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Activation Map Compression through Tensor Decomposition for Deep Learning

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How to save up to 98.4% activation memory at training time with tensor decomposition

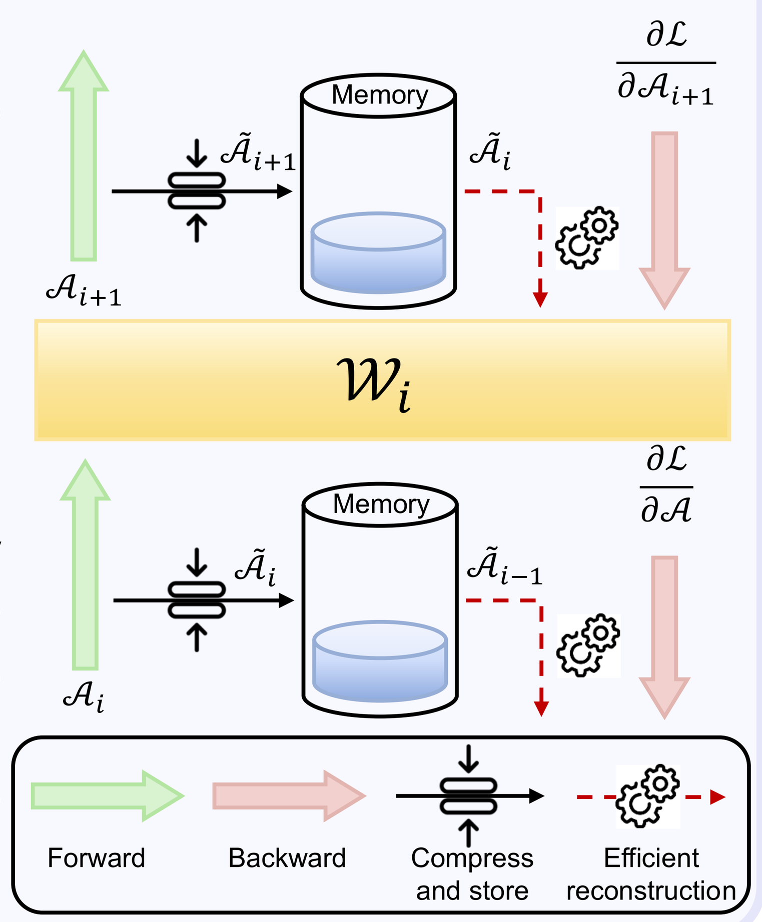
The Memory Bottleneck of Backpropagation

Considering a convolutional neural network, during the backward pass at the i^{th} layer, the following two values must be calculated:

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

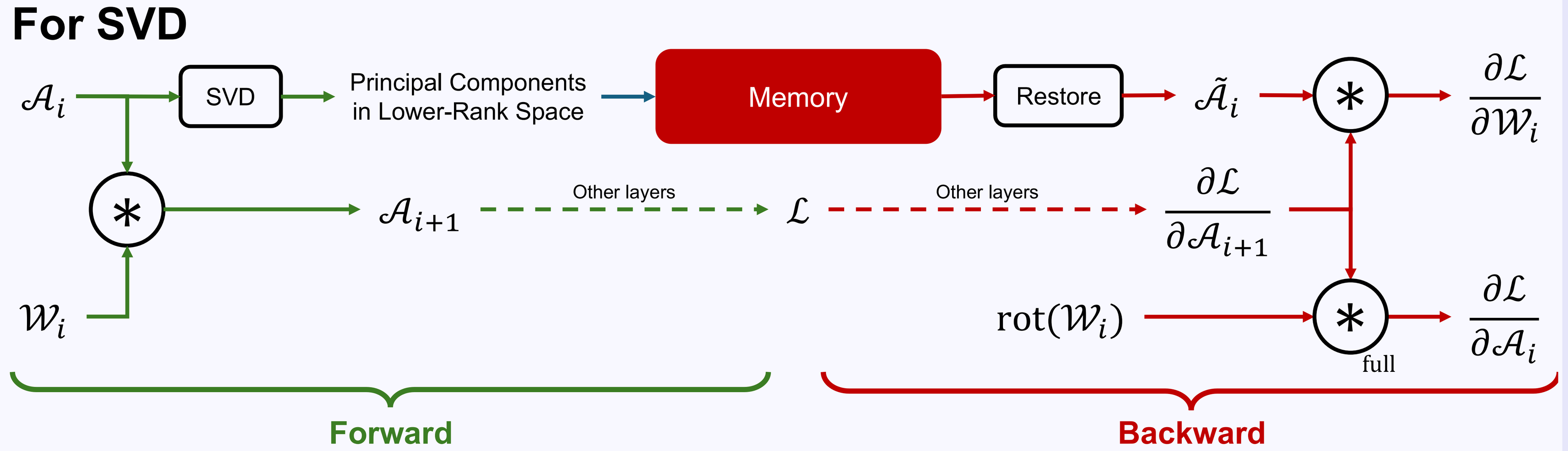
$$\frac{\partial \mathcal{L}}{\partial \mathcal{A}_i} = \frac{\partial \mathcal{L}}{\partial \mathcal{A}_{i+1}} \cdot \frac{\partial \mathcal{A}_{i+1}}{\partial \mathcal{A}_i} = \text{conv}_{\text{full}}\left[\frac{\partial \mathcal{L}}{\partial \mathcal{A}_{i+1}}, \text{rot}(\mathcal{W}_i)\right]$$

