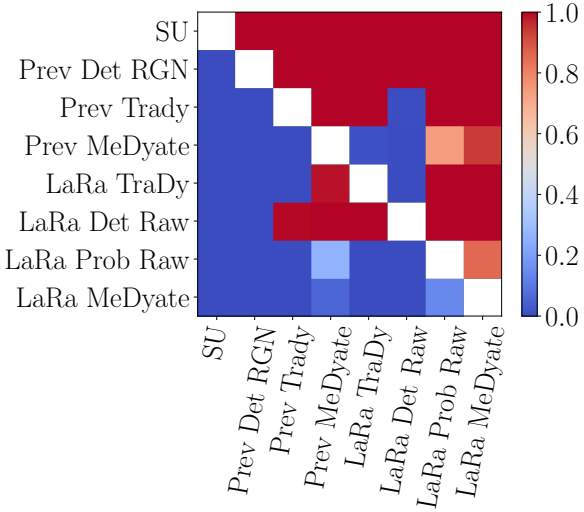

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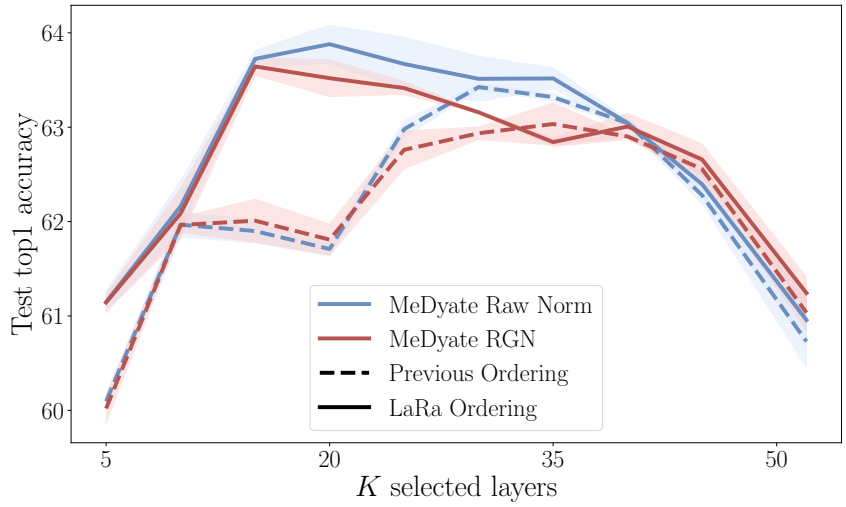


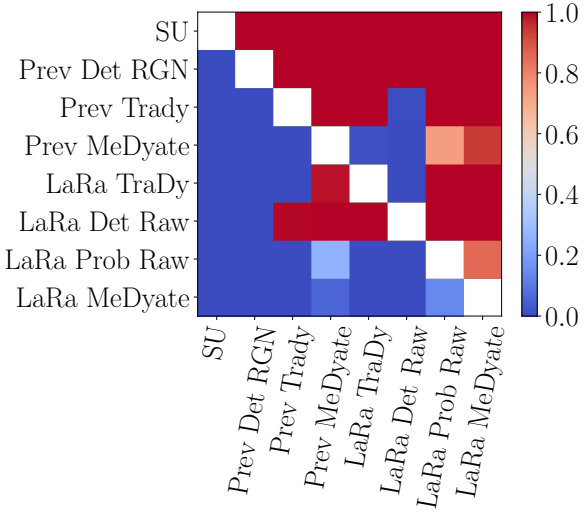


- LaRa enables more selective layer pruning
- Raw layer norm outperforms memory-normalized metric
- MeDyate matches full-gradient baseline performance

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- No on-device validation of practical feasibility and energy efficiency

# Publications

**Aël Quélennec**, Enzo Tartaglione, Pavlo Mozharovskyi and Van-Tam Nguyen. Towards on-device learning on the edge: Ways to select neurons to update under a budget constraint. In *WACV2024*.

**Aël Quélennec**, Nour Hezbri, Pavlo Mozharovskyi, Van-Tam Nguyen and Enzo Tartaglione. Study of training dynamics for memory-constrained fine-tuning. Under revision in *ICLR2026*.

**Aël Quélennec**, Pavlo Mozharovskyi, Van-Tam Nguyen and Enzo Tartaglione. Memory constrained dynamic subnetwork update for transfer learning. Under revision in *TMLR*.

# Outline

Introduction

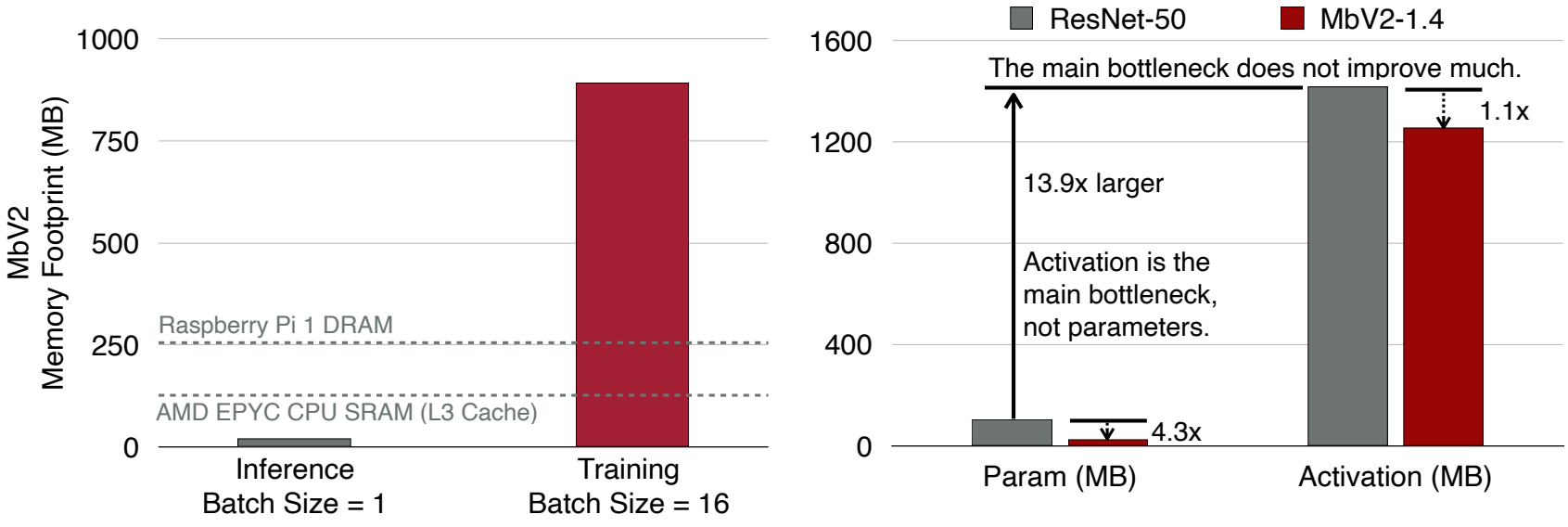
Subnetwork Selection for Fine-Tuning

Activation Map Compression

Conclusion

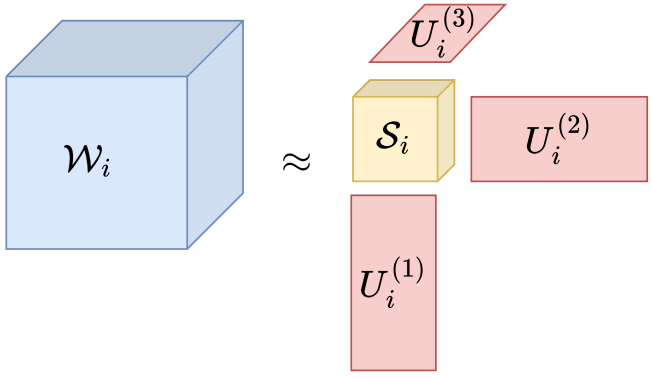
# Motivations

Cai et al. (2020) demonstrate that the main bottleneck during training corresponds to activation memory storage:



# Introducing Tensor Decomposition

Decomposes large tensors into products of smaller matrices:



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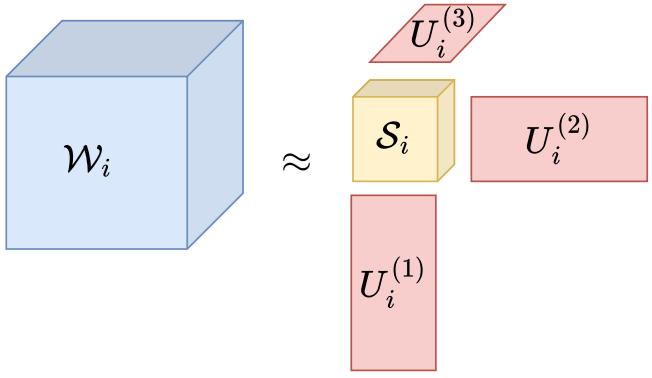


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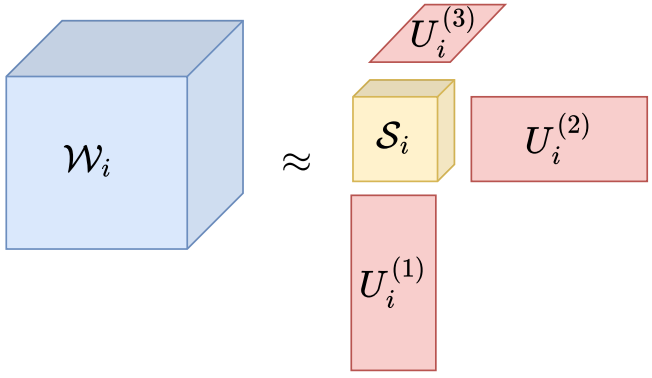


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Common methods in weight compression:

- SVD
- Canonical-Polyadic (CP)
- Generalized Kronecker Product (GKPD)
- Tucker Decomposition
- etc.

# Decomposing Activations

## Higher-Order Singular Value Decomposition (HOSVD)

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$\mathcal{A}_i \in \mathbb{R}^{B \times C_i \times H_i \times W_i}$ becomes:

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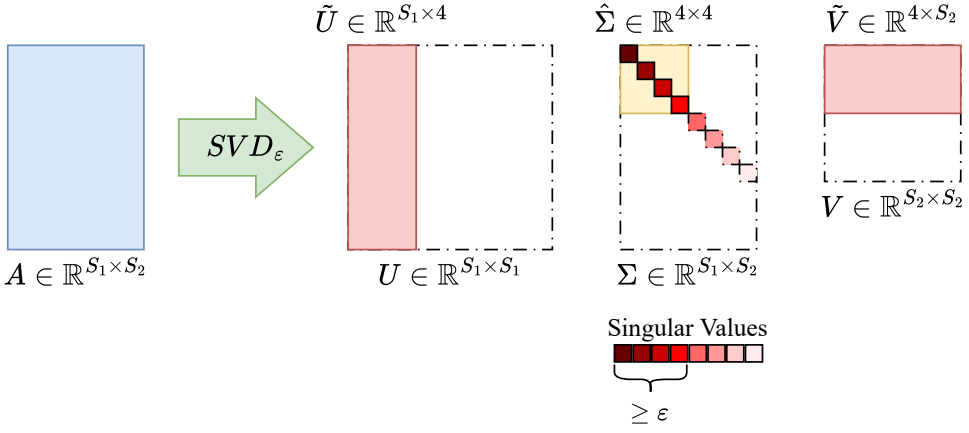
Explained variance $\varepsilon$ truncation:




$$\tilde{\mathcal{A}}_i = \hat{\mathcal{S}}_i \times_1 U_{i,J_{i,1}}^{(1)} \times_2 U_{i,J_{i,2}}^{(2)} \times_3 U_{i,J_{i,3}}^{(3)} \times_4 U_{i,J_{i,4}}^{(4)}$$

