

EfficientML.ai Lecture 19

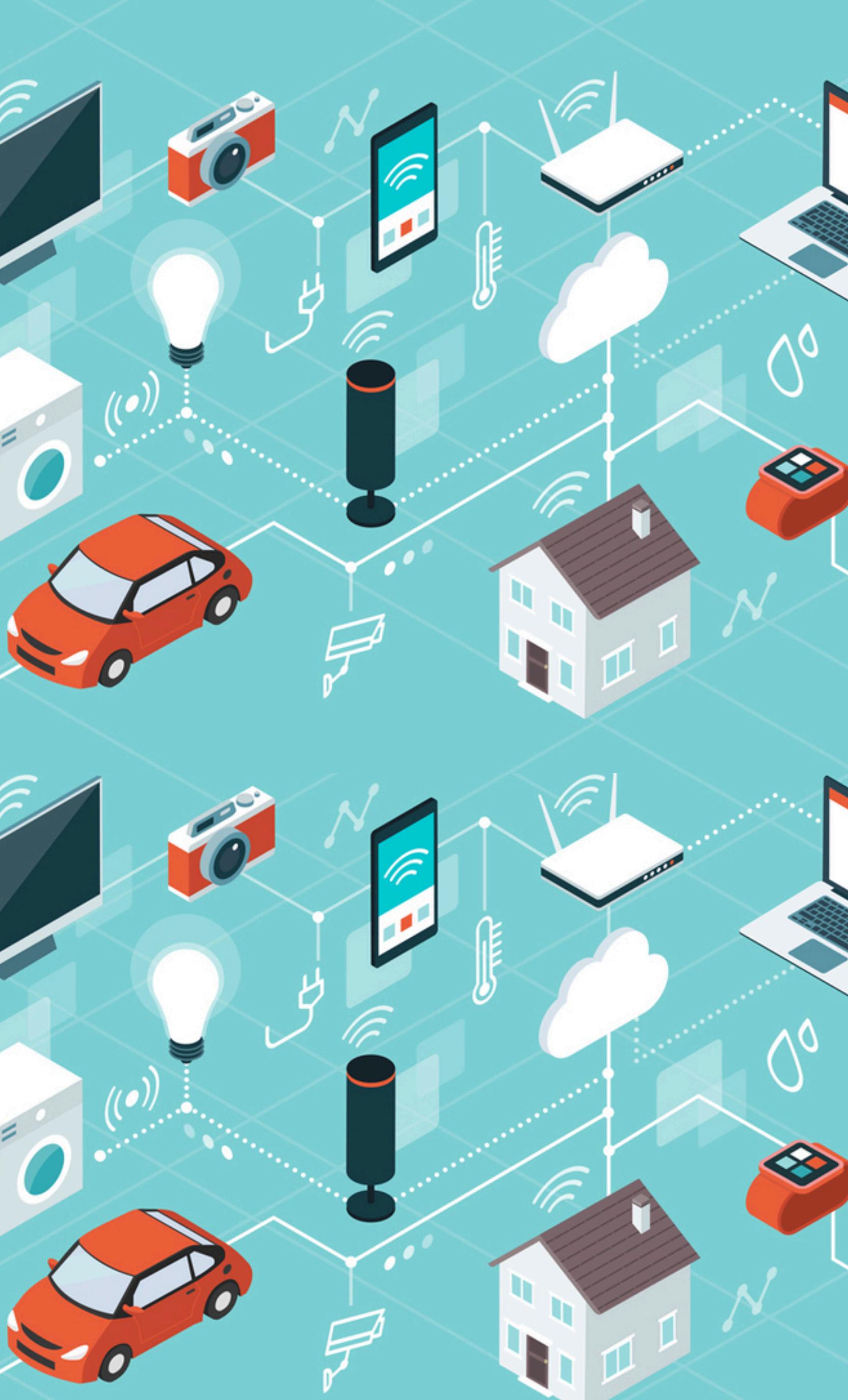
On-Device Training and Transfer Learning



Song Han

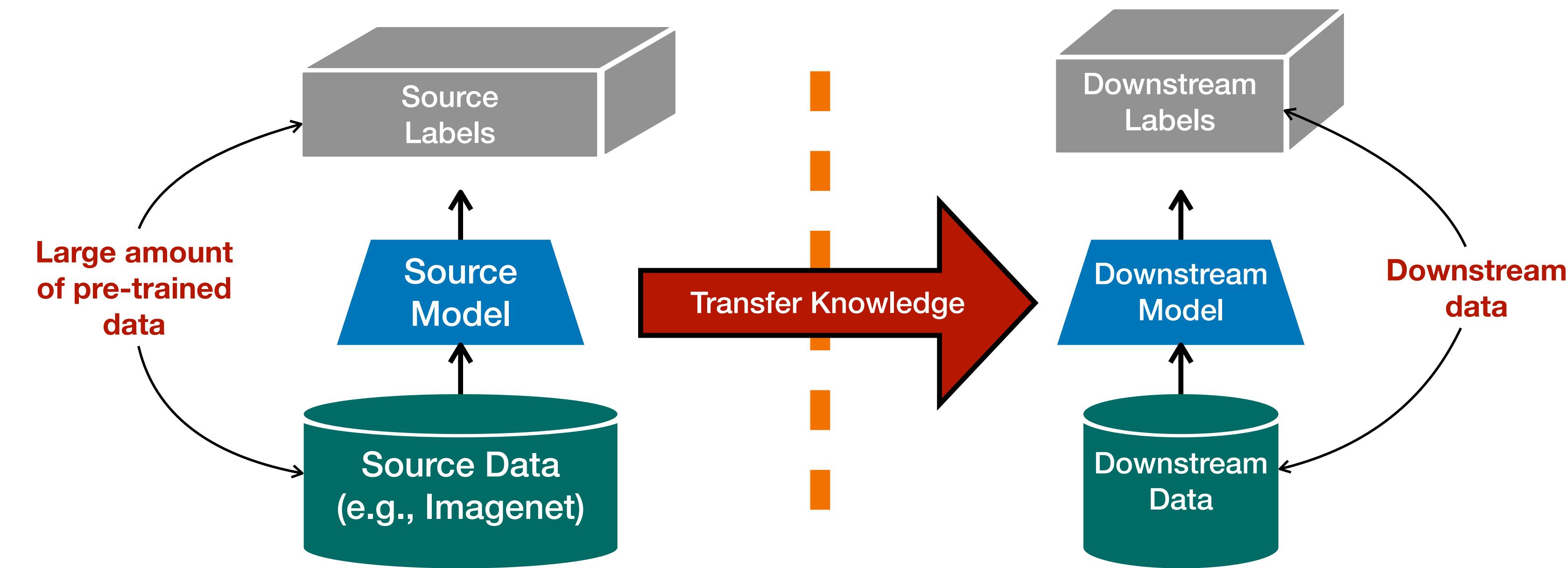
Associate Professor, MIT
Distinguished Scientist, NVIDIA

 @SongHan/MIT



Transfer Learning

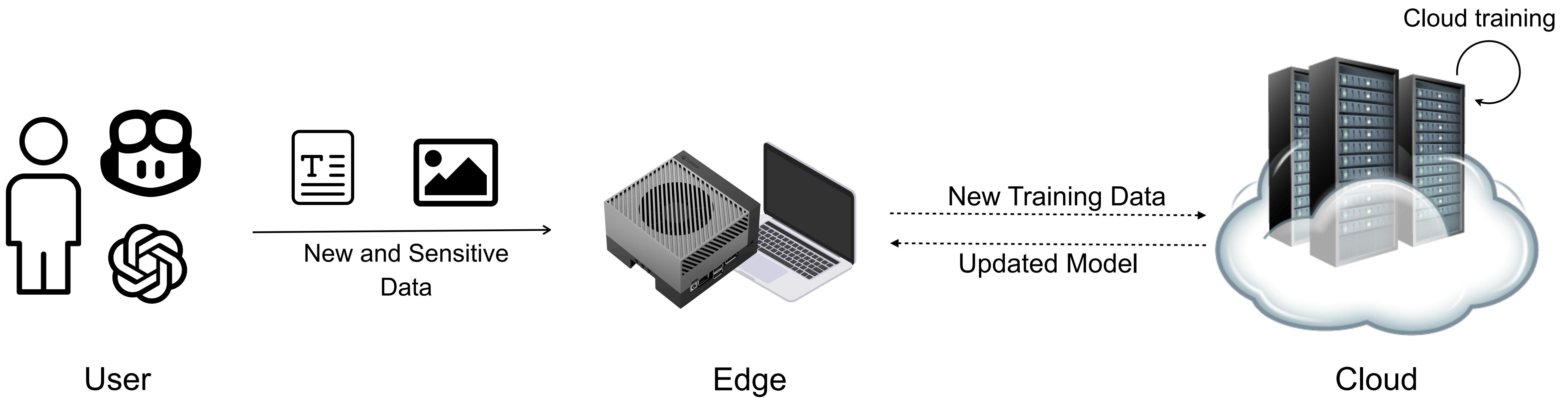
- Transfer learning is a technique in machine learning in which knowledge learned from a task is reused in order to boost performance on a related task.
- For example, for image classification, knowledge gained while learning to recognize cars could be applied when trying to recognize trucks.



https://en.wikipedia.org/wiki/Transfer_learning

On-Device Learning

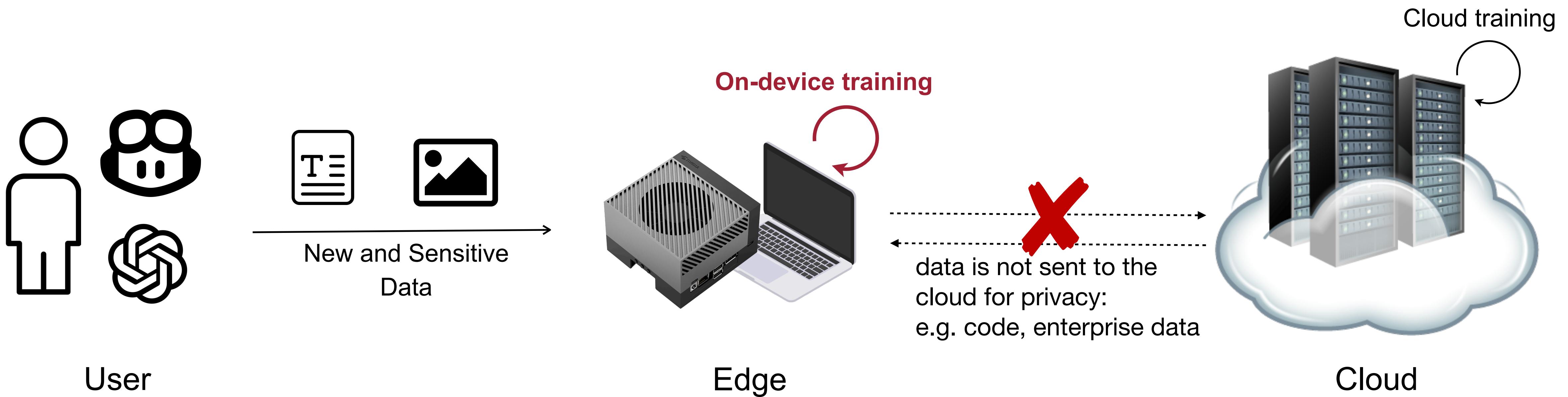
- Transfer learning at the "edge", rather than cloud.



- Customization: AI systems need to continually adapt to new data collected from the sensors.

On-Device Learning

- Transfer learning at the "edge", rather than cloud.

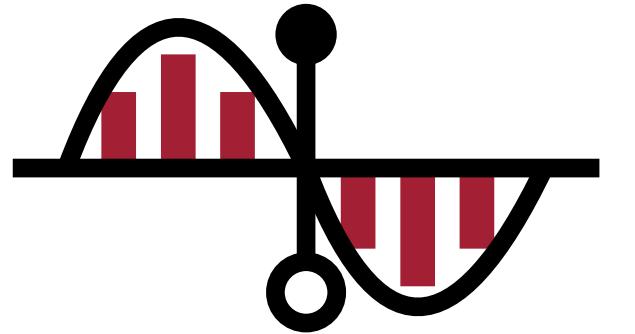


- Customization: AI systems need to continually adapt to new data collected from the sensors.
- Privacy: Data does not leave the device.