Storing $\mathcal{A}_i$ and $\mathcal{W}_i$ is the main cause of memory occupancy during backpropagation. In this work, we propose decomposing $\mathcal{A}_i$ during the forward pass using SVD and HOSVD, based on the desired amount of information to retain (noted ε). $\mathcal{W}_i$ is untouched to avoid error propagation through $\frac{\partial \mathcal{L}}{\partial \mathcal{A}_i}$.

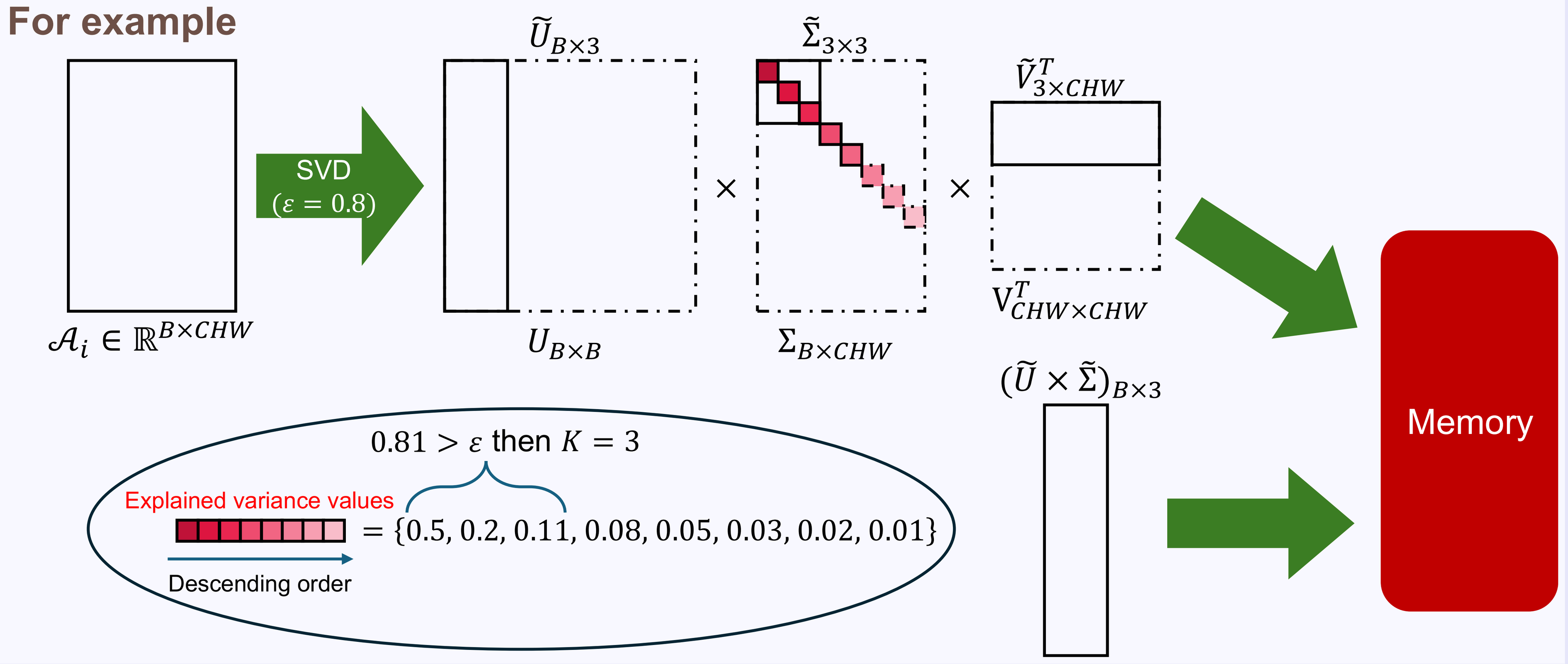


Method

For SVD



For example

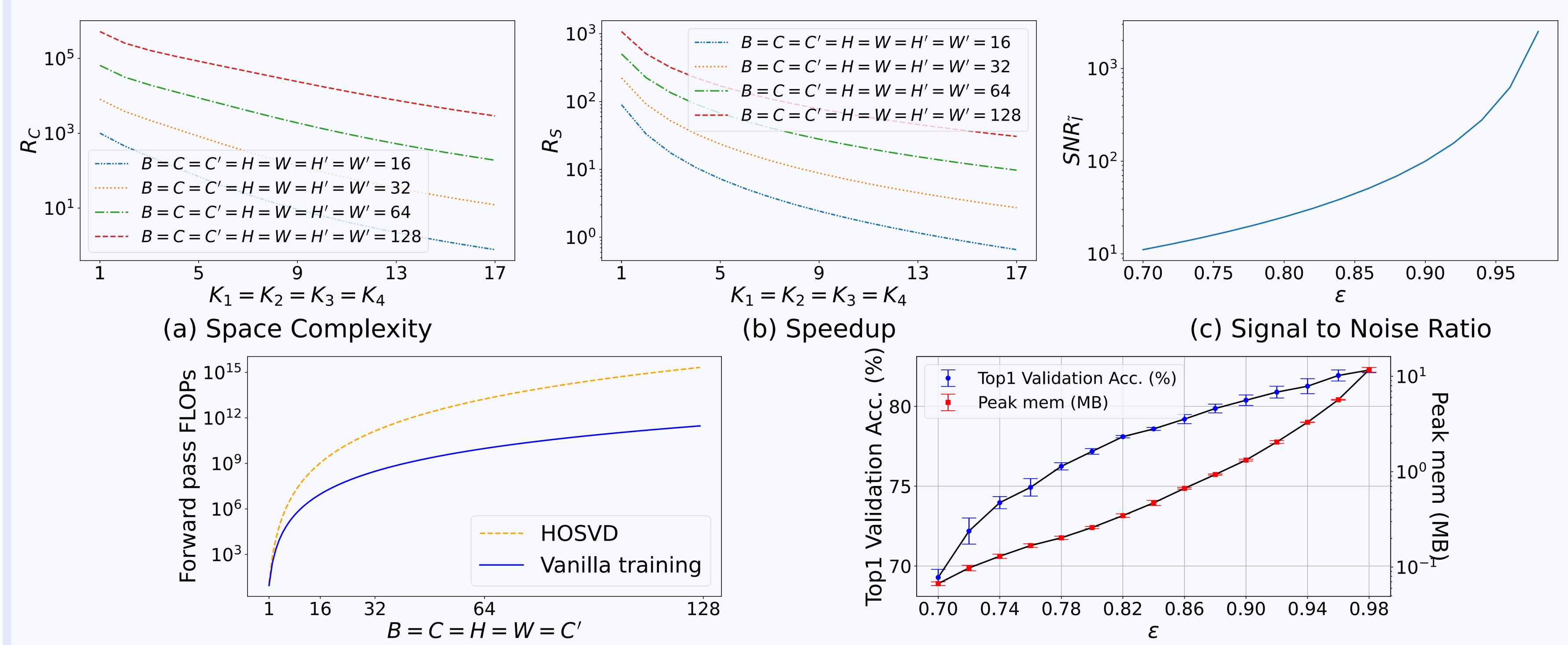


For HOSVD

- Performing SVD on all 4 modes of the activation map.
- Replacing "Restore" step and Frobenius Inner Product by 5 convolutions in lower-rank space.

