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# Beyond Low-rank Decomposition: A Shortcut Approach for Efficient On-Device Learning


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# How to save up to 120.09× activation memory and 1.86× computational cost during training?

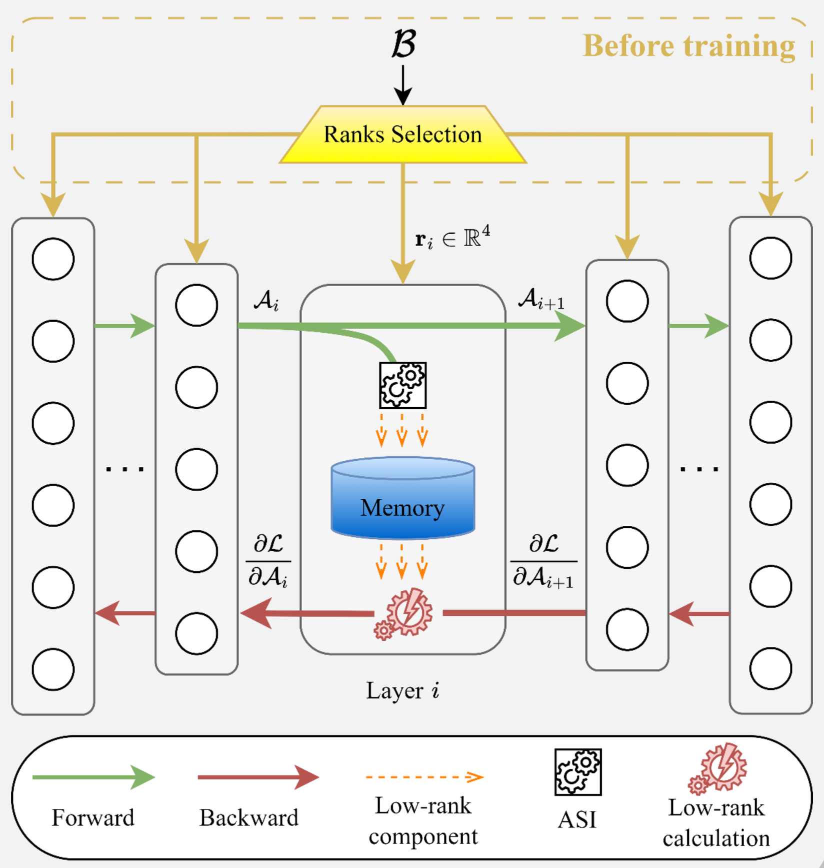
## The Memory Bottleneck of Backpropagation