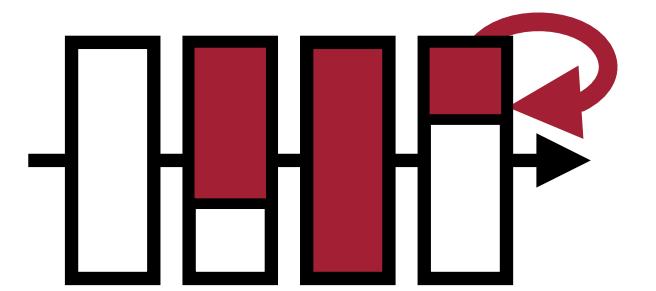
Lecture Plan

Today we will discuss:

1. Deep leakage from gradients, gradient is not safe to share
2. Memory bottleneck of on-device training
3. Tiny transfer learning (TinyTL)
4. Sparse back-propagation (SparseBP)
5. Quantized training with quantization aware scaling (QAS)
6. PockEngine: system support for sparse back-propagation



Quantized Training



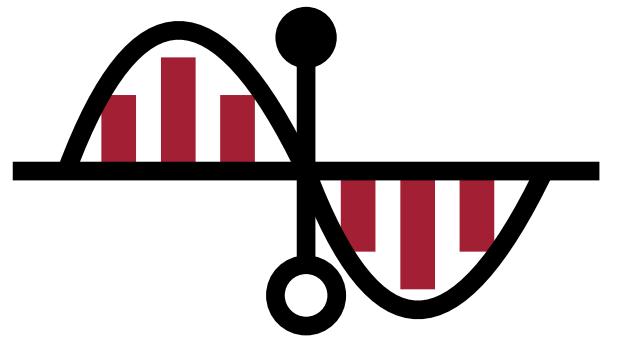
Sparse Training



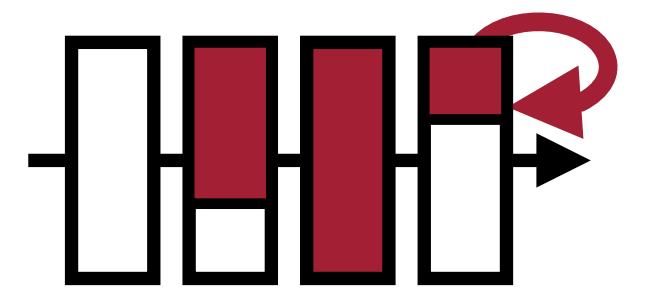
PockEngine

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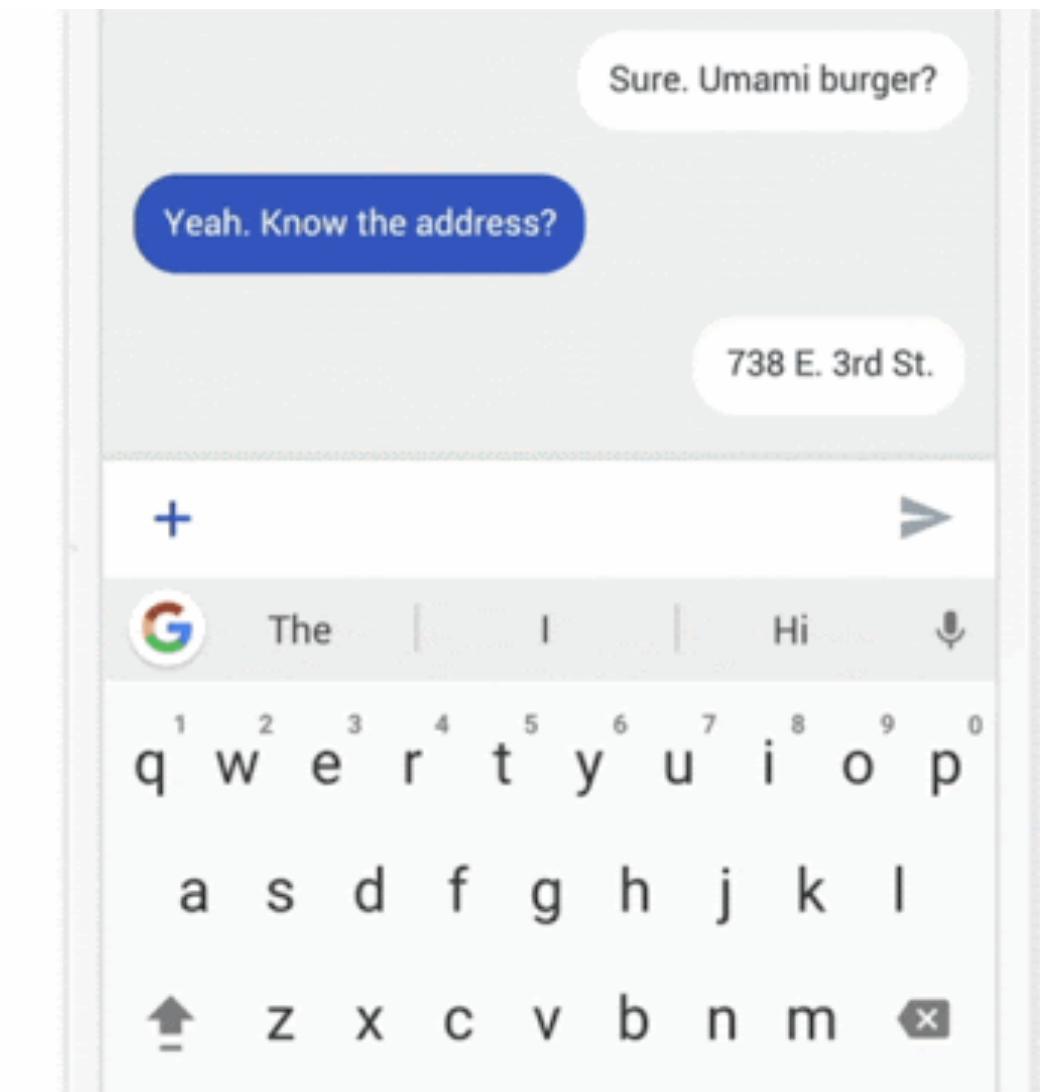
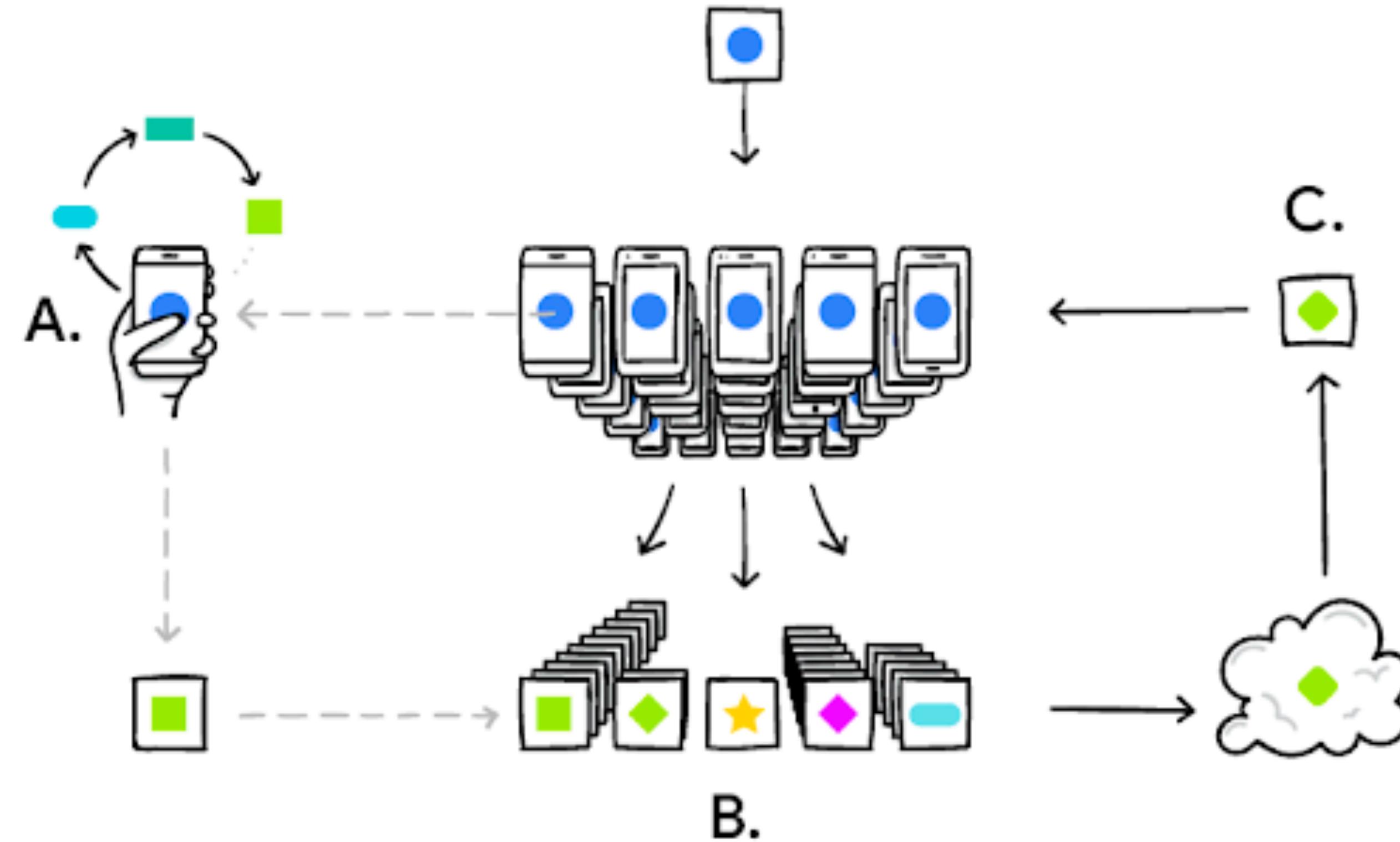
Sparse Training



PockEngine

On-Device Learning

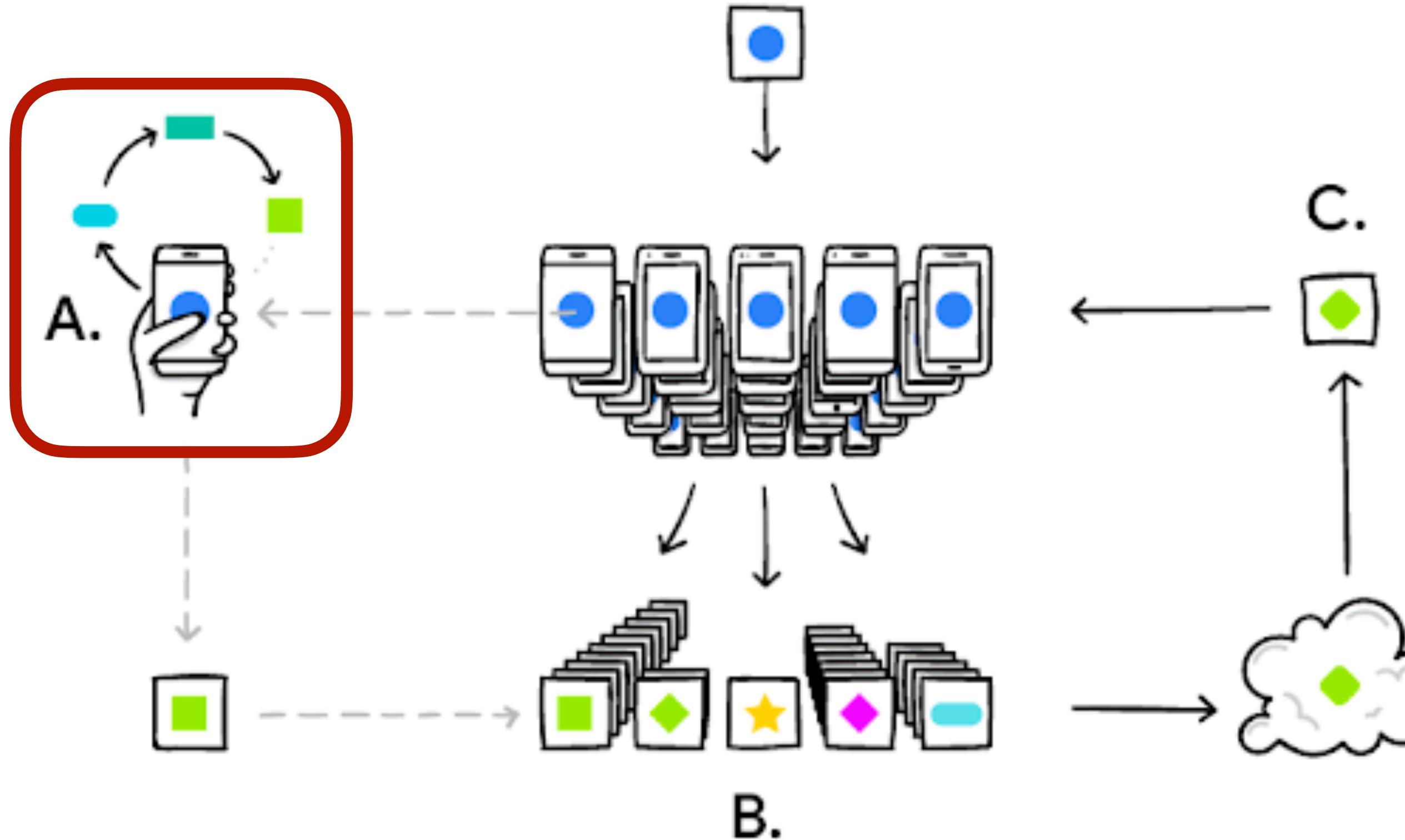
Federated learning: only share the gradients / weights, user data stays local.