Projected and Experimental Results

Projected results



(a) Space Complexity (b) Speedup (c) Signal to Noise Ratio

(d) Overhead FLOPs (e) Peak memory and Accuracy Vs. ε

- (a), (b), and (c) are theoretical predicted value for a single convolutional layer with one minibatch of data with size B.
- (d) is the result when applying HOSVD with different ε to finetune the last four layers of MCUNet.

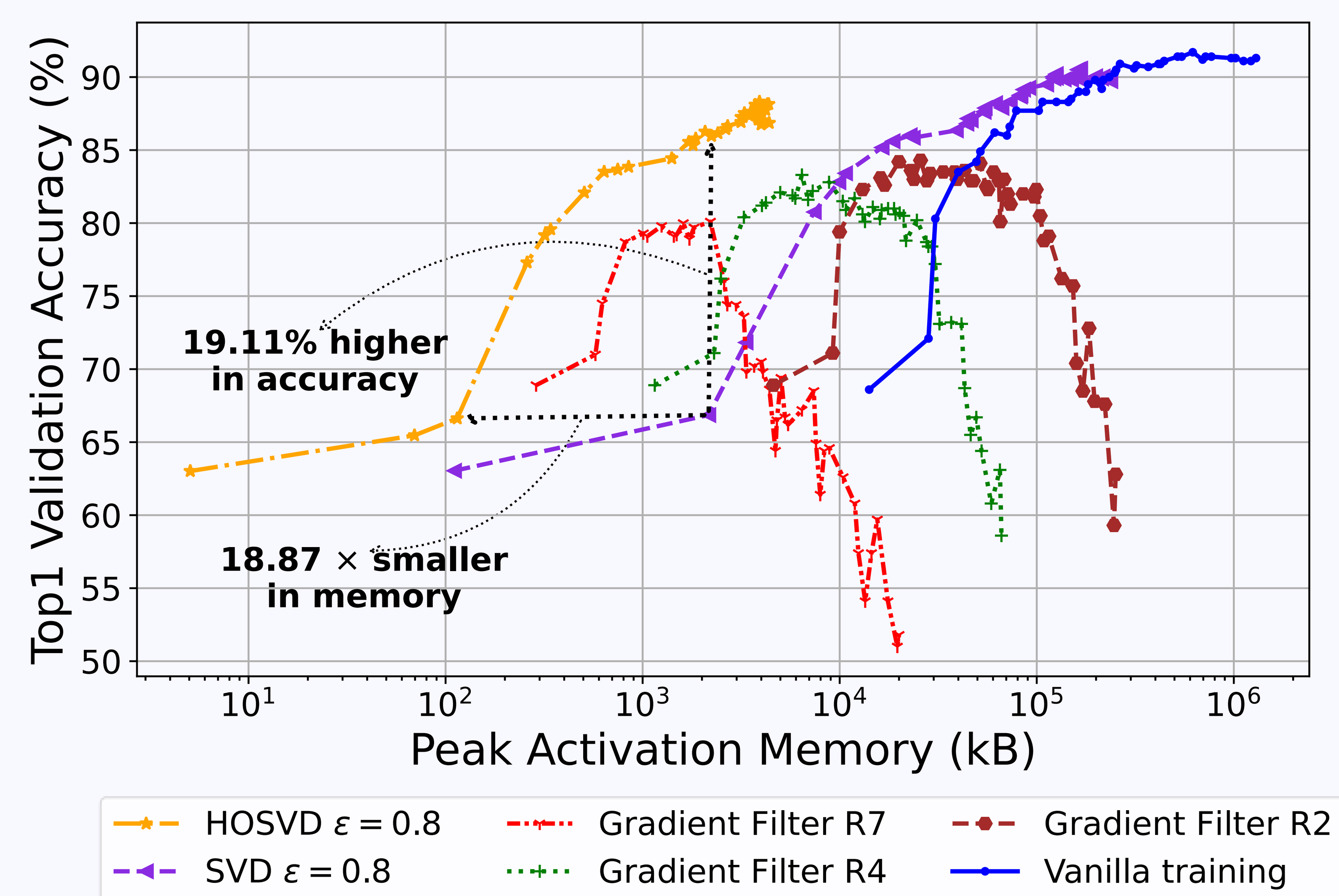
Experiment on ImageNet classification with different models