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

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

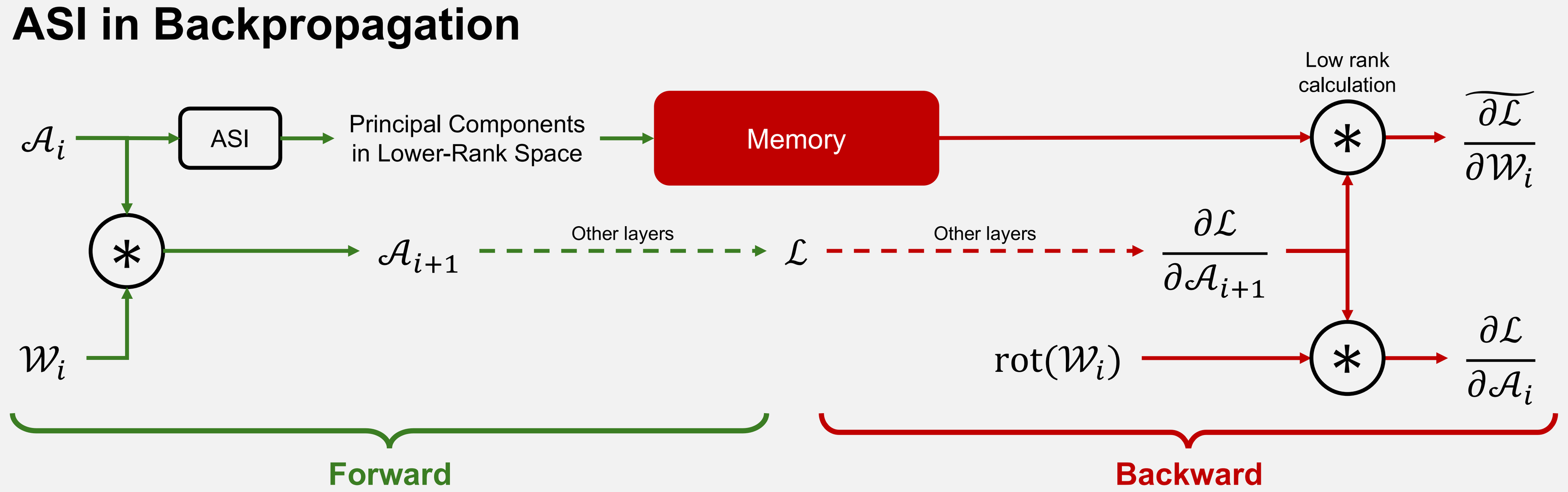
$$\frac{\partial \mathcal{L}}{\partial \mathcal{A}_i} = \frac{\partial \mathcal{L}}{\partial \mathcal{A}_{i+1}} \cdot \frac{\partial \mathcal{A}_{i+1}}{\partial \mathcal{A}_i} = \text{conv}_{\text{full}}\left[\frac{\partial \mathcal{L}}{\partial \mathcal{A}_{i+1}}, \text{rot}(\mathcal{W}_i)\right]$$

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 **Activation Subspace Iteration (ASI)**. $\mathcal{W}_i$ is untouched to avoid error propagation through $\frac{\partial \mathcal{L}}{\partial \mathcal{A}_i}$.