Communication-Efficient Learning of Deep Networks from Decentralized Data. [McMahan, 2016]

Background of Federated Learning

FedAvg Algorithm

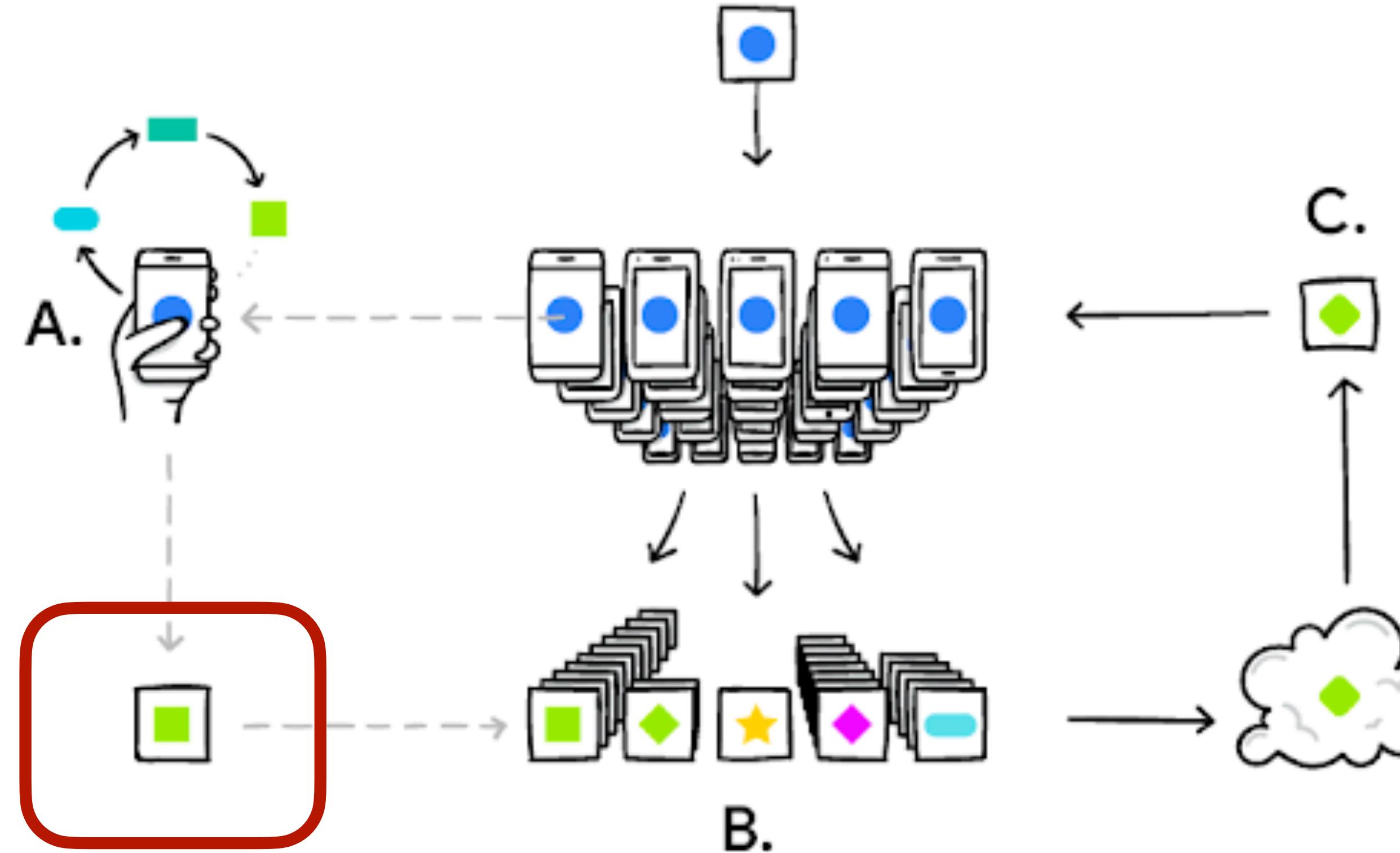


1. Users generate personal data on device and perform local training.

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Background of Federated Learning

FedAvg Algorithm

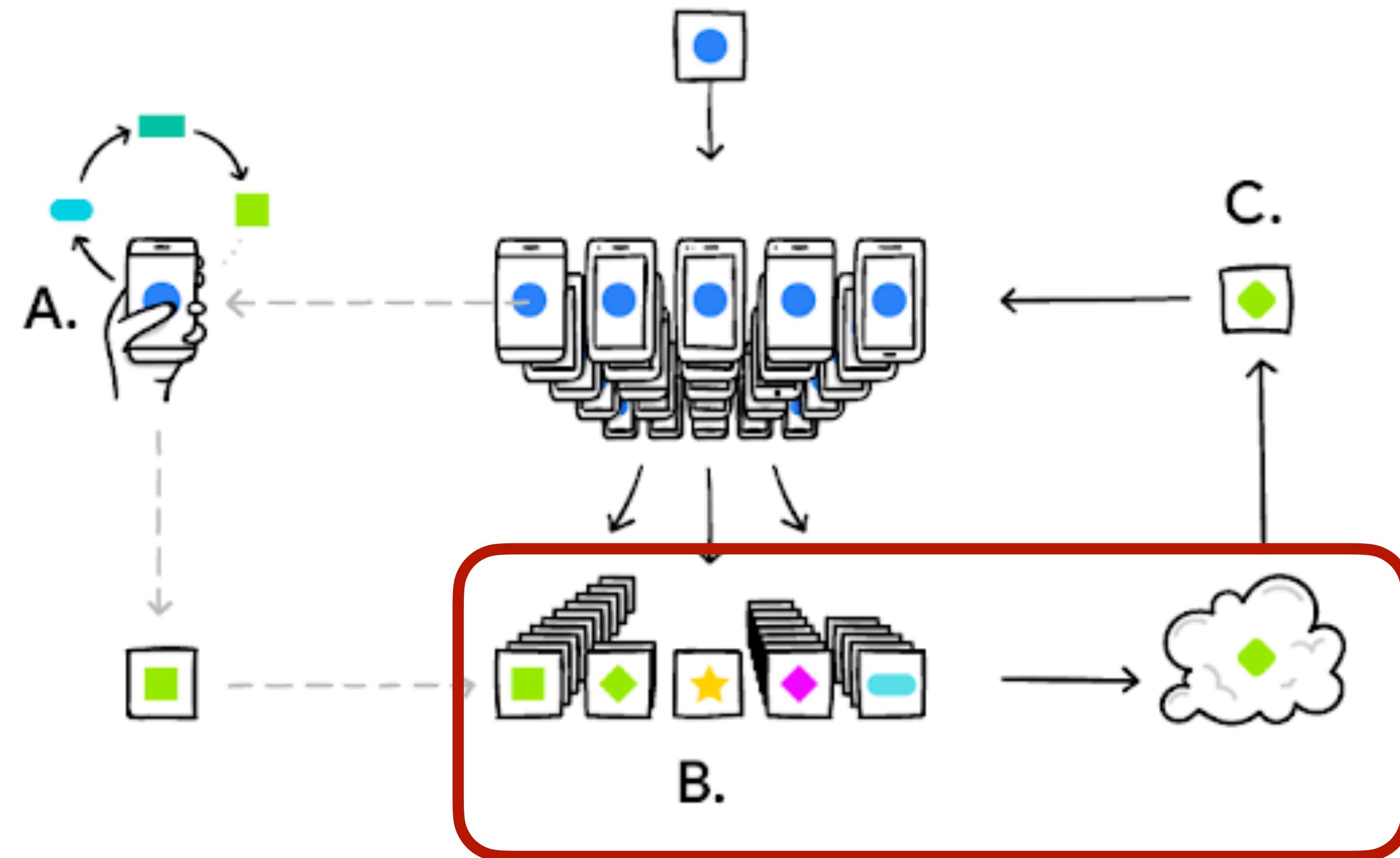


1. Users generate personal data on device and perform local training.
2. Each device update its model using local data for N iterations.

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Background of Federated Learning

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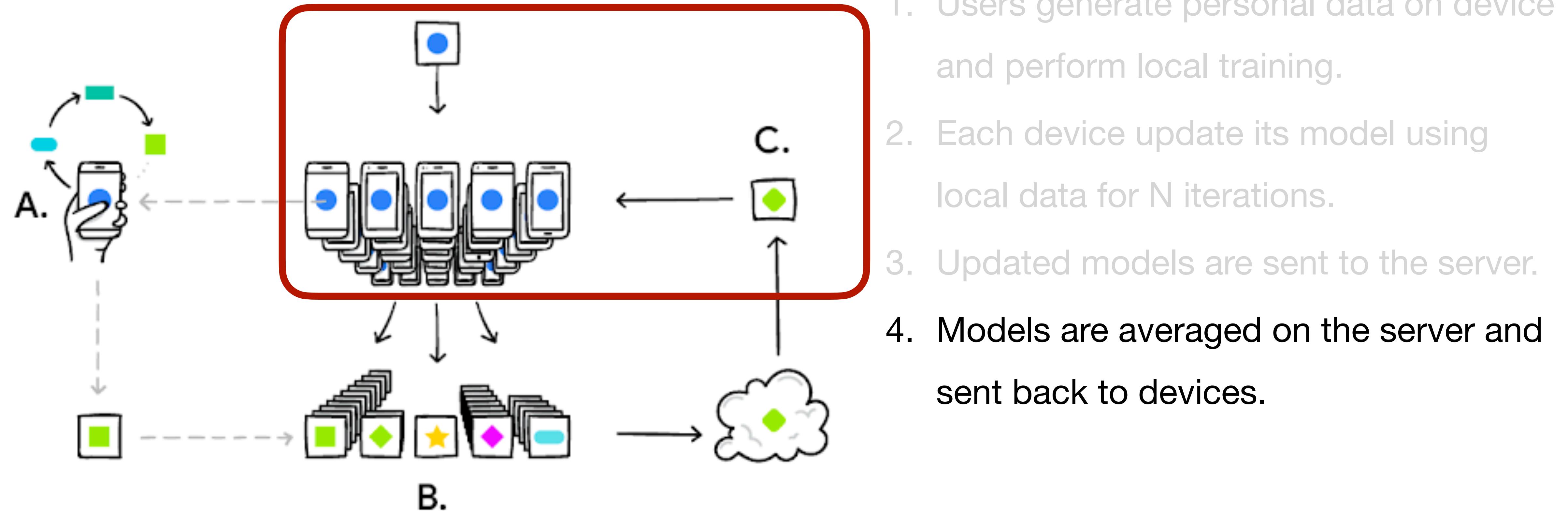


1. Users generate personal data on device and perform local training.
2. Each device update its model using local data for N iterations.
3. Updated models are sent to the server.