# Avoiding Recomposition

Injecting $\tilde{\mathcal{A}}_i$ in

$$\frac{\partial \mathcal{L}}{\partial \mathcal{W}_i} = \text{conv}\left(\mathcal{A}_i, \frac{\partial \mathcal{L}}{\partial \mathcal{A}_{i+1}}\right)$$

results in a sequence of smaller convolutions

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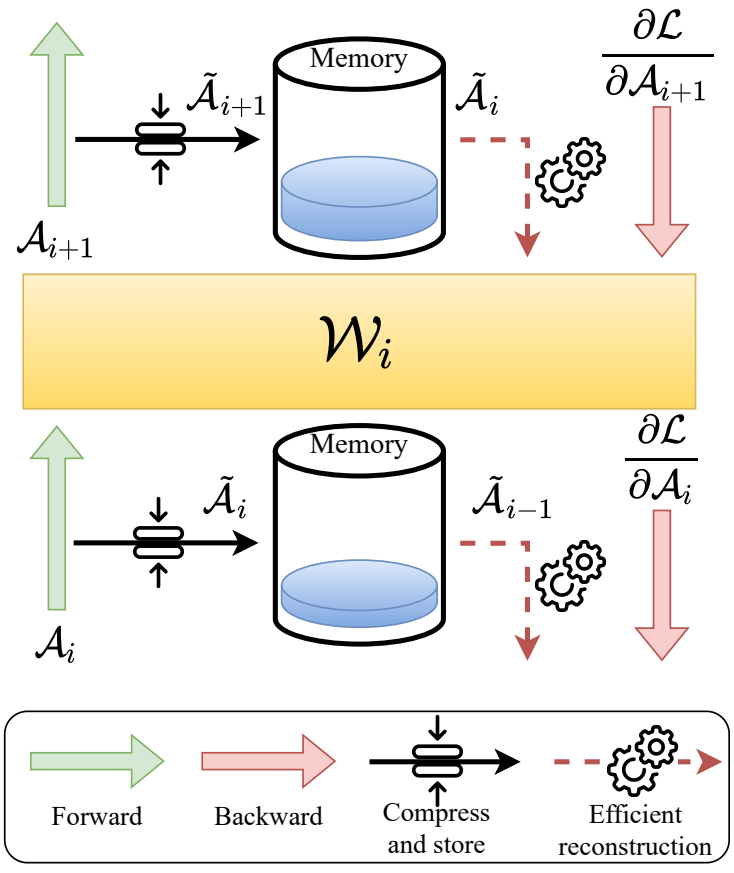
Backpropagation becomes:



# Algorithm Properties

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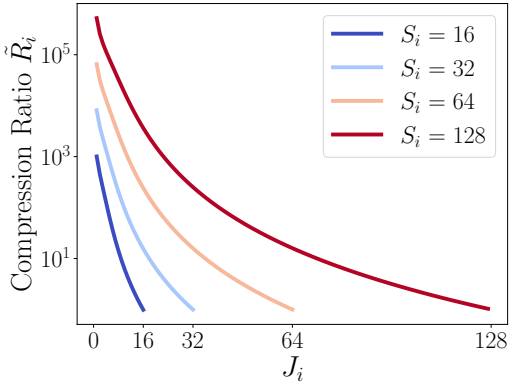
## Memory gain



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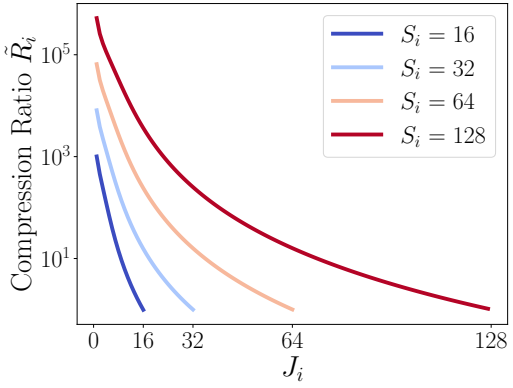


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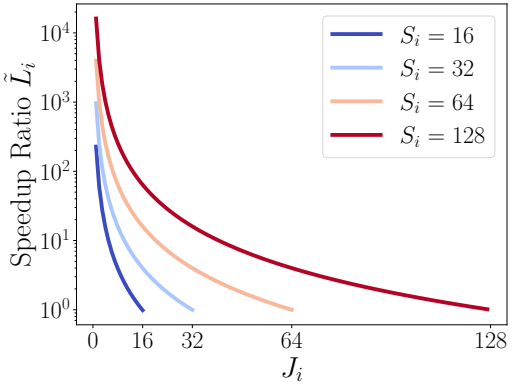

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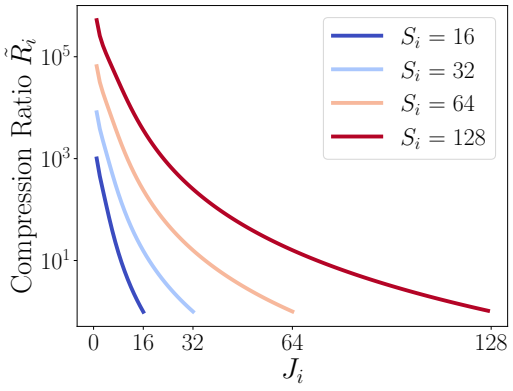


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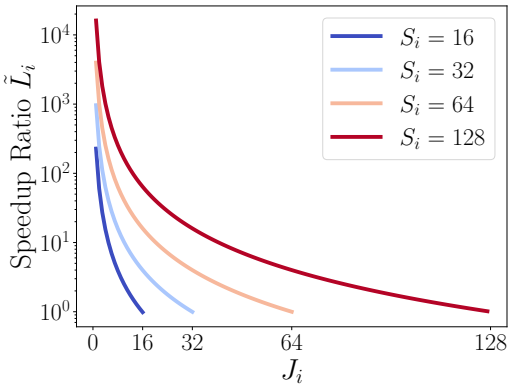


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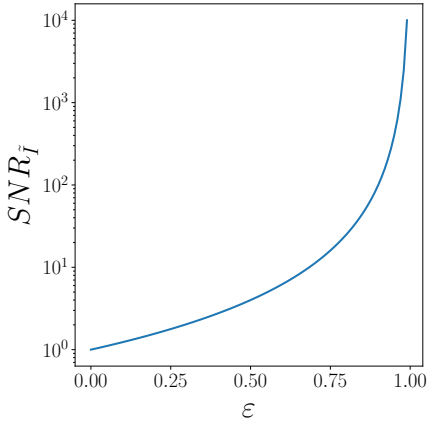

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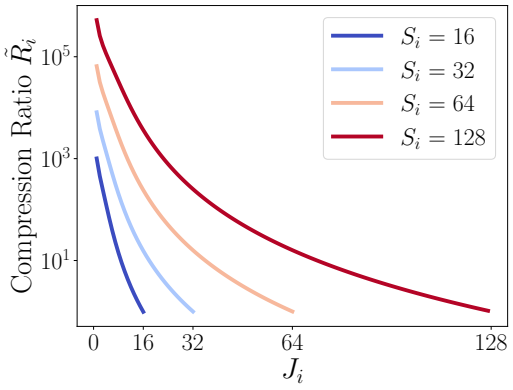


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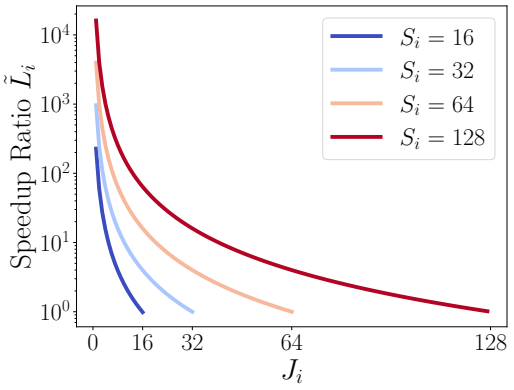


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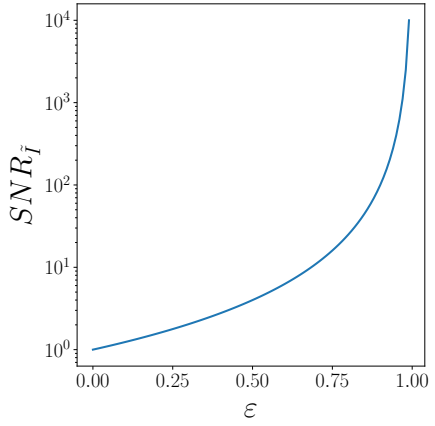


$\rightarrow$ Significant memory reduction and backward pass acceleration potential

$\rightarrow$ Favorable accuracy-compression trade-off expected

# Explained Variance Analysis

Fine-tuning last 4 layers of MCUNet on CIFAR-10 using HOSVD:

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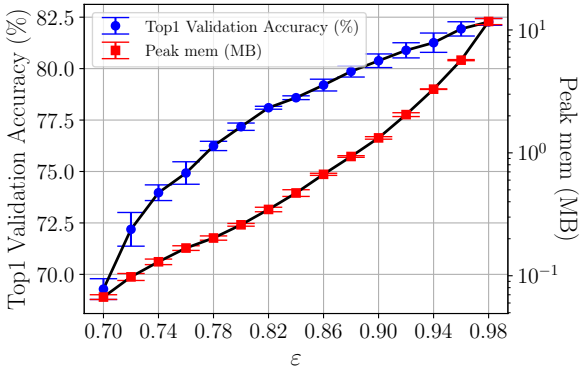

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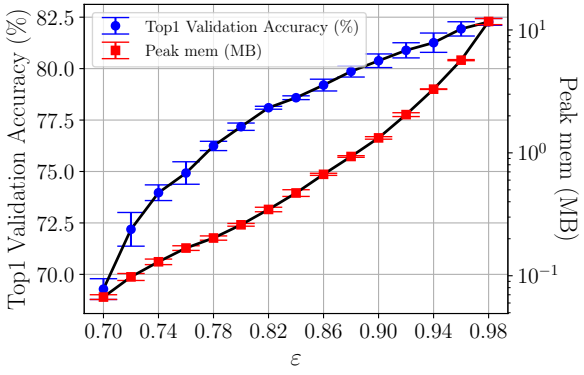