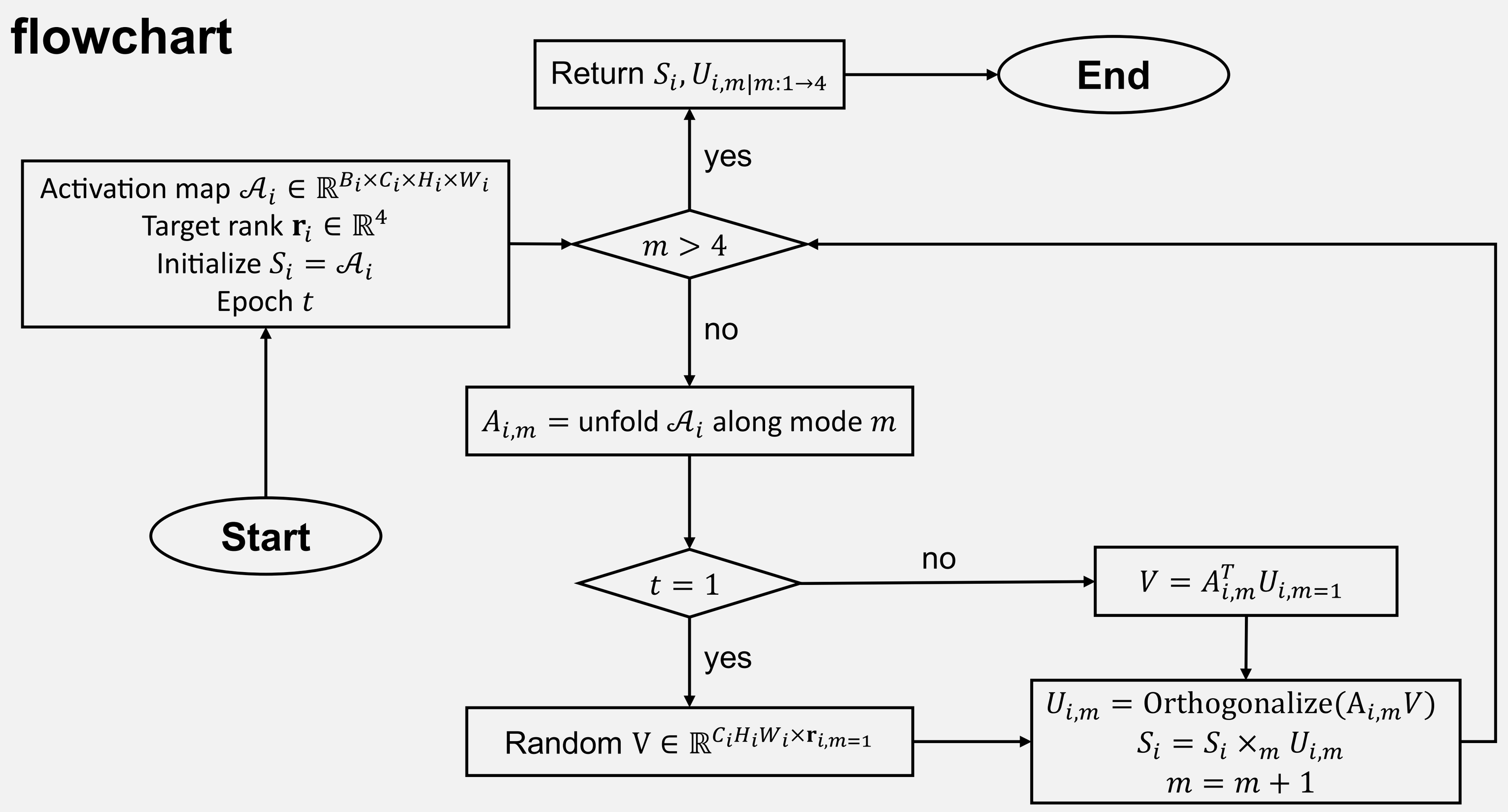



## Method

### ASI in Backpropagation



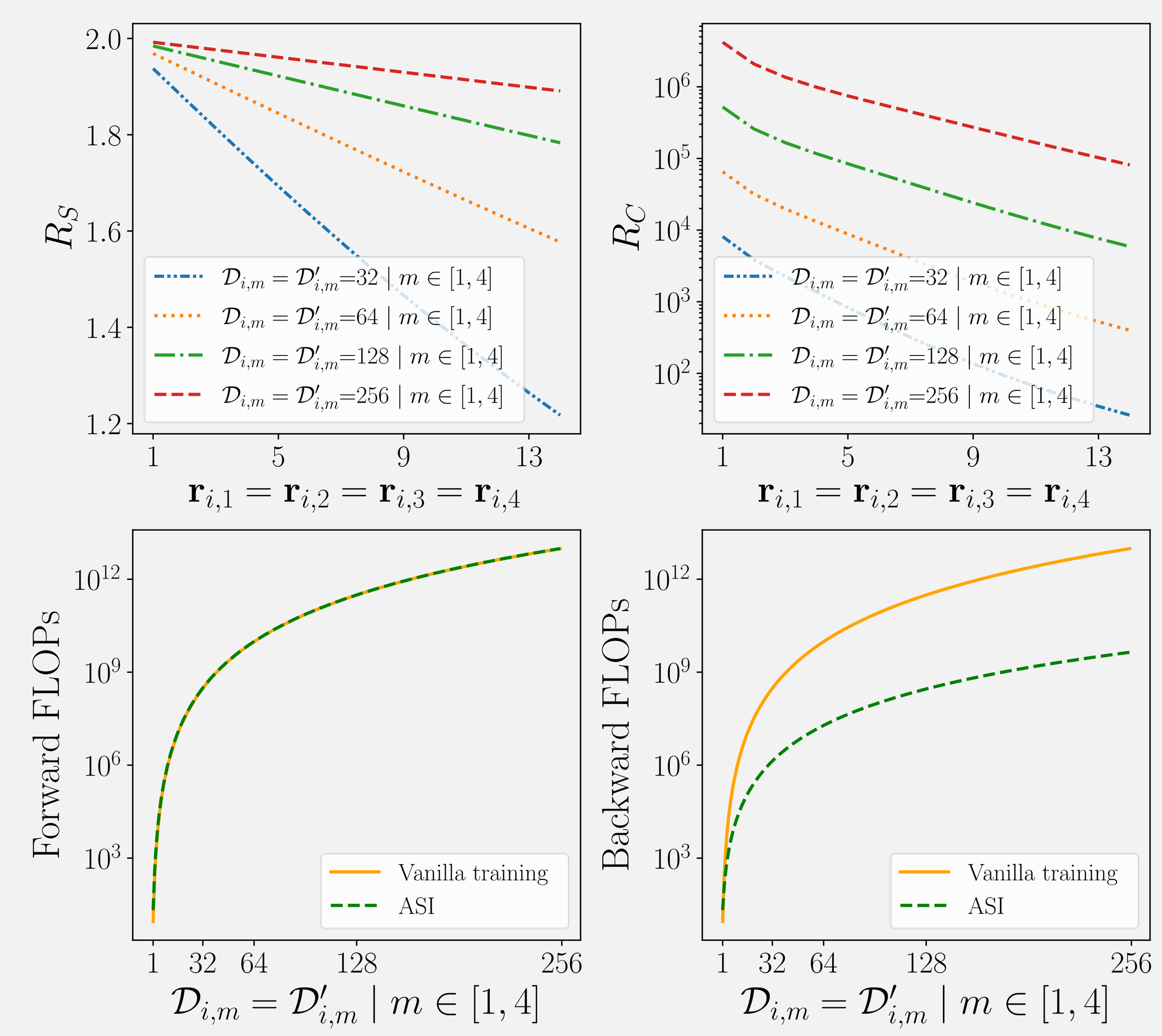

### ASI flowchart



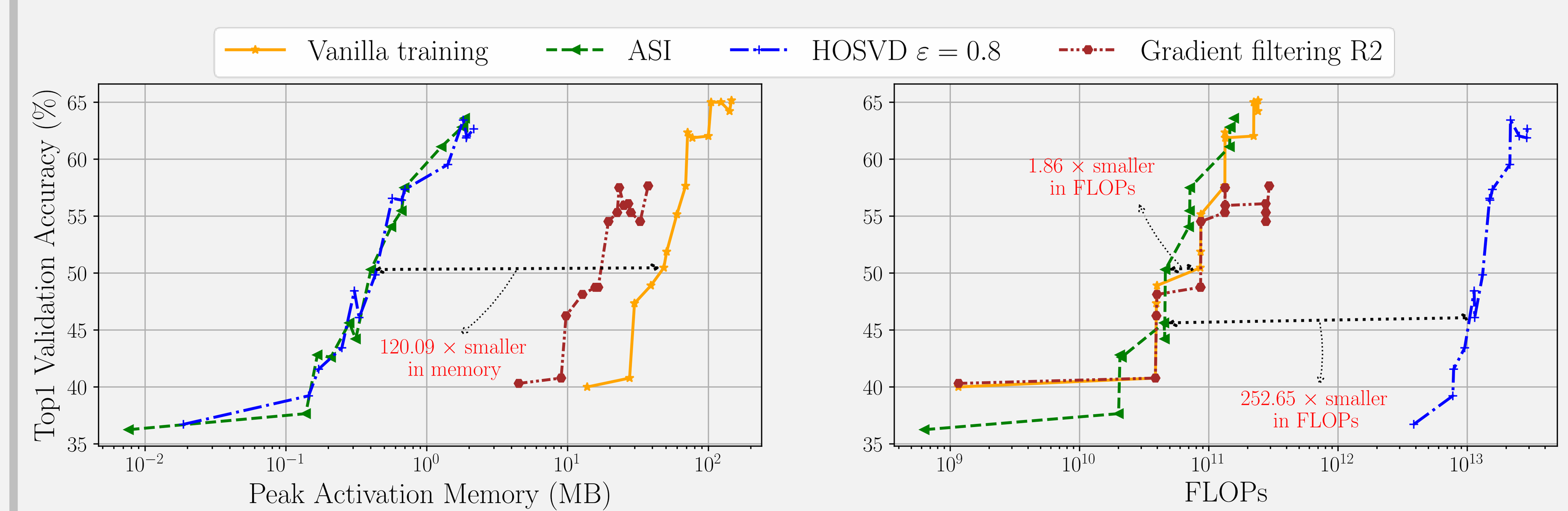

## Results

### Expected results

- Consider activation maps of the $i^{th}$ and the $(i+1)^{th}$ layers as $\mathcal{A}_i \in \mathbb{R}^{B \times C_i \times