Communication-Efficient Learning of Deep Networks from Decentralized Data. [McMahan, 2016]

Background of Federated Learning

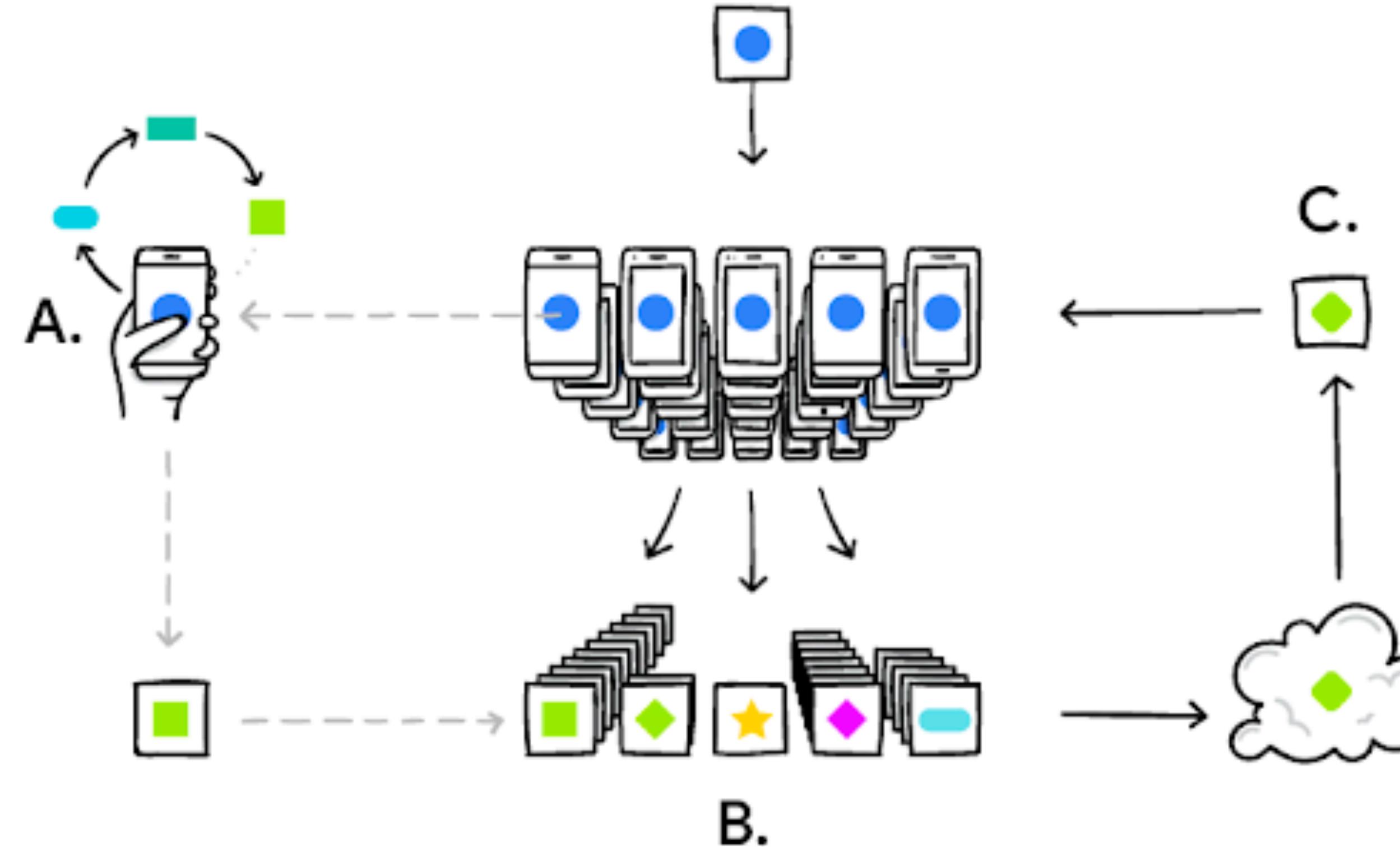
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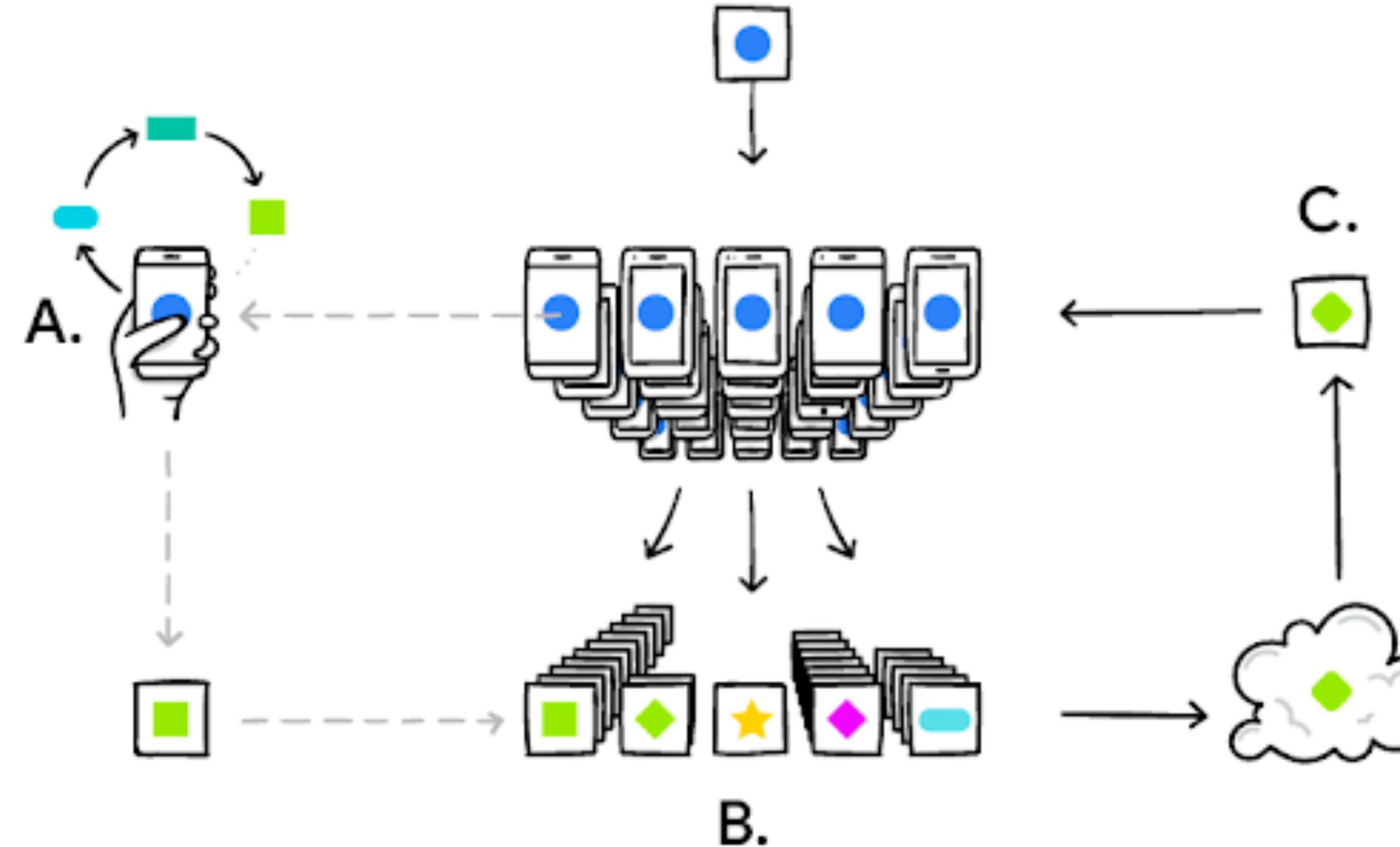
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4. Models are averaged on the server and sent back to devices.

The important & private user data **NEVER** leaves local devices.

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Background of Federated Learning

FedAvg Algorithm



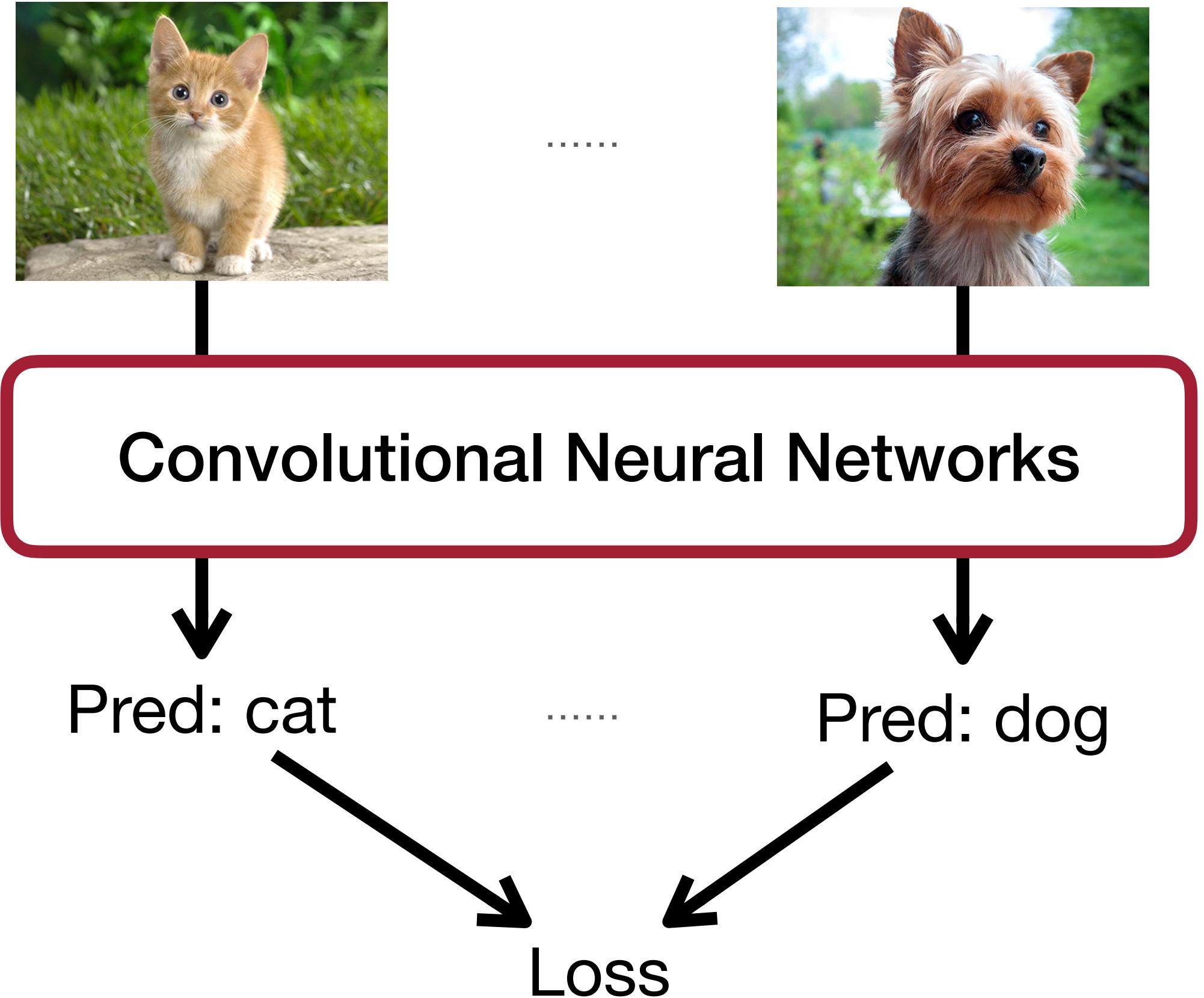
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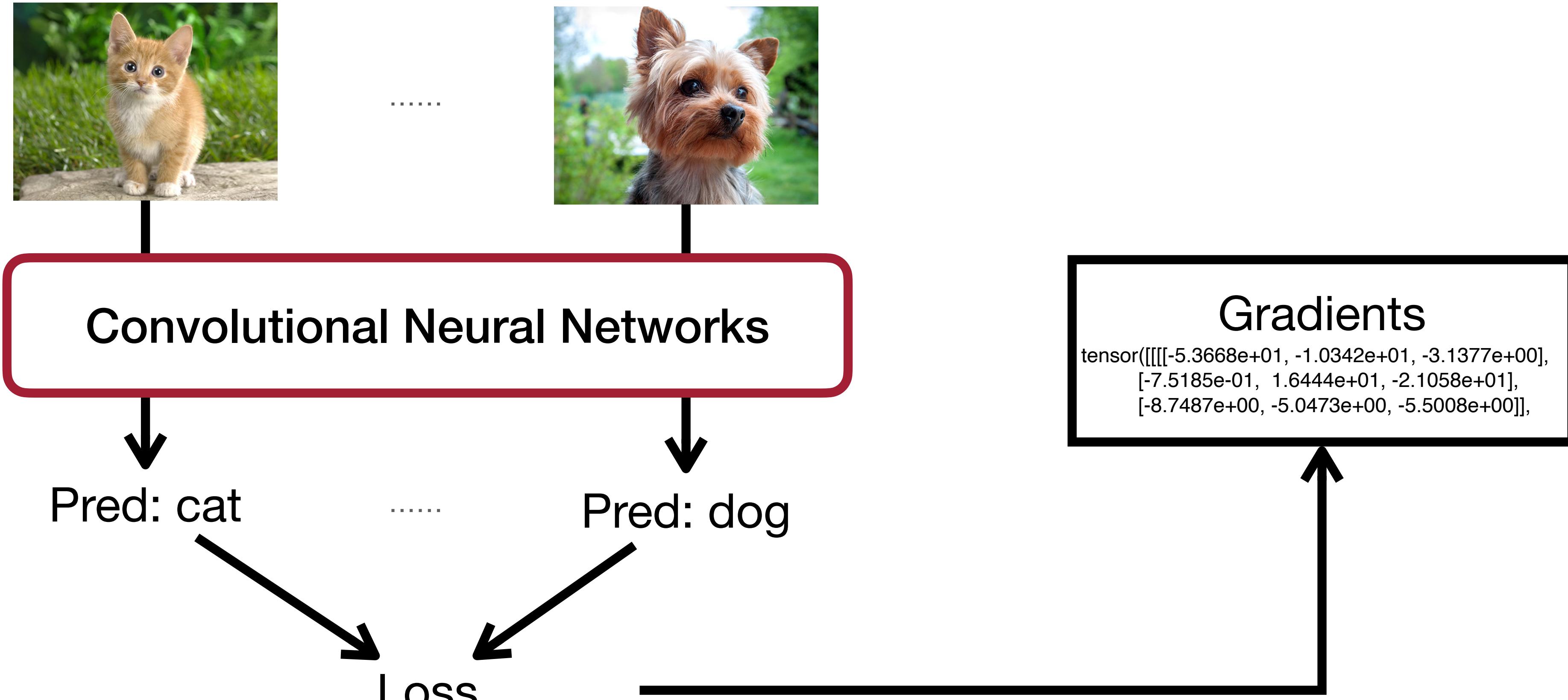
Safe...?