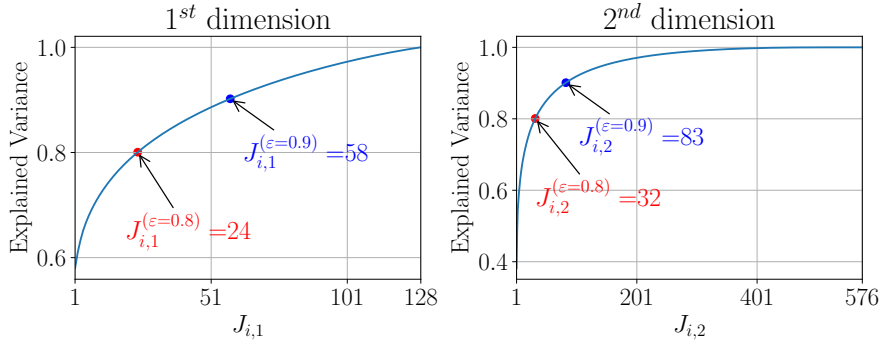

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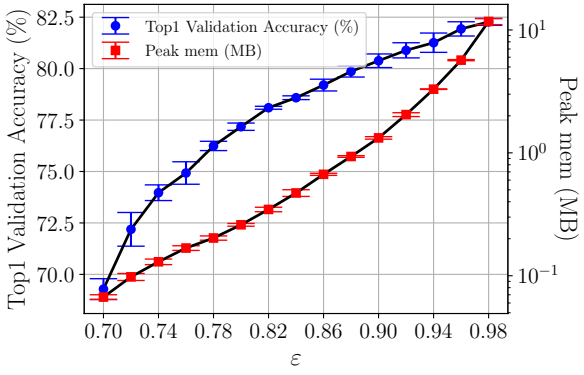
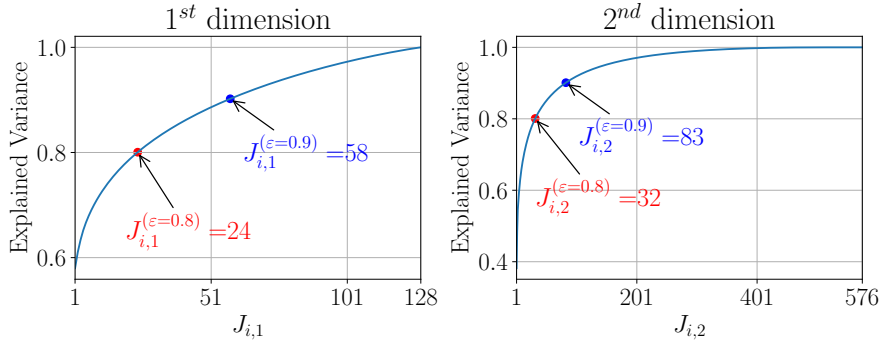
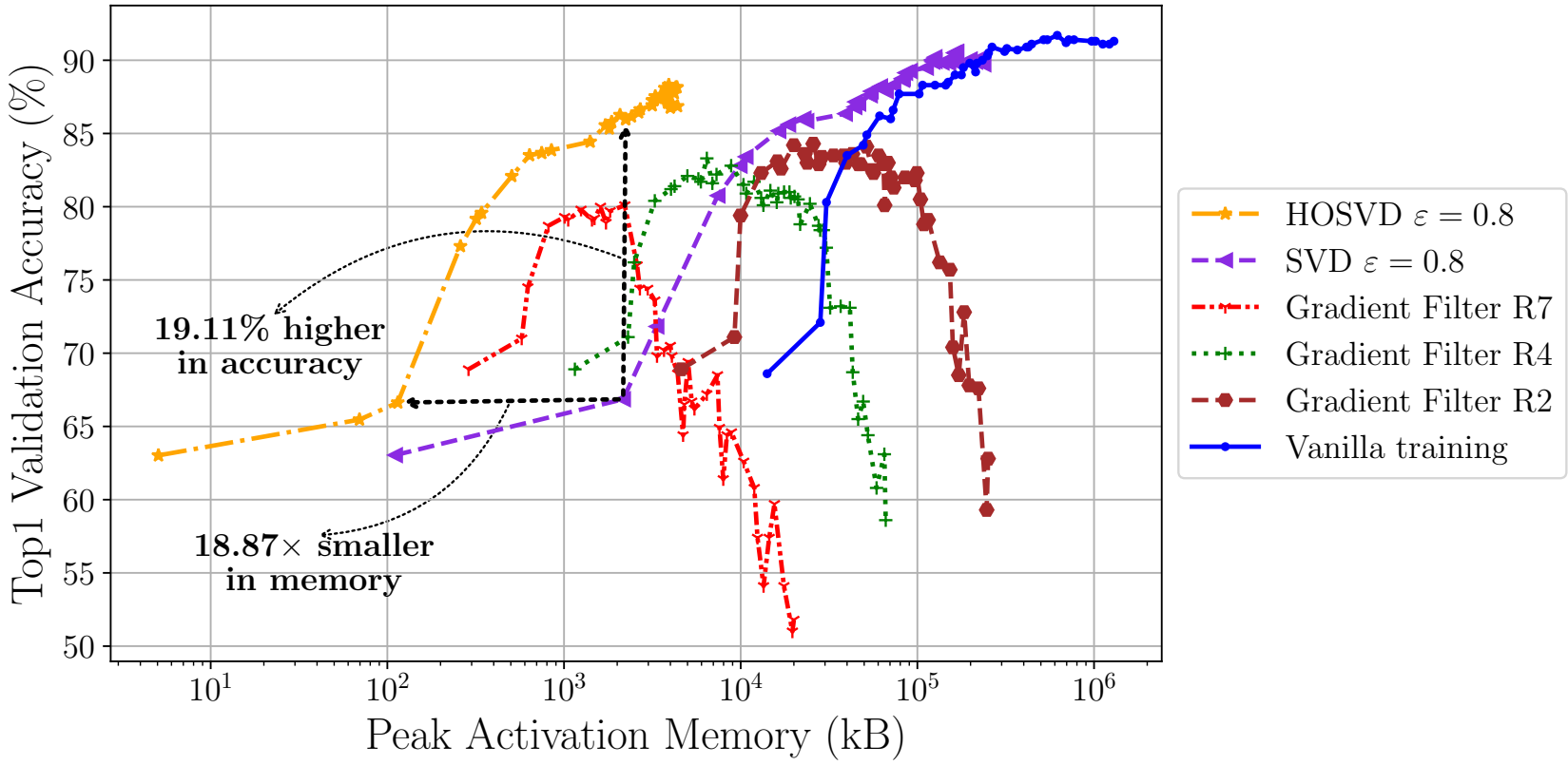



Variance concentrated in few singular values $\rightarrow$ experiments conducted with $\varepsilon = 0.8$ and $\varepsilon = 0.9$

# Experimental Results



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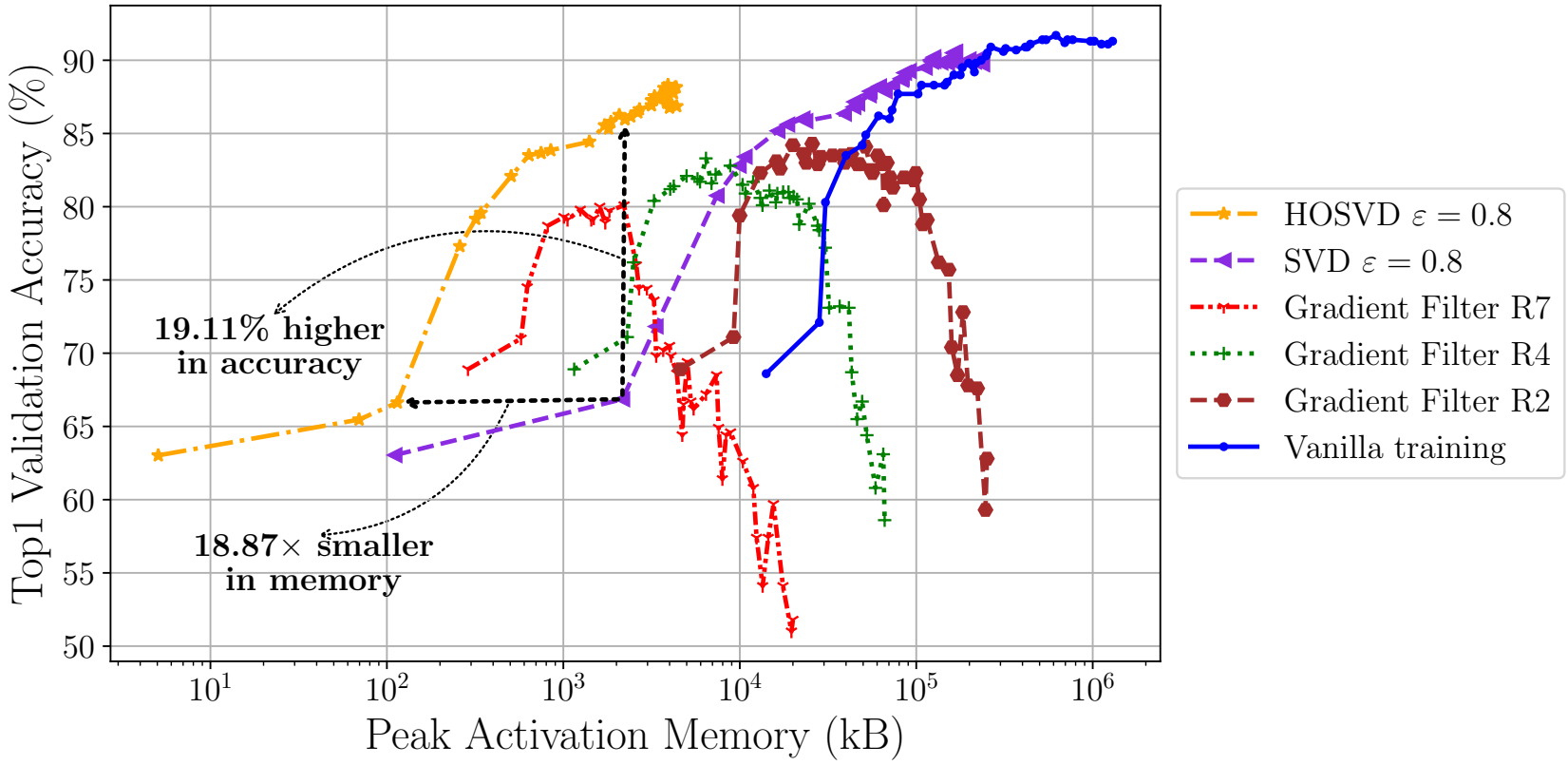


Cumulative compressed activation memory $<$ Single uncompressed layer memory

# Limitations

Comparing latency of Vanilla and HOSVD training:

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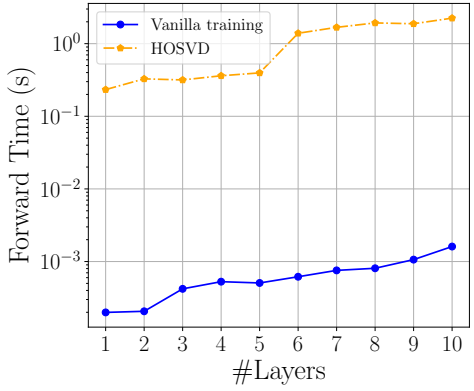

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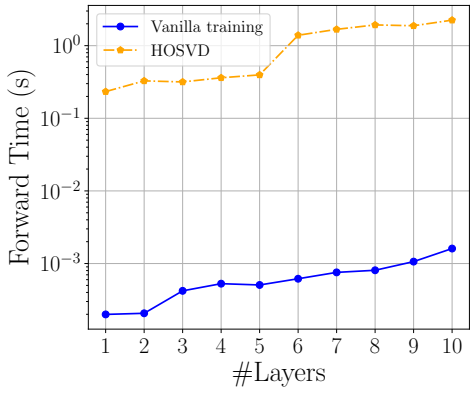


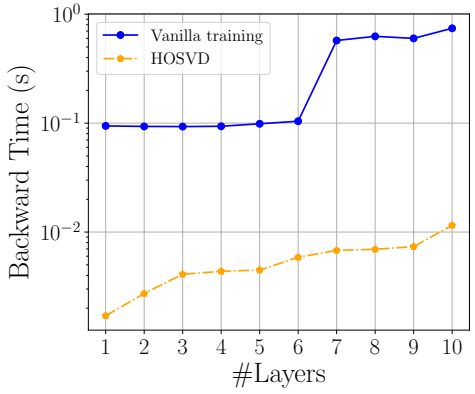

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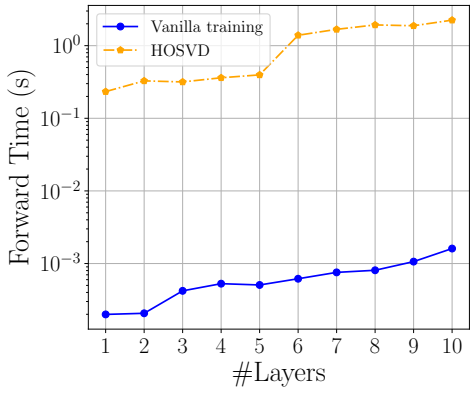