Method	MobileNetV2 #Layers	Acc ↑	Peak Mem (MB) ↓	Mean Mem (MB) ↓	Method	ResNet18 #Layers	Acc ↑	Peak Mem (MB) ↓	Mean Mem (MB) ↓
Vanilla training	All	74.0	1651.84	1651.84 ± 0.00	Vanilla training	All	72.8	532.88	532.88 ± 0.00
	2	62.6	15.31	15.31 ± 0.00		2	69.9	12.25	12.25 ± 0.00
	4	65.8	28.71	28.71 ± 0.00		4	71.5	30.63	30.63 ± 0.00
Gradient Filter R2	2	62.6	5.00	5.00 ± 0.00	Gradient Filter R2	2	68.7	4.00	4.00 ± 0.00
	4	65.2	9.38	9.38 ± 0.00		4	69.3	7.00	7.00 ± 0.00
SVD ($\varepsilon = 0.8$)	2	61.7	4.97	4.92 ± 0.08	SVD ($\varepsilon = 0.8$)	2	69.5	7.88	7.71 ± 0.21
	4	65.2	14.76	14.61 ± 0.09		4	71.1	19.98	19.72 ± 0.28
SVD ($\varepsilon = 0.9$)	2	62.3	8.97	8.91 ± 0.08	SVD ($\varepsilon = 0.9$)	2	69.7	9.86	9.77 ± 0.13
	4	65.5	20.35	20.20 ± 0.07		4	71.3	24.81	24.66 ± 0.17
HOSVD ($\varepsilon = 0.8$)	2	61.1	0.15	0.15 ± 0.00	HOSVD ($\varepsilon = 0.8$)	2	69.2	0.97	0.91 ± 0.05
	4	63.9	0.73	0.68 ± 0.03		4	70.5	2.89	2.74 ± 0.12
HOSVD ($\varepsilon = 0.9$)	2	61.8	0.43	0.43 ± 0.01	HOSVD ($\varepsilon = 0.9$)	2	69.5	2.73	2.63 ± 0.10
	4	64.8	1.92	1.76 ± 0.08		4	71.1	7.96	7.66 ± 0.21

Method	MCUNet #Layers	Acc ↑	Peak Mem (MB) ↓	Mean Mem (MB) ↓	Method	ResNet34 #Layers	Acc ↑	Peak Mem (MB) ↓	Mean Mem (MB) ↓
Vanilla training	All	67.4	632.98	632.98 ± 0.00	Vanilla training	All	75.6	839.04	839.04 ± 0.00
	2	62.1	13.78	13.78 ± 0.00		2	69.6	12.25	12.25 ± 0.00
	4	64.7	19.52	19.52 ± 0.00		4	72.2	24.50	24.50 ± 0.00
Gradient Filter R2	2	61.8	4.50	4.50 ± 0.00	Gradient Filter R2	2	68.8	4.00	4.00 ± 0.00
	4	64.4	6.38	6.38 ± 0.00		4	70.9	8.00	8.00 ± 0.00
SVD ($\varepsilon = 0.8$)	2	62.0	7.62	7.51 ± 0.12	SVD ($\varepsilon = 0.8$)	2	69.2	6.70	6.49 ± 0.29
	4	64.5	10.59	10.37 ± 0.20		4	71.8	14.68	14.24 ± 0.50
SVD ($\varepsilon = 0.9$)	2	62.1	10.32	10.26 ± 0.08	SVD ($\varepsilon = 0.9$)	2	69.4	9.10	8.96 ± 0.23
	4	64.6	14.39	14.26 ± 0.13		4	72.0	19.11	18.83 ± 0.37
HOSVD ($\varepsilon = 0.8$)	2	61.7	0.48	0.43 ± 0.04	HOSVD ($\varepsilon = 0.8$)	2	68.7	0.30	0.27 ± 0.02
	4	63.9	0.88	0.78 ± 0.07		4	71.1	1.11	1.02 ± 0.07
HOSVD ($\varepsilon = 0.9$)	2	62.0	1.32	1.27 ± 0.06	HOSVD ($\varepsilon = 0.9$)	2	69.2	0.71	0.65 ± 0.05
	4	64.4	2.52	2.36 ± 0.15		4	71.9	3.24	3.09 ± 0.13