Communication-Efficient Learning of Deep Networks from Decentralized Data. [McMahan, 2016]

Rethink the Safety of Gradients

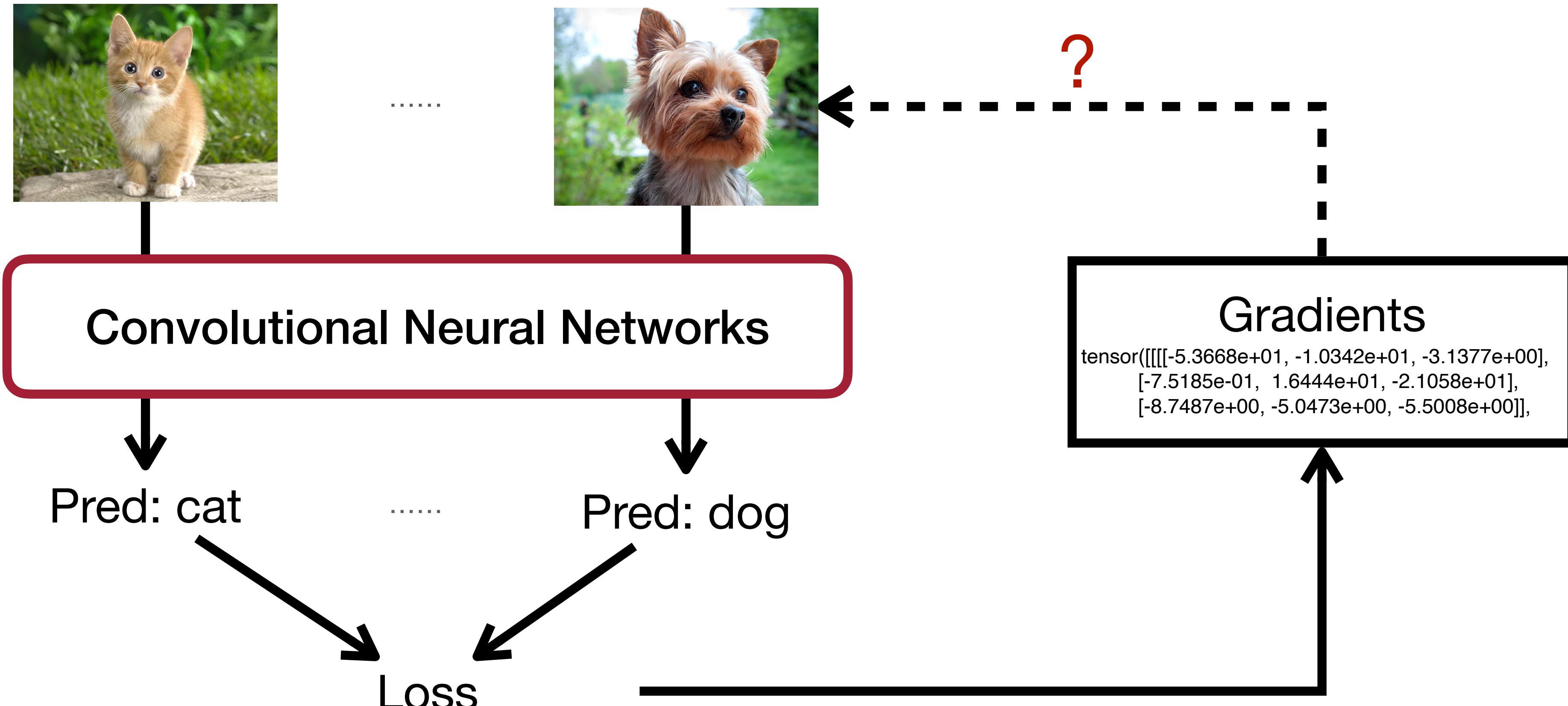


Rethink the Safety of Gradients



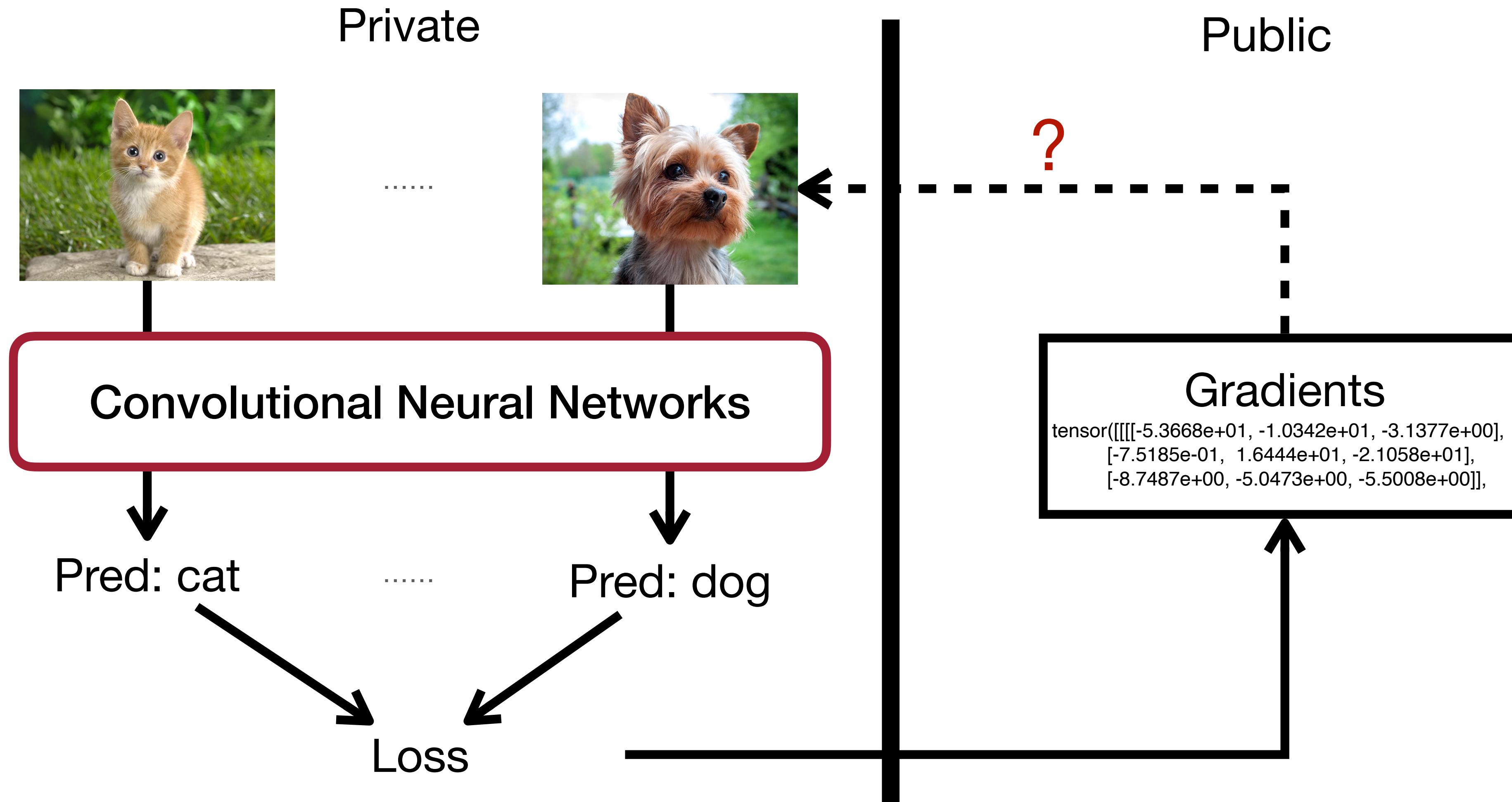
derive gradients from model and training data.

Rethink the Safety of Gradients



Can we derive the training data from gradients?

Rethink the Safety of Gradients



If that is possible, then sharing the gradient is not safe!

Rethink the Safety of Gradients

Existing Work of Gradient Inversion

Membership Inference [Shokri 2016]

- Given gradients, it's possible to find whether a data point belongs to the batch.

Property Inference [Melis 2018]

- Given gradients, it's possible to find whether a data point with certain property is in the batch.

Gradients

```
tensor([[[[-5.3668e+01, -1.0342e+01, -3.1377e+00],  
        [-7.5185e-01,  1.6444e+01, -2.1058e+01],  
        [-8.7487e+00, -5.0473e+00, -5.5008e+00]],
```



Membership Inference

Whether a record is used in the batch.

Property Inference

Whether a sample with certain property is in the batch.

Exploiting unintended feature leakage in collaborative learning. [Melis 2018]
Membership inference attacks against machine learning models. [Shokri 2016]

Rethink the Safety of Gradients

Existing Work of Gradient Inversion

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- Given gradients, it's possible to find whether a data point belongs to the batch.

Property Inference [Melis 2018]

- Given gradients, it's possible to find whether a data point with certain property is in the batch.

Gradients contain certain information about the training data.

Can we obtain the **raw training data** from **gradient**?

Exploiting unintended feature leakage in collaborative learning. [Melis 2018]
Membership inference attacks against machine learning models. [Shokri 2016]

Deep Leakage from Gradients

Normal Training:
forward-backward, update **model weights**



Deep Learning Model

Pred: cat

Loss

Label

MSE

Gradients

Deep Leakage Attack:
forward-backward, update **the dummy data**

Dummy input



Deep Learning Model

Pred: [random]