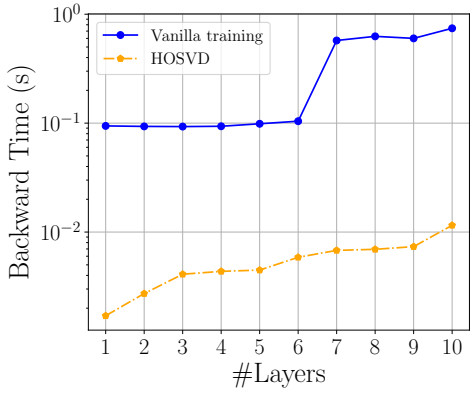


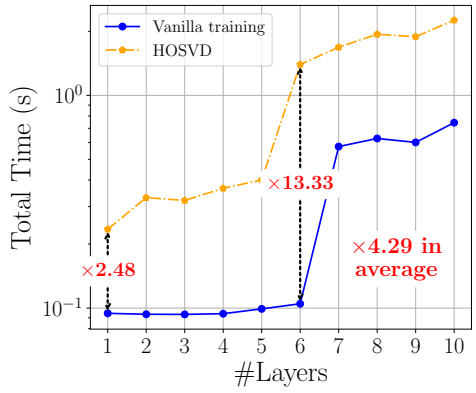

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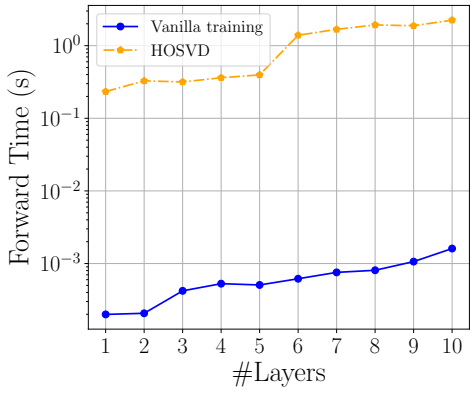


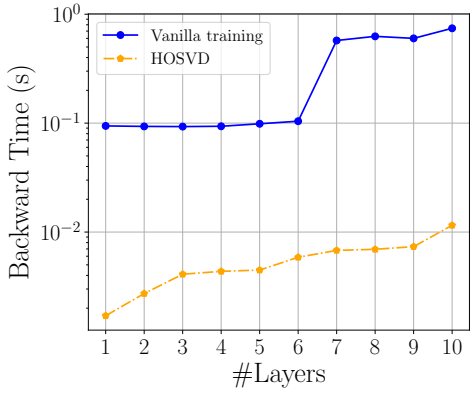


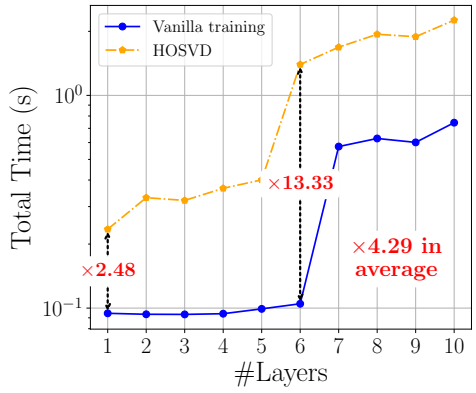


+ No control over peak memory

# Subspace Iteration

**Algorithm 1:** Subspace Iteration with Warm-start at epoch $t$

**Require:** Epoch index $t$, gradient matrix $M^{(t)} \in \mathbb{R}^{m \times n}$, target rank $r \in [1, \min(m, n)]$.

**if** $t = 0$ **then**
  Initialize $Q^{(t)} \in \mathbb{R}^{n \times r}$ from an i.i.d standard normal distribution.
**else**
  Warm-start initialization, $Q^{(t)} \leftarrow Q^{(t-1)}$.
$P^{(t)} \leftarrow M^{(t)} Q^{(t)}$.
$\hat{P}^{(t)} \leftarrow \text{Orthogonalize}(P^{(t)})$.
$Q^{(t)} \leftarrow M^{(t)^T} \hat{P}^{(t)}$.
**Return** $\hat{P}^{(t)}, Q^{(t)}$.

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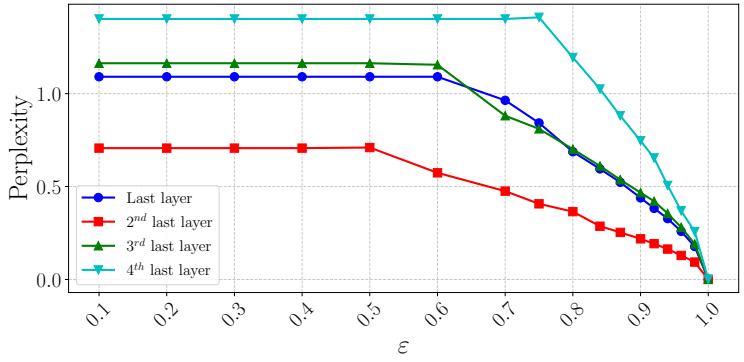
- Enables budget-constrained rank selection via optimization (recursive backtracking algorithm)

# Preliminary Experiments

## Perplexity variations:



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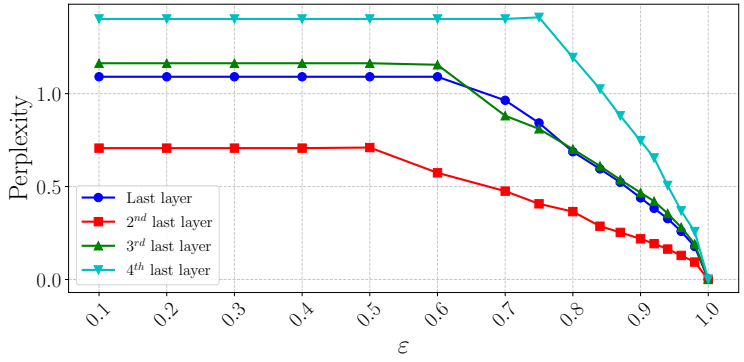


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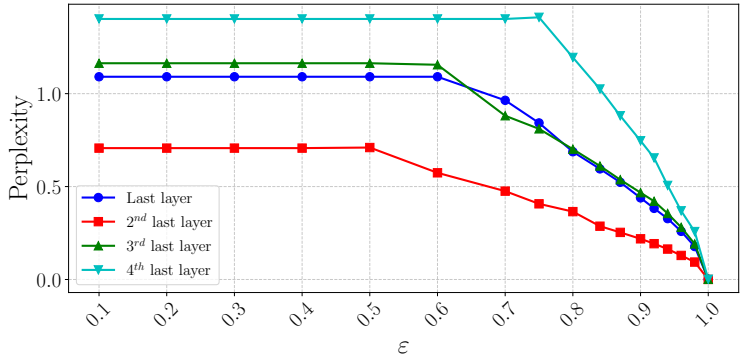


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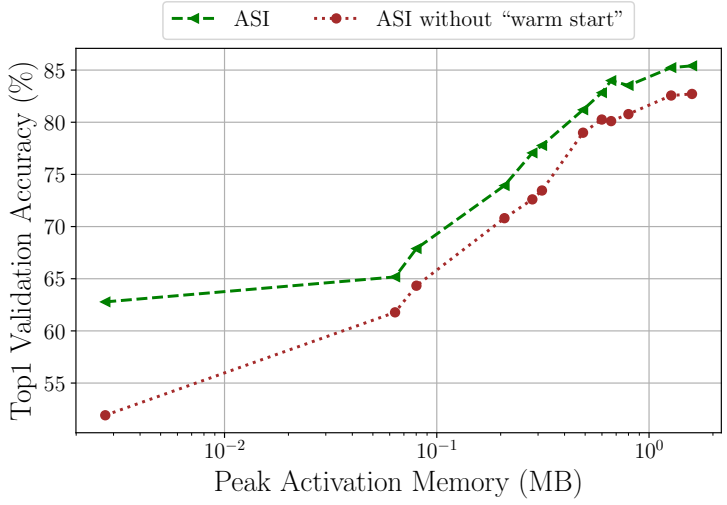

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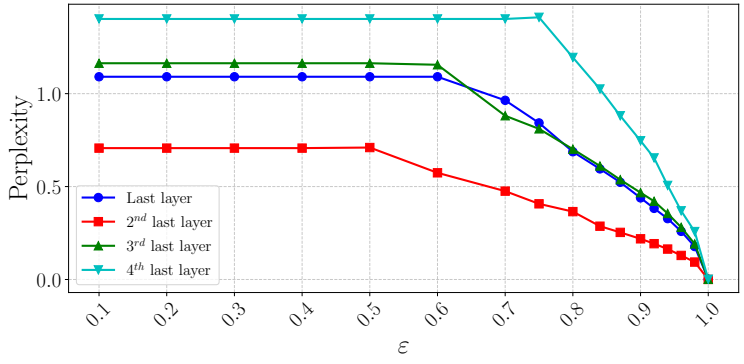


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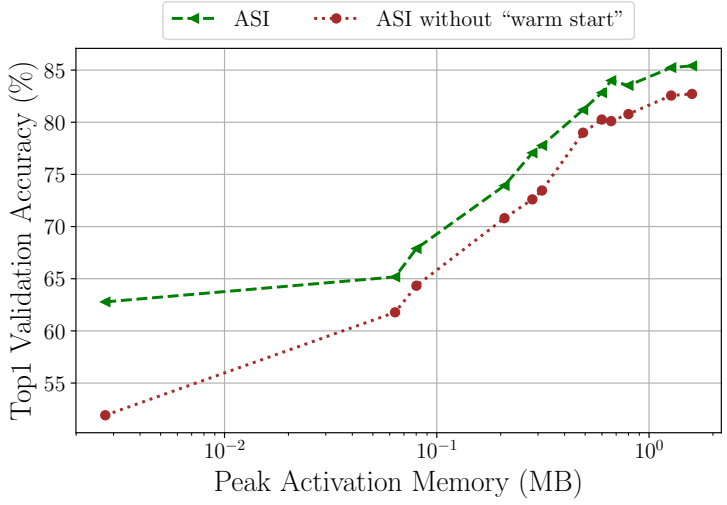
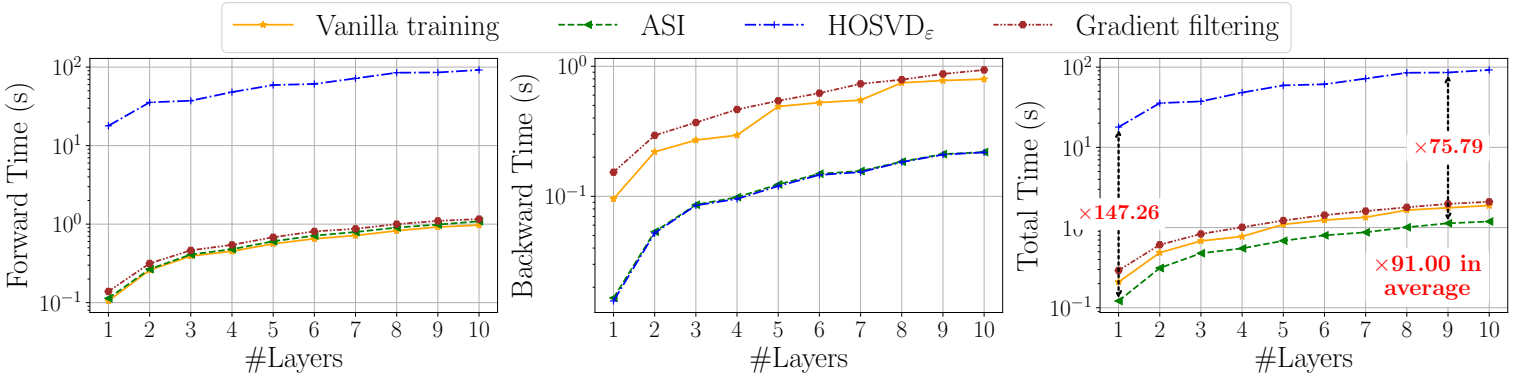