H_i \times W_i}$ and $\mathcal{A}'_i \in \mathbb{R}^{B \times C'_i \times H'_i \times W'_i}$, respectively.
- Let $\mathcal{D}_{i,m} = \{B, C_i, H_i, W_i\}$ and $\mathcal{D}'_{i,m} = \{B, C'_i, H'_i, W'_i\}$.
- The target rank for compression is $\mathbf{r} \in \mathbb{R}^{N \times 4}$, where $N$ is total number of layers and 4 is number of tensor mode of the activation maps.




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



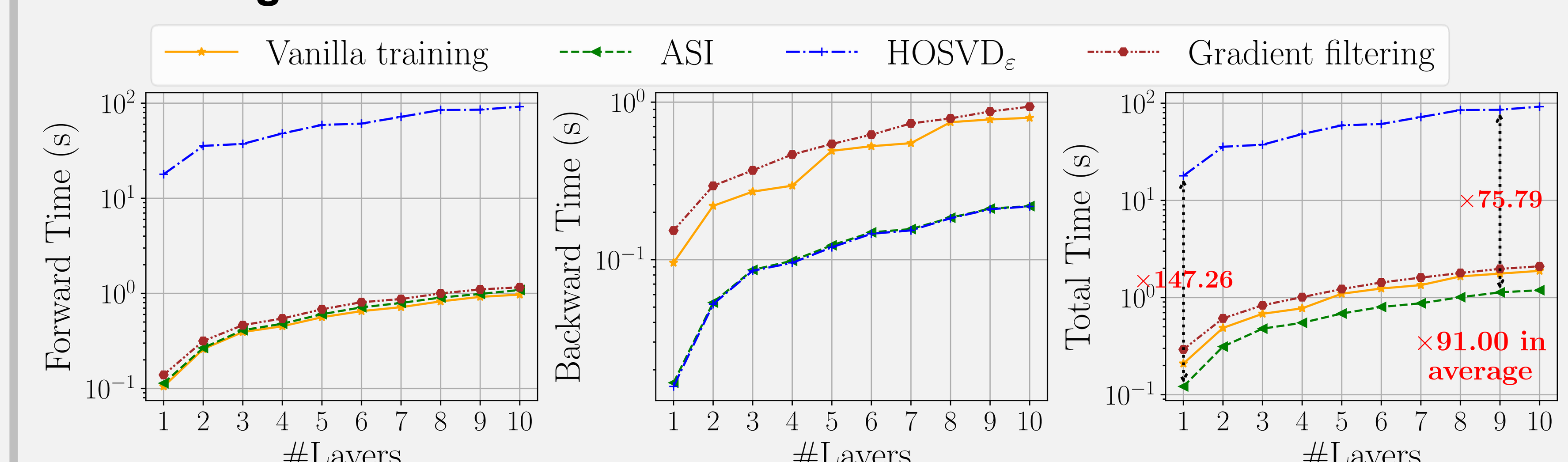

- ASI has similar performance to HOSVD in terms of memory compression, but it is significantly more efficient.
- For the same accuracy, ASI saves 120.09× more memory and is 1.86× cheaper than vanilla training.