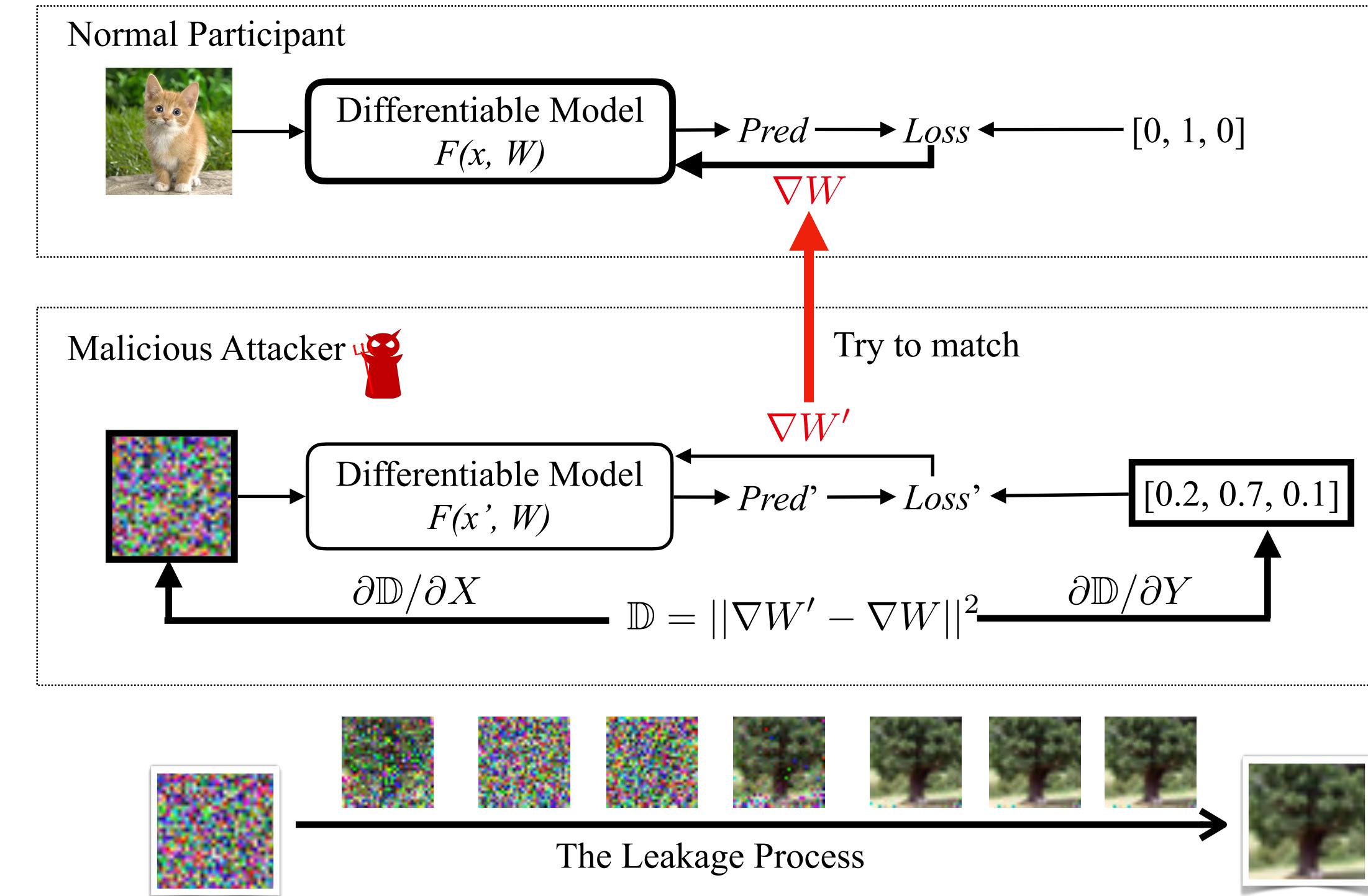
Loss

Dummy label

Deep Leakage from Gradient. [Zhu et al, NeurIPS 2019]

Deep Leakage from Gradients

Deep Leakage Attack via Gradients Matching



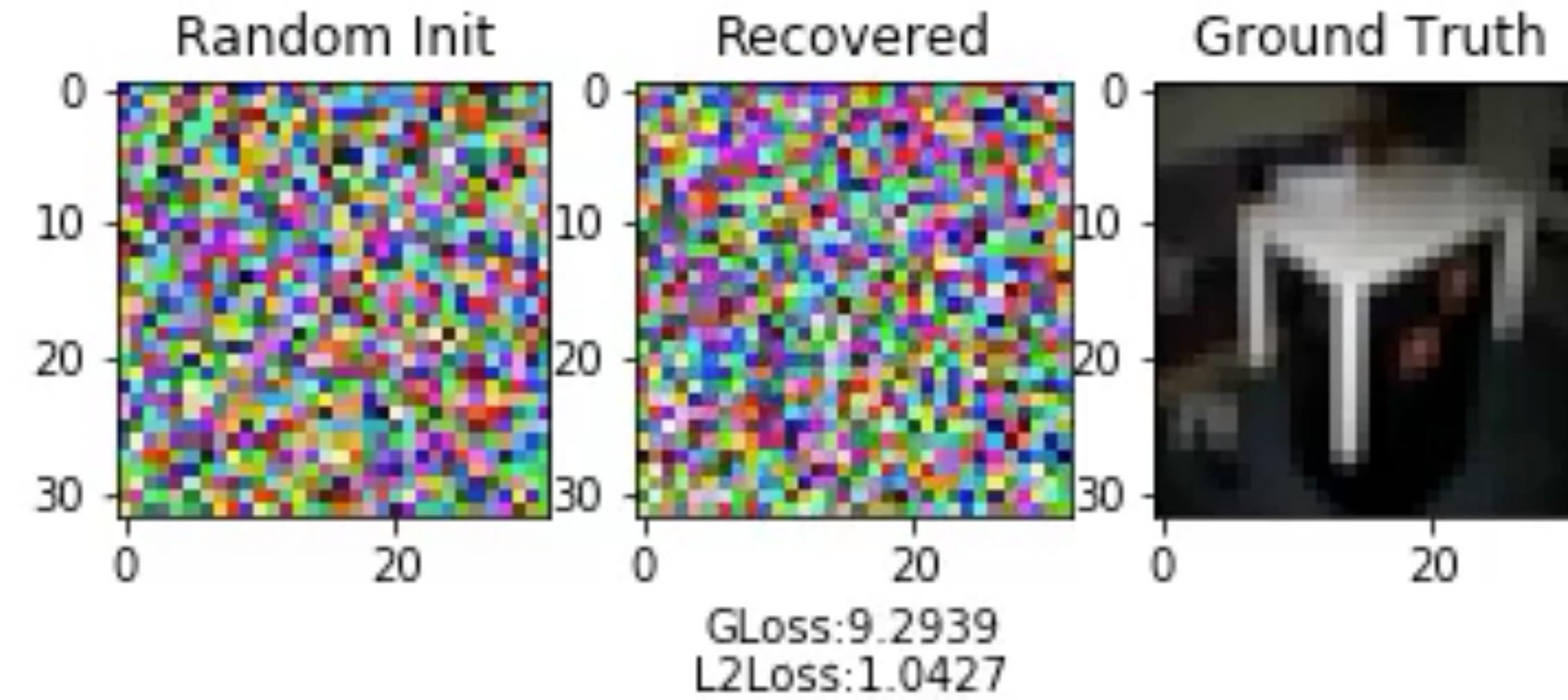
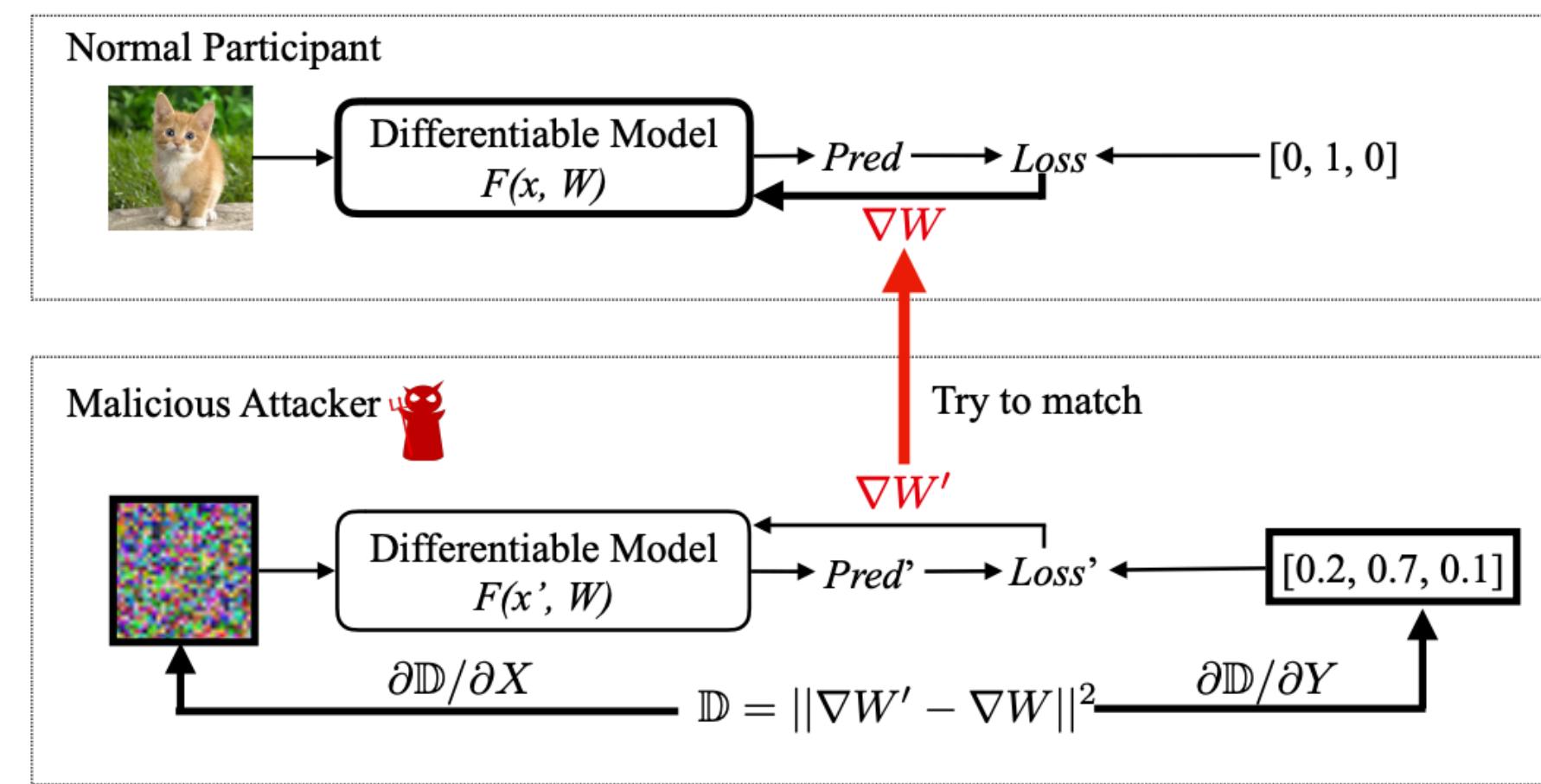
Only gradients are shared between malicious attacker and normal users.

But, this action indeed **leaks the privacy!**

Deep Leakage from Gradient. [Zhu et al, NeurIPS 2019]