→ Warm-start provides clear improvement

→ Acceptable accuracy without warm-start

# Validation Experiments



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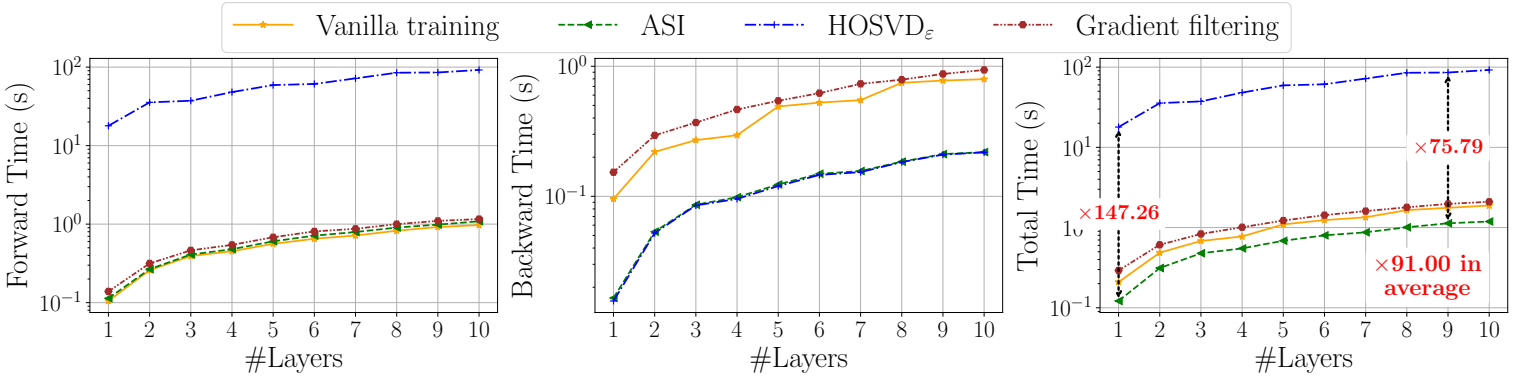


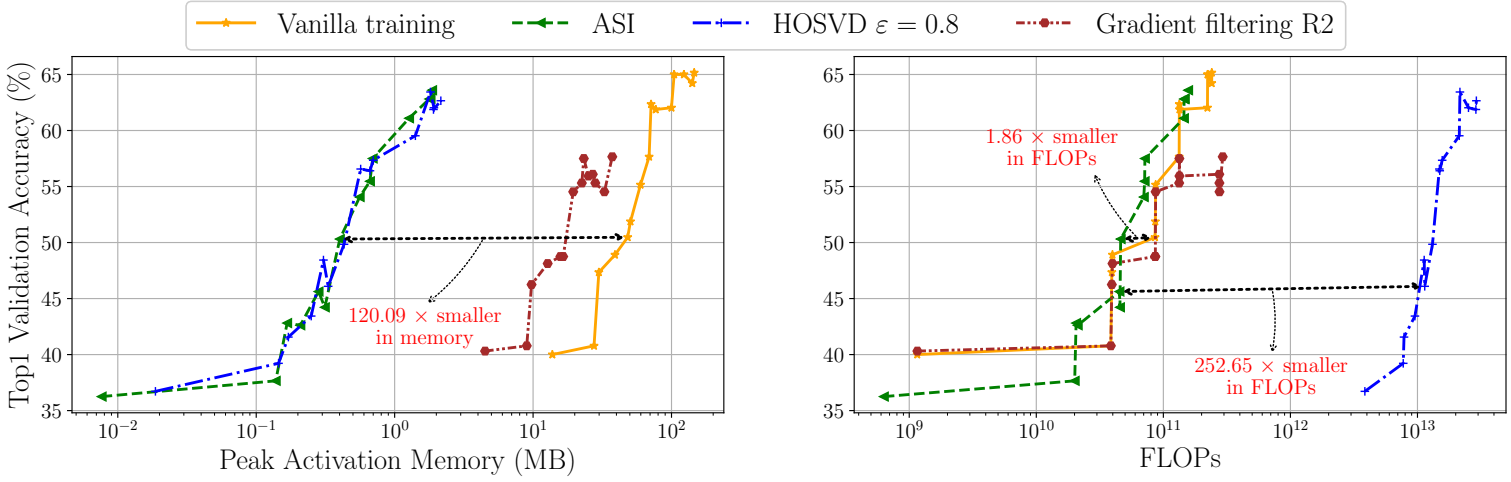

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- Integration with pruning and quantization

# Publications

Le-Trung Nguyen, **Aël Quélennec**, Enzo Tartaglione, Samuel Tardieu and Van-Tam Nguyen. Activation map compression through tensor decomposition for deep learning. In *NeurIPS2024*.

Le-Trung Nguyen, **Aël Quélennec**, Van-Tam Nguyen, and Enzo Tartaglione. Beyond low-rank decomposition: A shortcut approach for efficient on-device learning. In *ICML2025*.

# Outline

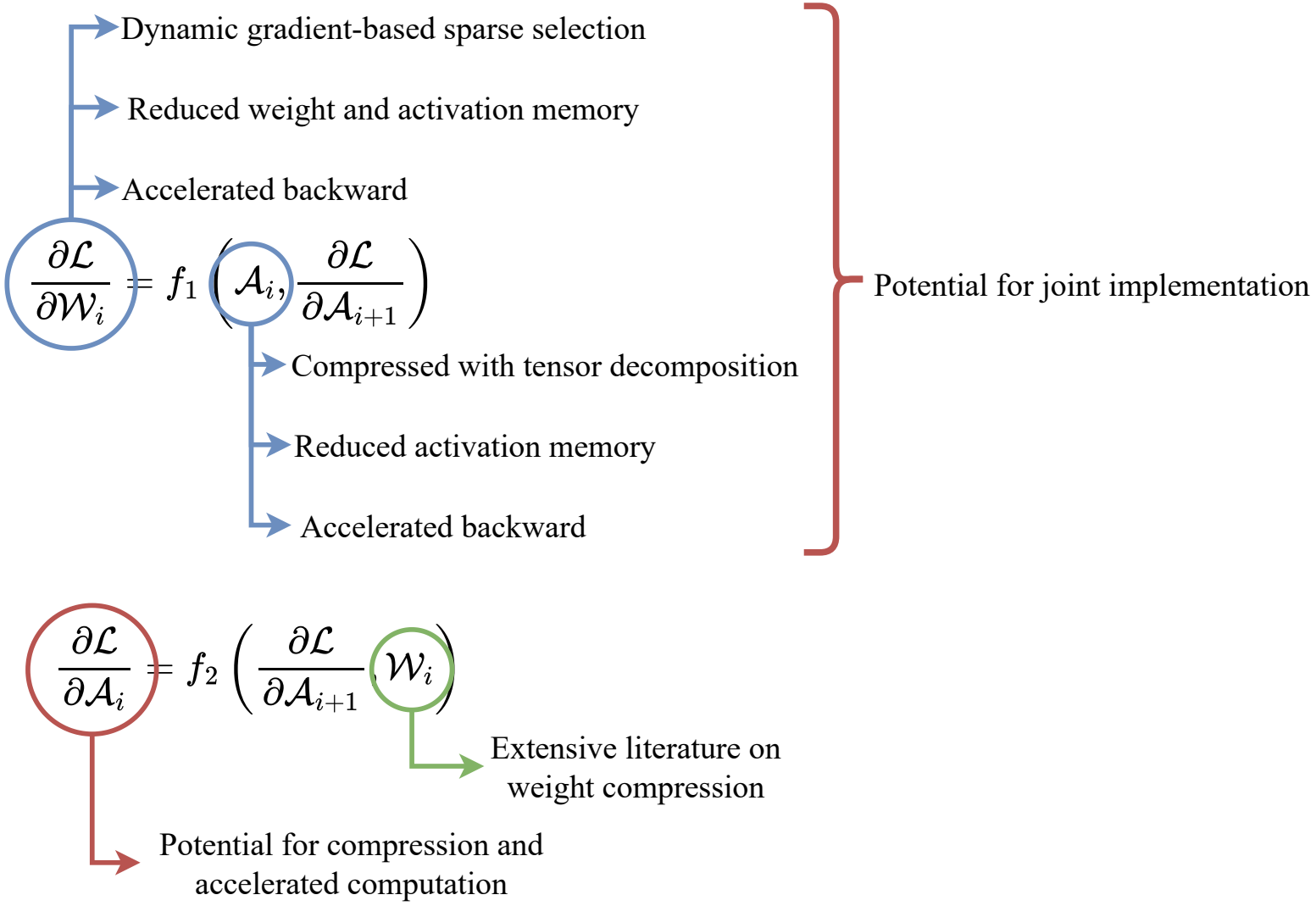
Introduction

Subnetwork Selection for Fine-Tuning

Activation Map Compression

Conclusion

# Contributions and Future Directions (1/2)



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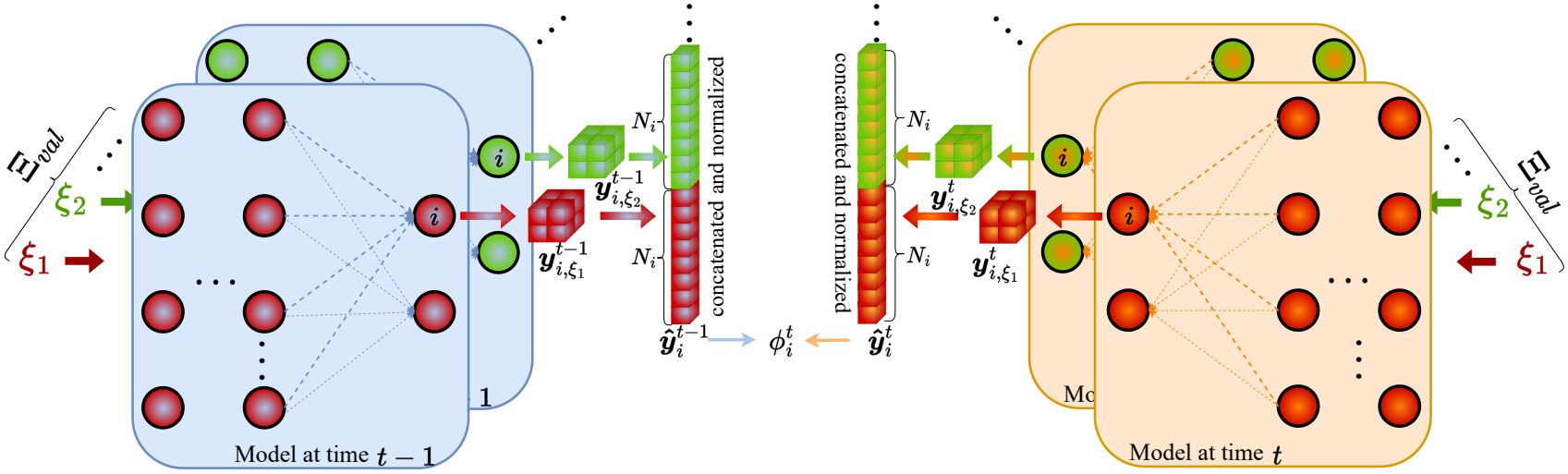
- **Green AI:** Reduce energy footprint and support sustainability objectives