### Experiment on ImageNet classification with different models

| Method | MobileNetV2 | | | | Method | ResNet18 | | | |
|---|---|---|---|---|---|---|---|---|---|
| | #Layers | Acc ↑ | Mem (MB) ↓ | GFLOPs ↓ | | #Layers | Acc ↑ | Mem (MB) ↓ | GFLOPs ↓ |
| Vanilla training | All | 74.0 | 1651.84 | 830.82 | Vanilla training | All | 72.8 | 532.88 | 291.79 |
| | 2 | 62.6 | 15.31 | 4.50 | | 2 | 69.9 | 12.25 | 29.60 |
| | 4 | 65.8 | 28.71 | 57.48 | | 4 | 71.5 | 30.63 | 46.45 |
| Gradient filtering R2 | 2 | 62.6 | 5.00 | 4.50 | Gradient filtering R2 | 2 | 68.7 | 4.00 | 29.60 |
| | 4 | 65.2 | 9.38 | 57.50 | | 4 | 69.3 | 7.00 | 47.70 |
| HOSVD ($\varepsilon = 0.8$) | 2 | 61.1 | 0.15 | 3049.71 | HOSVD ($\varepsilon = 0.8$) | 2 | 69.2 | 0.97 | 1581.42 |
| | 4 | 63.9 | 0.73 | 5895.31 | | 4 | 70.5 | 2.89 | 4048.56 |
| ASI | 2 | 60.3 | 0.13 | 2.81 | ASI | 2 | 68.9 | 0.93 | 19.04 |
| | 4 | 64.0 | 0.71 | 31.54 | | 4 | 70.6 | 2.63 | 33.14 |
| **Method** | **MCUNet** | | | | **Method** | **ResNet34** | | | |
| | #Layers | Acc ↑ | Mem (MB) ↓ | GFLOPs ↓ | | #Layers | Acc ↑ | Mem (MB) ↓ | GFLOPs ↓ |
| Vanilla training | All | 67.4 | 632.98 | 248.84 | Vanilla training | All | 75.6 | 839.04 | 528.55 |
| | 2 | 62.1 | 13.78 | 19.31 | | 2 | 69.6 | 12.25 | 29.60 |
| | 4 | 64.7 | 19.52 | 19.88 | | 4 | 72.2 | 24.50 | 59.19 |
| Gradient filtering R2 | 2 | 61.8 | 4.50 | 19.31 | Gradient filtering R2 | 2 | 68.8 | 4.00 | 29.60 |
| | 4 | 64.4 | 6.38 | 19.89 | | 4 | 70.9 | 8.00 | 59.21 |
| HOSVD ($\varepsilon = 0.8$) | 2 | 61.7 | 0.48 | 1988.05 | HOSVD ($\varepsilon = 0.8$) | 2 | 68.7 | 0.30 | 1579.64 |
| | 4 | 63.9 | 0.88 | 2457.59 | | 4 | 71.1 | 1.11 | 3160.46 |
| ASI | 2 | 61.7 | 0.38 | 11.01 | ASI | 2 | 68.3 | 0.25 | 16.44 |
| | 4 | 63.5 | 0.83 | 11.93 | | 4 | 71.1 | 1.09 | 35.31 |

For the same #Layers, ASI saves significantly more memory and GLOPS than the others.

### Processing time




- The forward processing time of ASI is approximately the same as that of vanilla training, while the backward pass is up to an order of magnitude faster.
- Overall, ASI is on average 1.5× faster than vanilla training.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Paper

Code