Deep Leakage Attack Results

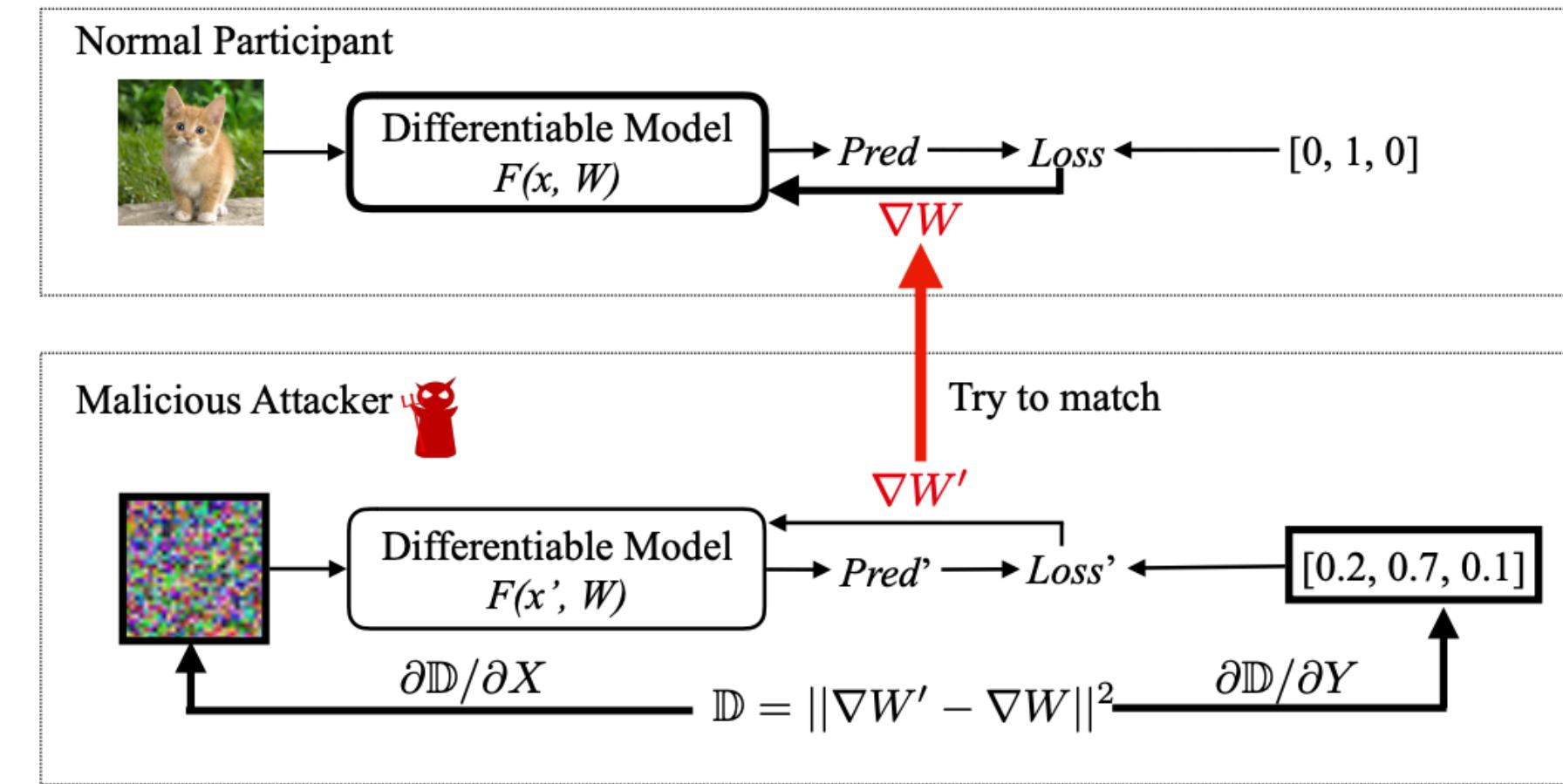
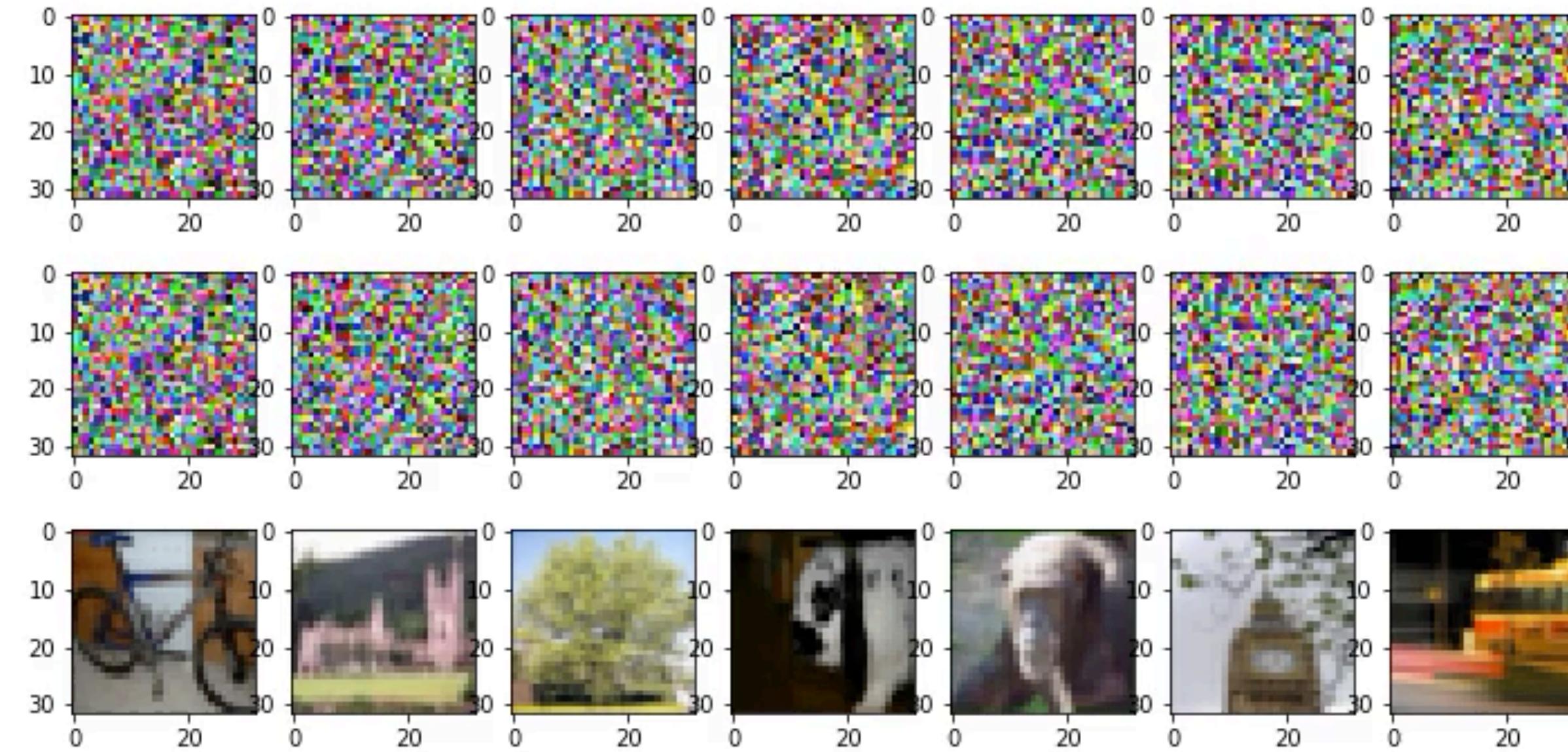
Attack on Vision Model (bs=1)



Deep Leakage from Gradient. [Zhu et al, NeurIPS 2019]

Deep Leakage Attack Results

Attack on Vision Model (bs=8)



Deep Leakage from Gradient. [Zhu et al, NeurIPS 2019]

Deep Leakage Attack Results

Attack on Language Model (BERT, Masked Language Model)

Iters=0: tilting fill given **less word **itude fine **nton overheard living vegas **vac **vation *f forte **dis cerambycidae ellison **don yards marne **kali

Iters=10: tilting fill given **less full solicitor other ligue shrill living vegas rider treatment carry played sculptures lifelong ellison net yards marne **kali

Iters=20: registration , volunteer applications , at student travel application open the ; week of played ; child care will be glare .

Iters=30: registration, volunteer applications, and student travel application open the first week of september . child care will be available

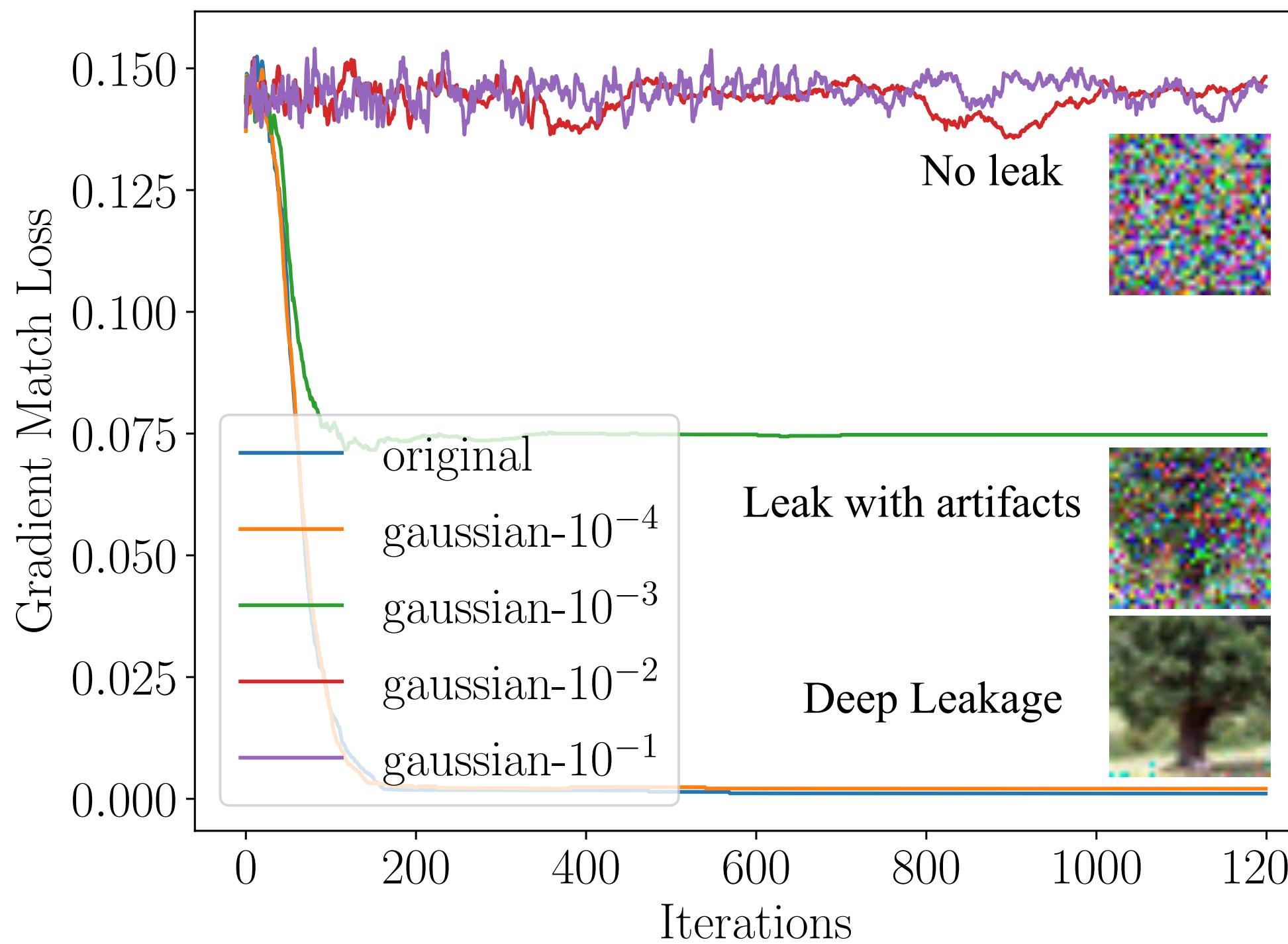
Original text: Registration, volunteer applications, and student travel application open the first week of September. Child care will be available.

Unmatched words are marked with red.

Deep Leakage from Gradient. [Zhu et al, NeurIPS 2019]

Defense Strategy for Deep Leakage

Gaussian and laplacian noise



	Original	$\mathbf{G-10^{-4}}$	$\mathbf{G-10^{-3}}$	$\mathbf{G-10^{-2}}$	$\mathbf{G-10^{-1}}$
Accuracy	76.3%	75.6%	73.3%	45.3%	$\leq 1\%$
Defendability	-	✗	✗	✓	✓
	$\mathbf{L-10^{-4}}$	$\mathbf{L-10^{-3}}$	$\mathbf{L-10^{-2}}$	$\mathbf{L-10^{-1}}$	
Accuracy	-	75.6%	73.4%	46.2%	$\leq 1\%$
Defendability	-	✗	✗	✓	✓

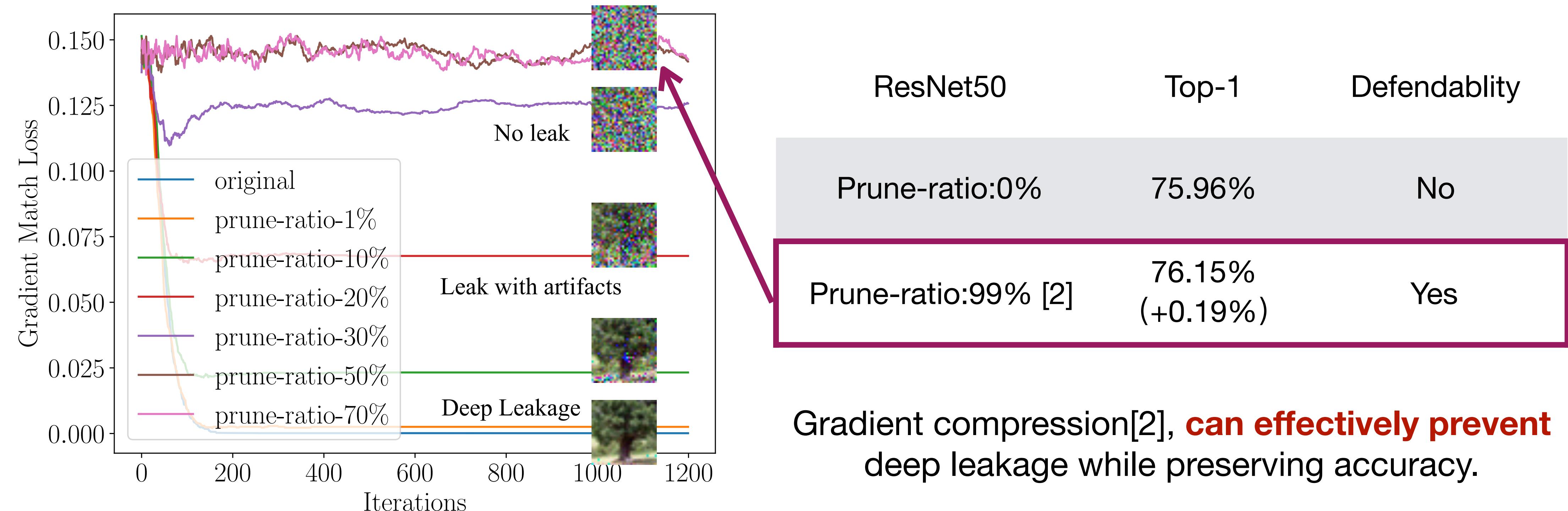
“G” denotes gaussian noise, “L” denotes laplacian noise

Simply applying noise cannot prevent deep leakage unless we allow significant accuracy drop (purple and red lines)

Deep Leakage from Gradient. [Zhu et al, NeurIPS 2019]

Defense Strategy for Deep Leakage

Gradient compression



Besides compression, DGC[2] further applies local accumulation to obfuscate gradients thus better protect users' privacy.