# Outline

## Appendix

# Velocity's inspiration: NEq

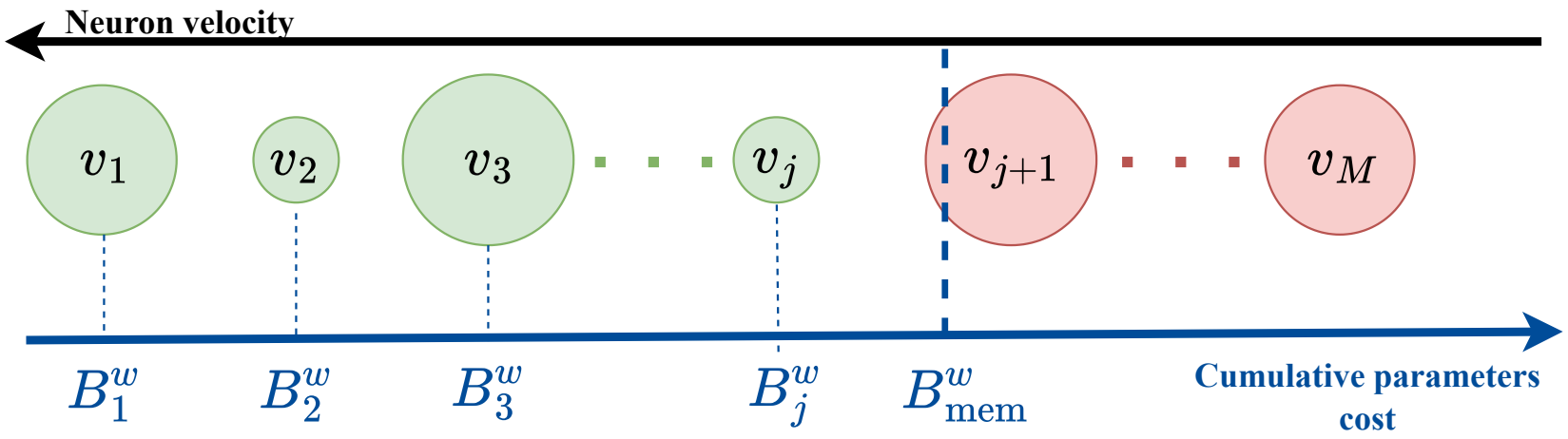
Bragagnolo et al. (2022)'s Neurons at Equilibrium




Velocity computation:

$$\left|v_i^t\right| < \varepsilon, \qquad \varepsilon \geq 0$$

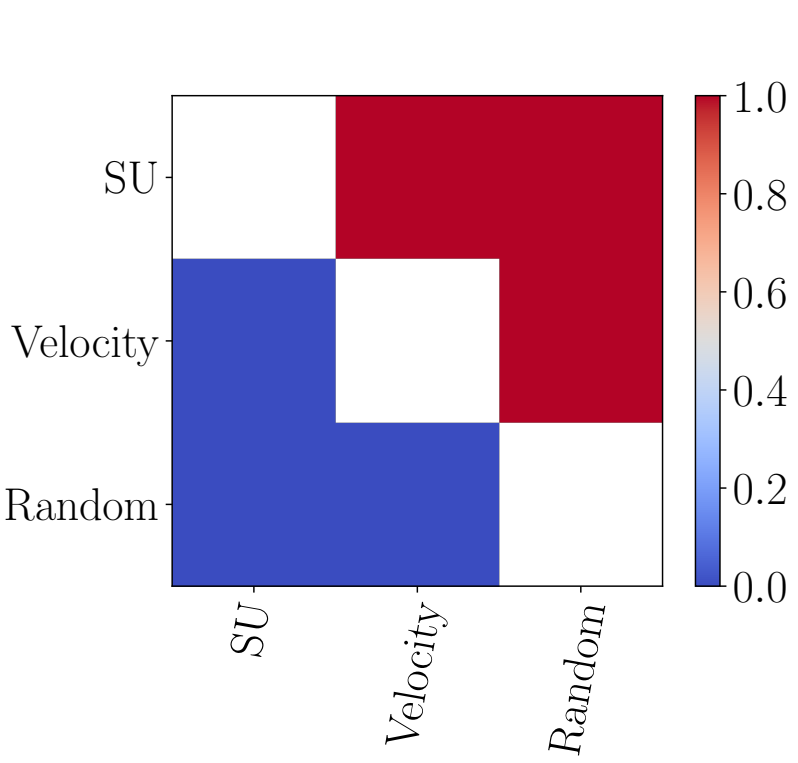
# Memory-Constrained Adaptation

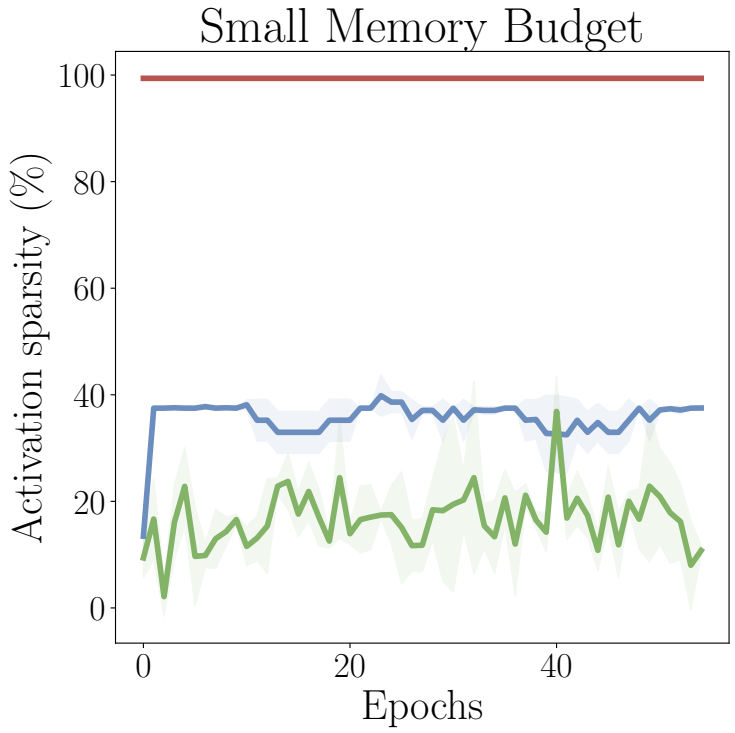



Introduction of memory normalization:

$$\tilde{v}_i = \frac{v_i}{C_i^{\text{w}}}$$

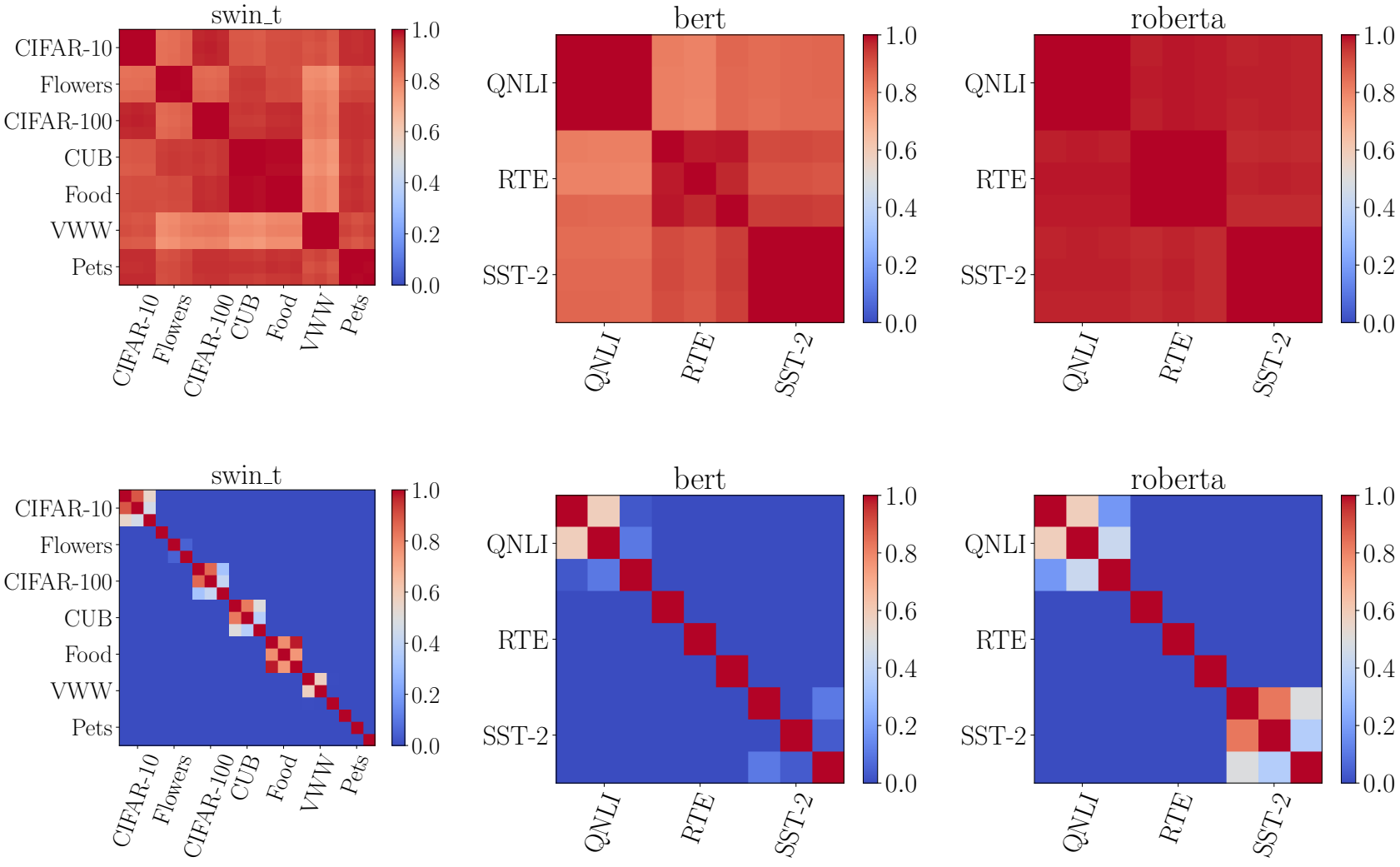
# Experimental Results



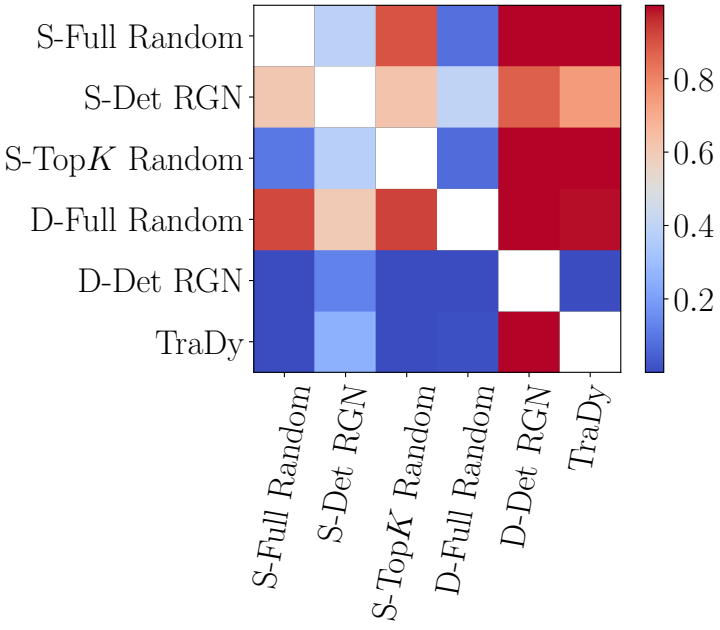




- Outperformed by random strategy
- Poor activation sparsity levels
- Relies on existence of a validation set
- Necessitates storage of all neurons activation