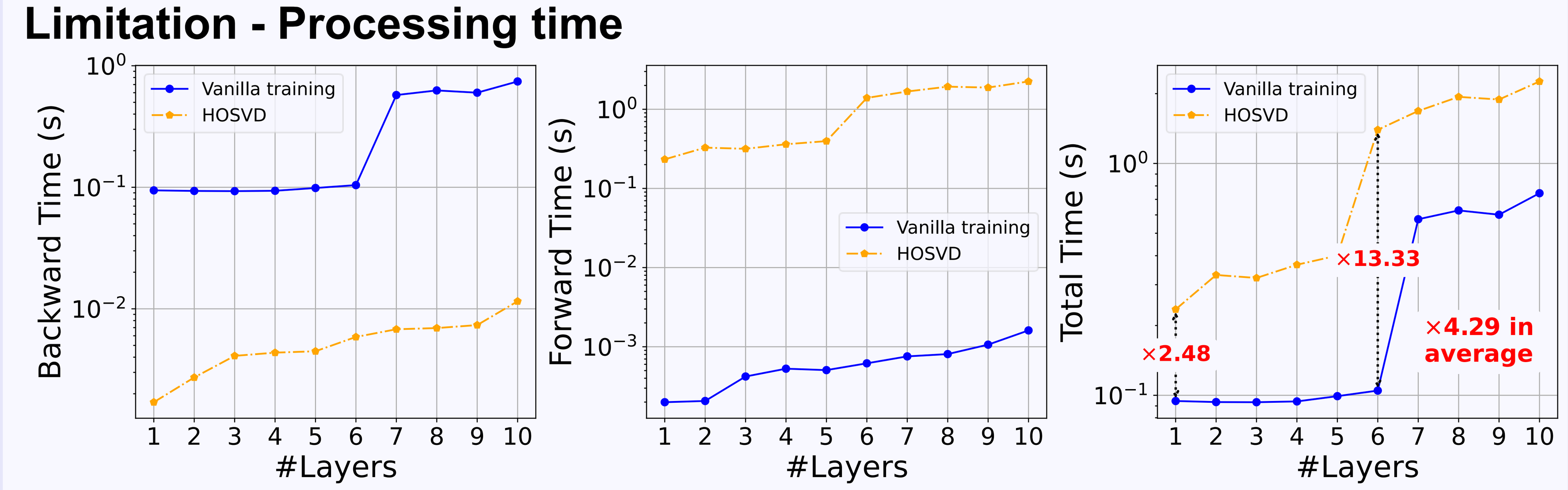
For the same #Layers, our techniques save significantly more memory than the others

Fine-tuning different number of layers of MCUNet pretrained on ImageNet with CIFAR-10 as downstream dataset



- Fine-tuning all layers with HOSVD costs less memory than fine-tuning only one layer with vanilla training.
- HOSVD and SVD do not accumulate error contrary to Gradient Filter.
- In a same context, HOSVD performs better than SVD.

Limitation - Processing time



(a) Backward (b) Forward (c) total

- Backward processing of HOSVD is tens of times faster than vanilla training, while forward is up to a thousand times slower.
- HOSVD is on average 4.29 times slower than vanilla training overall.

References

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Paper Code