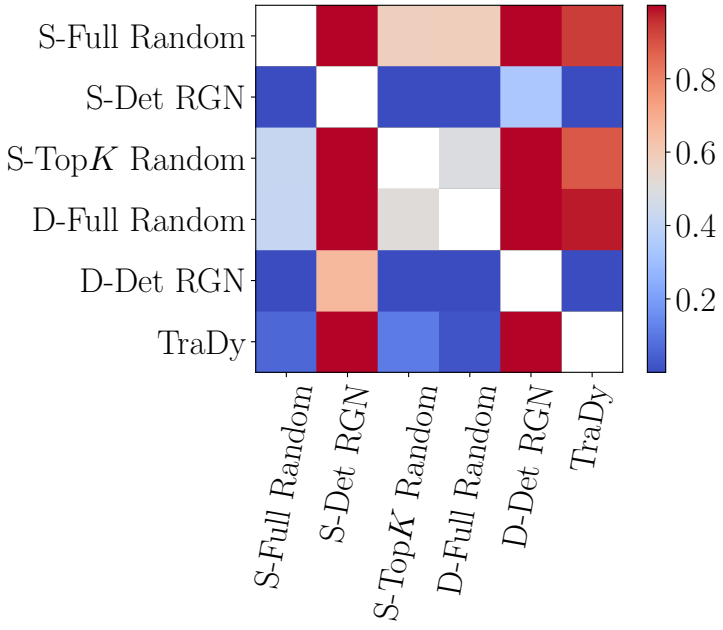
# Proposition Validation for Transformers



# TraDy Ablation for Transformers



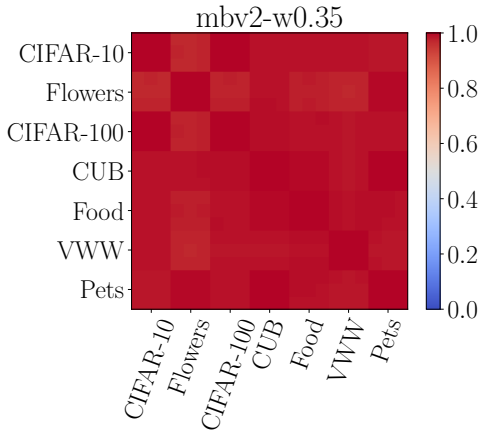

SwinT model

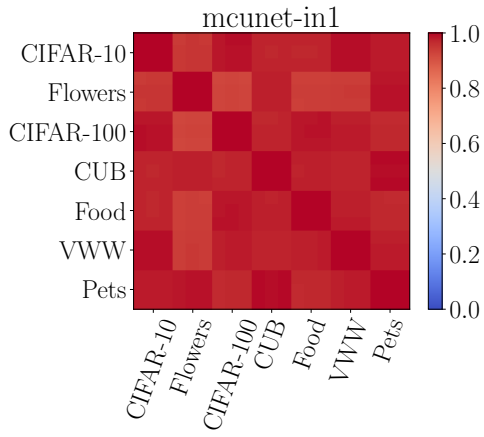


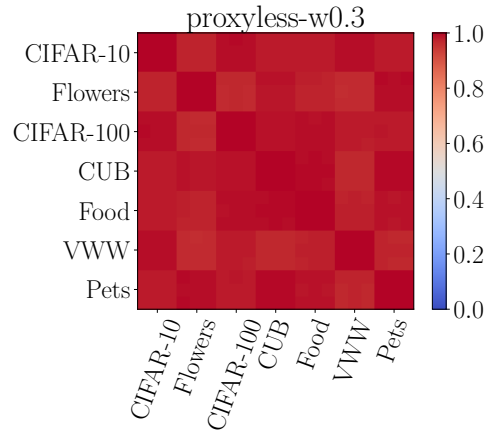

BERTs models

# MeDyate Proposition Validation

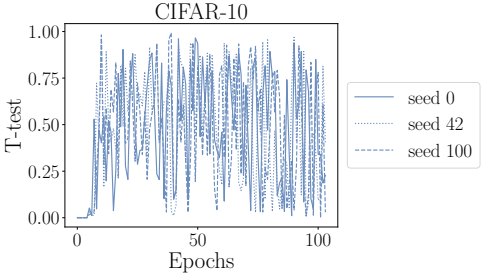
## LaRa Spearman:

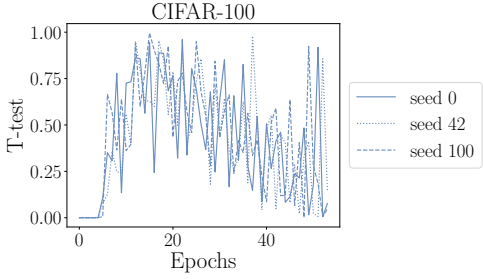


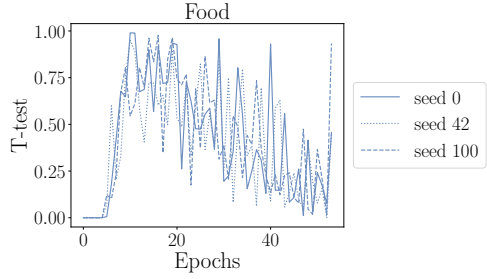




## Channel gradient norm inter-epoch T-test:



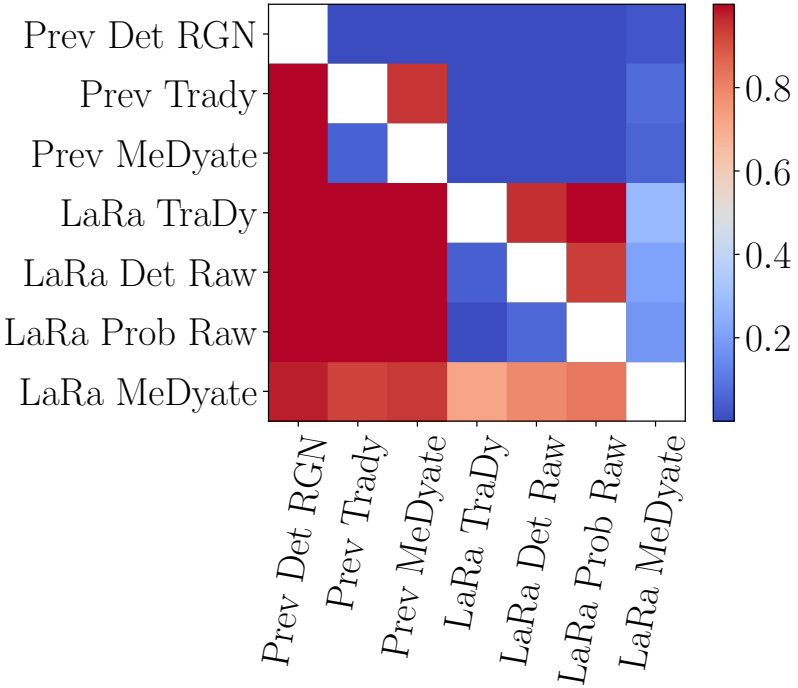



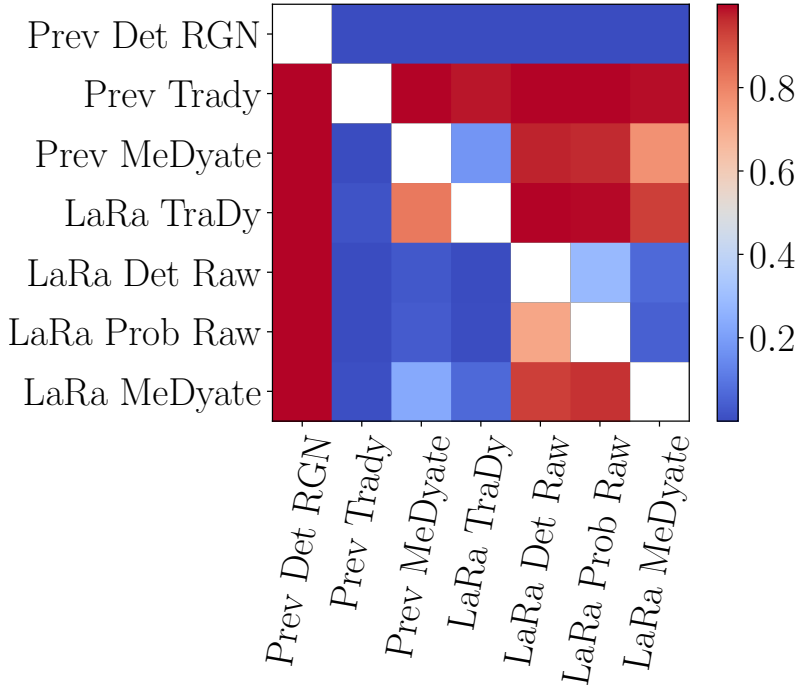
# MeDyate Ablation for Transformers

Two absolute budgets and two proportional budgets

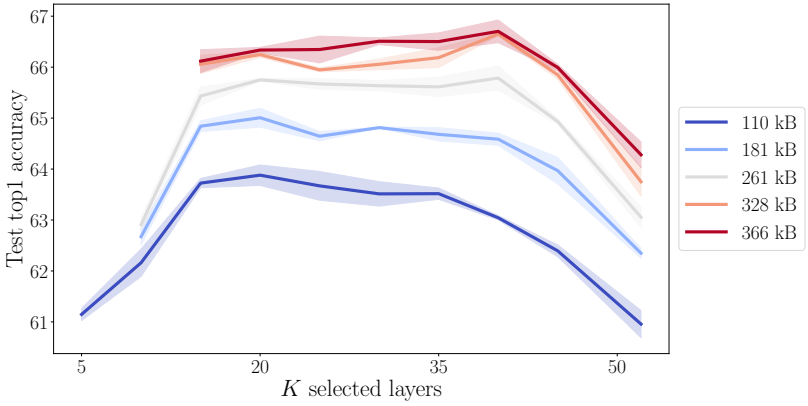
## SwinT

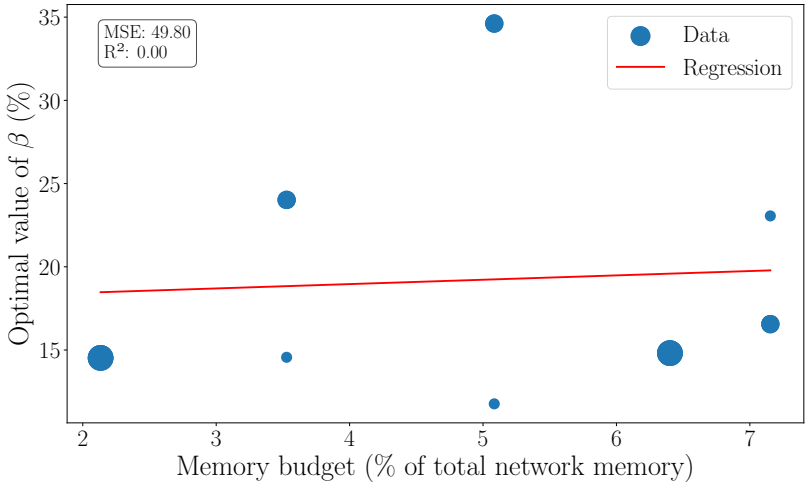



## BERTs



# $\beta_{\text{opt}}$ Selection Process

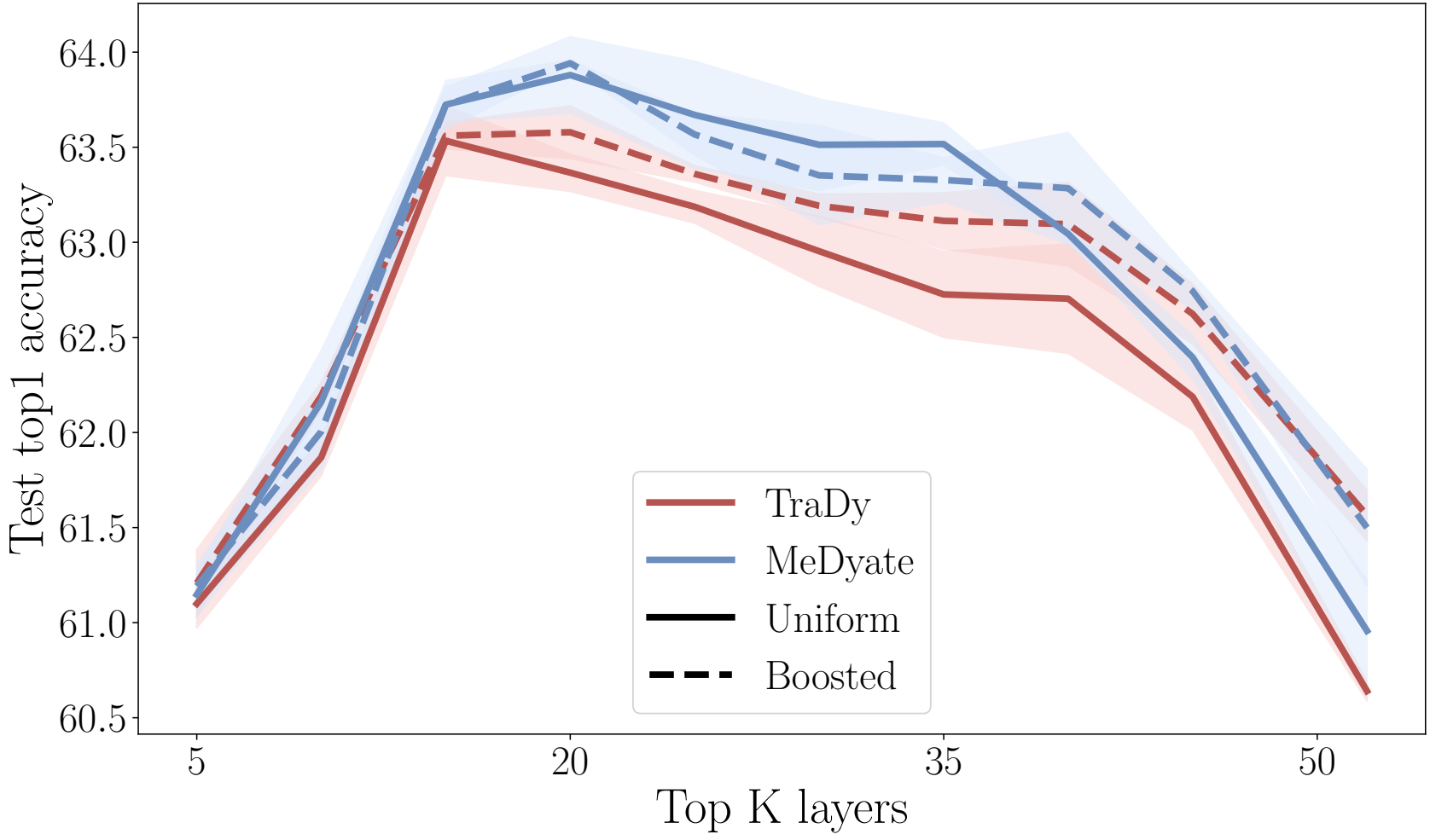



→ Results in $\beta_{\text{opt}} = 0.2$

→ Allows for exploration of all channels in less than 20 epochs

# Exploration of Alternative MeDyate Initialization



# HOSVD Mathematical Details

Weight derivatives extended formula:

$$\frac{\tilde{\partial}\mathcal{L}}{\partial \mathcal{W}_i} = \text{conv}_{1\times1}\left\{\text{conv}_{*}\left[\text{conv}_{1\times1}\left(\text{conv}_{1\times1}\left(\hat{\mathcal{S}}_{\rangle}, \underline{U}^{(3)}_{i,J_{i,3}}\right), \underline{U}^{(4)}_{i,J_{i,4}}\right), \text{conv}_{1\times1}\left(\frac{\partial\mathcal{L}}{\partial\mathcal{A}_{i+1}}, U^{(1)}_{i,J_{i,1}}\right)\right] U^{(2)}_{i,J_{i,2}}\right\},$$

Signal to Noise Ratio analysis:

$$SNR_{\tilde{I}} = \frac{\sum_{(u,v)} I[u,v]^2}{\sum_{(u,v)}(I[u,v] - \varepsilon I[u,v])^2} = \frac{1}{(1-\varepsilon)^2}$$

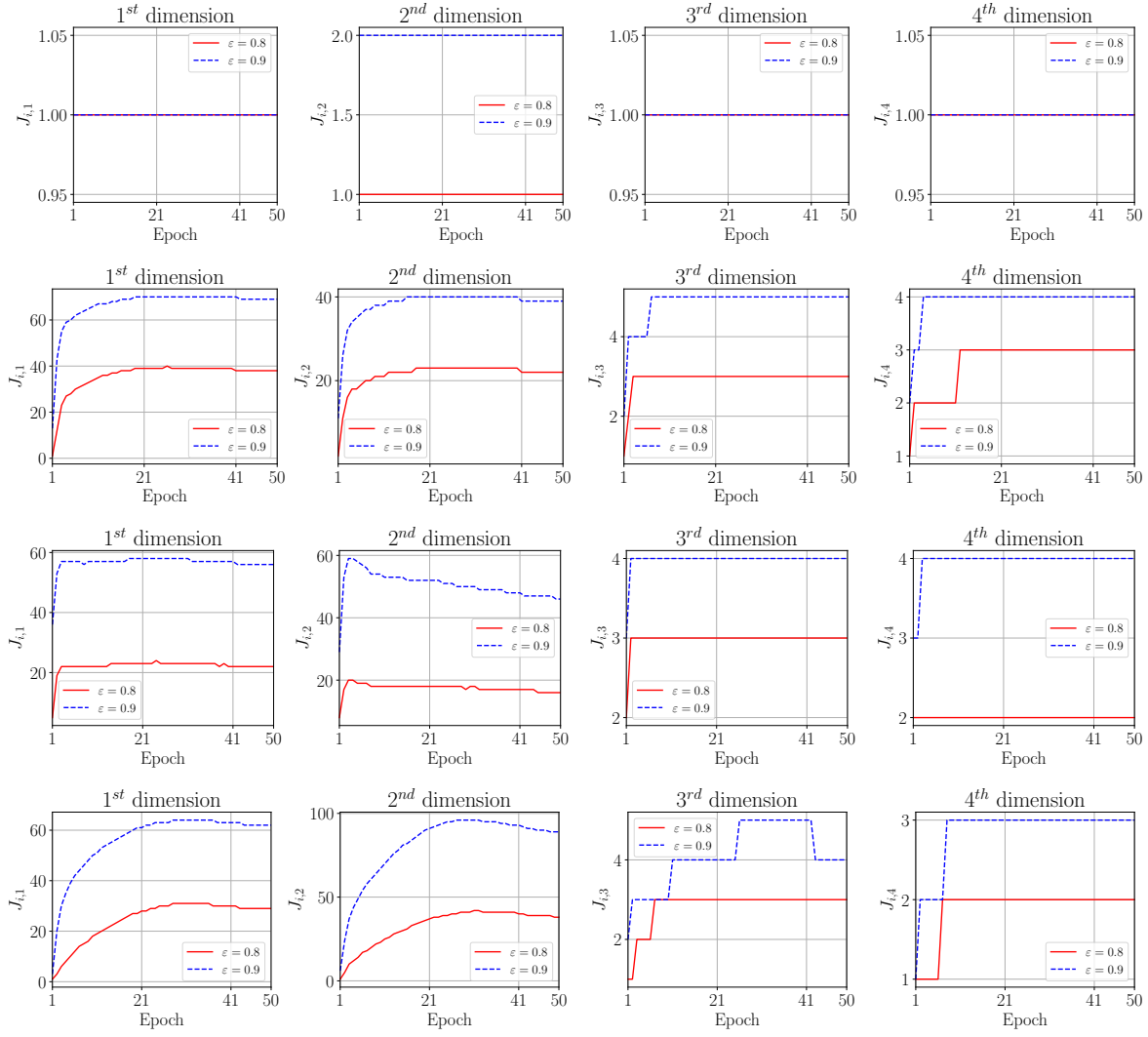
Compression ratio:

$$R_i = \frac{BC_iH_iW_i}{J_{i,1}J_{i,2}J_{i,3}J_{i,4} + BJ_{i,1} + C_iJ_{i,2} + H_iJ_{i,3} + W_iJ_{i,4}}$$

Simplified backward speedup ratio:

$$\tilde{L}_i = \frac{S_i^6}{J_i(J_i^3 + J_i^2S_i + J_iS_i^4 + 2S_i^3)}$$

# Analysis of Rank Evolution with HOSVD



# Detailed ASI Algorithm

**Algorithm 2:** ASI for layer $i$ with preselected set of target ranks $R_{\text{opt}_i}$

**Require:** Activation map $\mathcal{A}_i^{(t)} \in \mathbb{R}^{B \times C_i \times H_i \times W_i}$ at epoch $t$, set of target ranks $R_{\text{opt}_i}$.

Initialize $\mathcal{S}_i = \mathcal{A}_i^{(t)}$.;
**for** $k = 1$ ***to*** $4$ **do**
    $A_{i,k} \leftarrow \text{Unfold}(\mathcal{A}_i^{(t)})$ along mode $k$.;
    **if** $t = 0$ **then**
        Initialize $V_{i,k} \in \mathbb{R}^{S_{i,k} \times J_{i,k}}$ from an i.i.d standard normal distribution.;
    **else**
        $V_{i,k} \leftarrow A_{i,k}^T U_{i,k}^{(t-1)}$.;
    $U_{i,k}^{(t)} \leftarrow \text{Orthogonalize}\,(A_{i,k} V_{i,k})$.;
    $\mathcal{S}_i \leftarrow \mathcal{S}_i \times_k U_{i,k}^{(t)}$.;
**Return** $\mathcal{S}_i$, $U_{i,k}^{(t)}$ with $k : 1 \rightarrow 4$.;

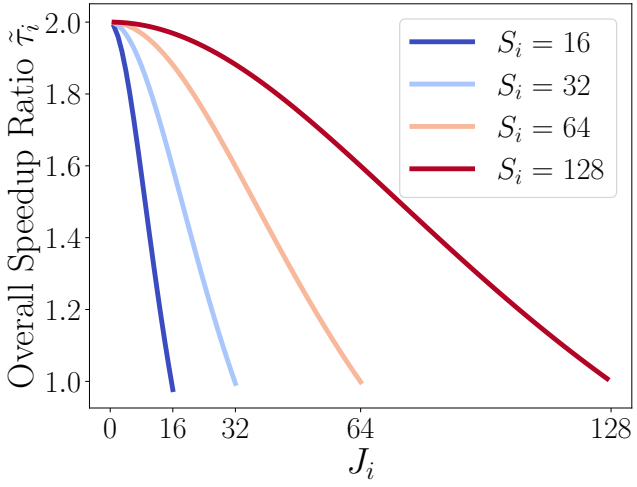
# Additional ASI Details

Rank selection mathematical formulation:

$$R_{\text{opt}_i} = \mathcal{R}_{i,e} \mid e = \mathcal{J}_{\text{opt}}[i],$$

$$\mathcal{J}_{\text{opt}} = \arg\min_{\mathcal{J}} \left( \sum_{i,e \in \mathcal{J}} \mathcal{P}_{i,e} \right) \Bigg| \sum_{i=1}^{|\mathcal{F}|} M_i(J_i^{(e)}) \leq B_{\text{mem}}^{\mathcal{A}}$$

Expected overall speedup:



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