[1] Deep Leakage from Gradient. [Zhu et al, NeurIPS 2019]

[2] Deep Gradient Compression: Reducing the Communication Bandwidth for Distributed Training [Lin et al, ICLR 2018]

Deep Leakage from Gradients

Sharing gradients is as dangerous as sharing the original user data!

Simple ~20 lines PyTorch implementation

```
def deep_leakage_from_gradients(model, origin_grad):
    dummy_data = torch.randn(origin_data.size())
    dummy_label = torch.randn(dummy_label.size())
    optimizer = torch.optim.LBFGS([dummy_data, dummy_label] )

    for iters in range(300):
        def closure():
            optimizer.zero_grad()
            dummy_pred = model(dummy_data)
            dummy_loss = criterion(dummy_pred, dummy_label)
            dummy_grad = grad(dummy_loss, model.parameters(), create_graph=True)

            grad_diff = sum(((dummy_grad - origin_grad) ** 2).sum() \
                for dummy_g, origin_g in zip(dummy_grad, origin_grad))

            grad_diff.backward()
            return grad_diff

        optimizer.step(closure)

    return dummy_data, dummy_label
```

Over > 1500 citations since 2019

Deep Leakage from Gradients

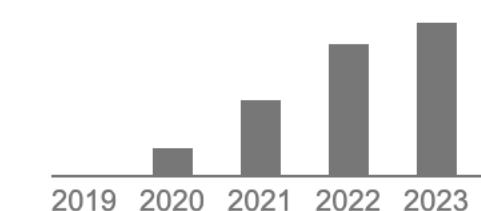
Authors Ligeng Zhu, Zhijian Liu, Song Han

Publication date 2019/9

Conference Neural Information Processing Systems (NeurIPS), 2019

Description Passing gradient is a widely used scheme in modern multi-node learning system (eg, distributed training, collaborative learning). In a long time, people used to believe that gradients are safe to share: ie, the training set will not be leaked by gradient sharing. However, in this paper, we show that we can obtain the private training set from the publicly shared gradients. The leaking only takes few gradient steps to process and can obtain the original training set instead of look-alike alternatives. We name this leakage as {deep leakage from gradient} and practically validate the effectiveness of our algorithm on both computer vision and natural language processing tasks. We empirically show that our attack is much stronger than previous approaches and thereby raise people's awareness to rethink the gradients' safety. We also discuss some possible strategies to defend this deep leakage.

Total citations Cited by 1545



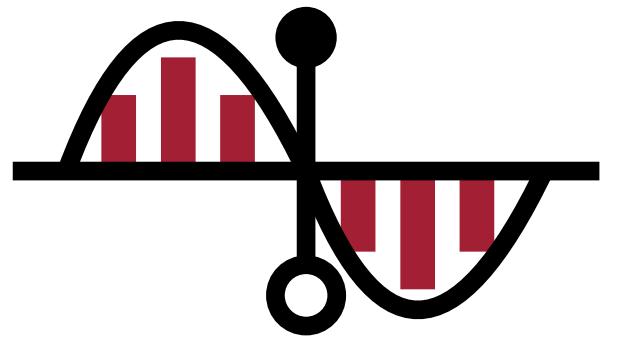
Scholar articles Deep leakage from gradients
L Zhu, Z Liu, S Han - Advances in neural information processing systems, 2019
Cited by 1545 Related articles All 15 versions

Github: <https://github.com/mit-han-lab/dlg>

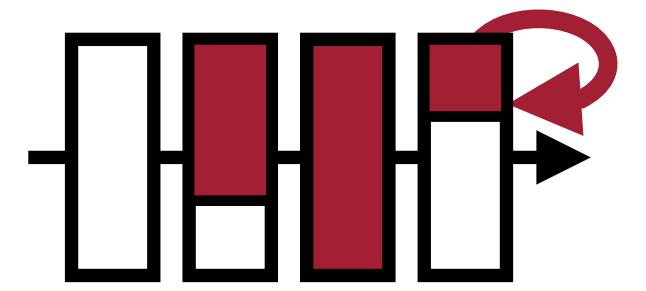
Website: <https://dlg.hanlab.ai>

Lecture Plan

1. Deep leakage from gradients, gradient is not safe to share
2. **Memory bottleneck of on-device training**
3. Tiny transfer learning (TinyTL)
4. Sparse back-propagation (SparseBP)
5. Quantized training with quantization aware scaling (QAS)
6. PockEngine: system support for sparse back-propagation



Quantized Training



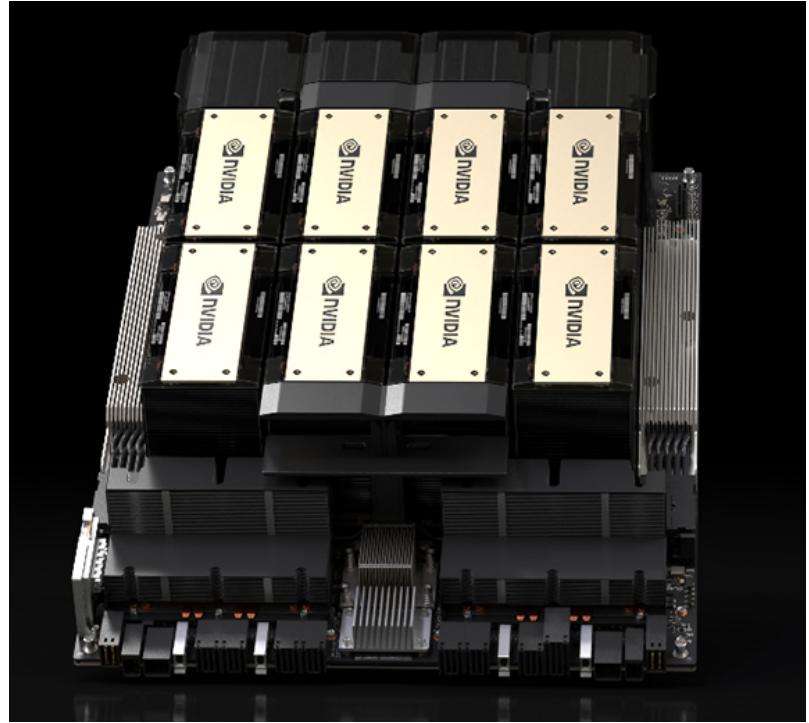
Sparse Training



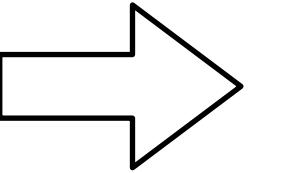
PockEngine

On-Device Training is Challenging

Memory size is too small to hold DNNs



Cloud AI



Mobile AI

Memory (Activation)

141GB

4GB

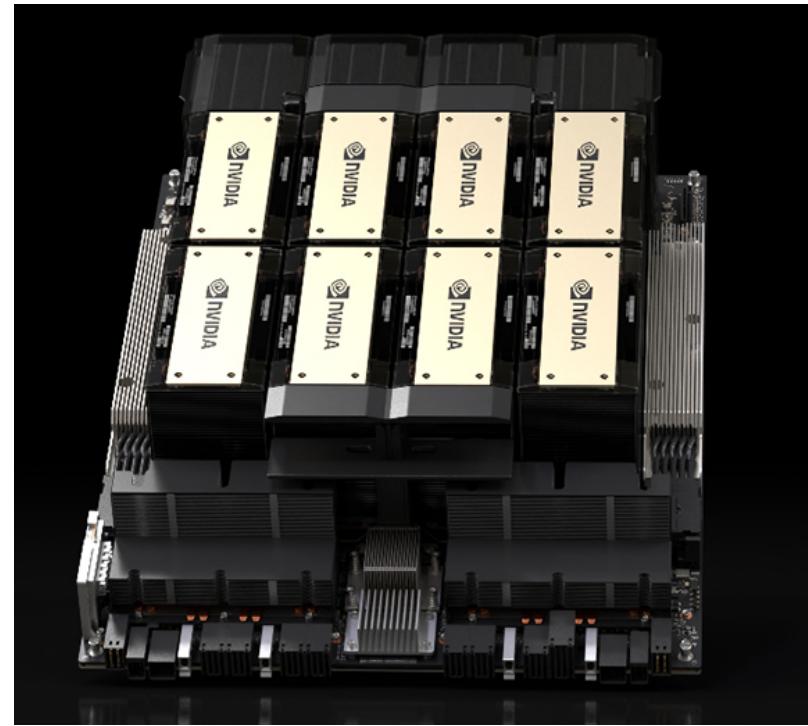
Storage (Weights)

~TB/PB

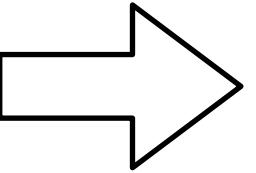
256GB

On-Device Training is Challenging

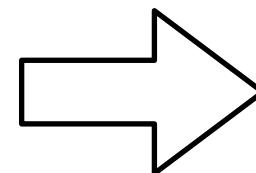
Memory size is too small to hold DNNs



Cloud AI



Mobile AI



Tiny AI

Memory (Activation)

141GB

4GB

320kB

Storage (Weights)

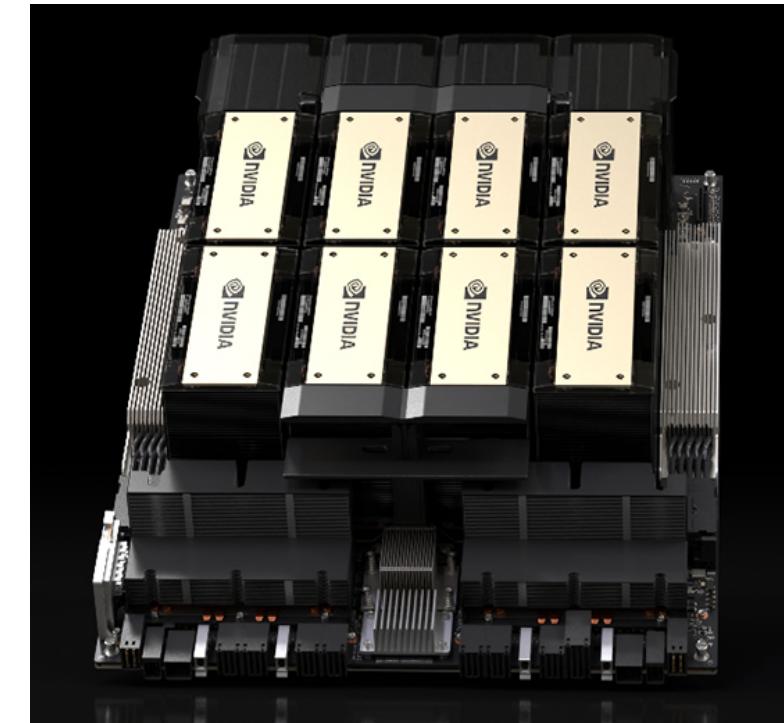
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256GB

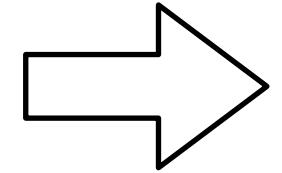
1MB

On-Device Training is Challenging

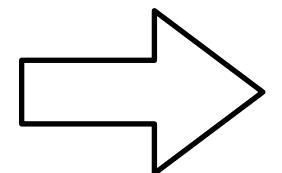
Memory size is too small to hold DNNs



Cloud AI



Mobile AI



Tiny AI

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141GB

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256GB

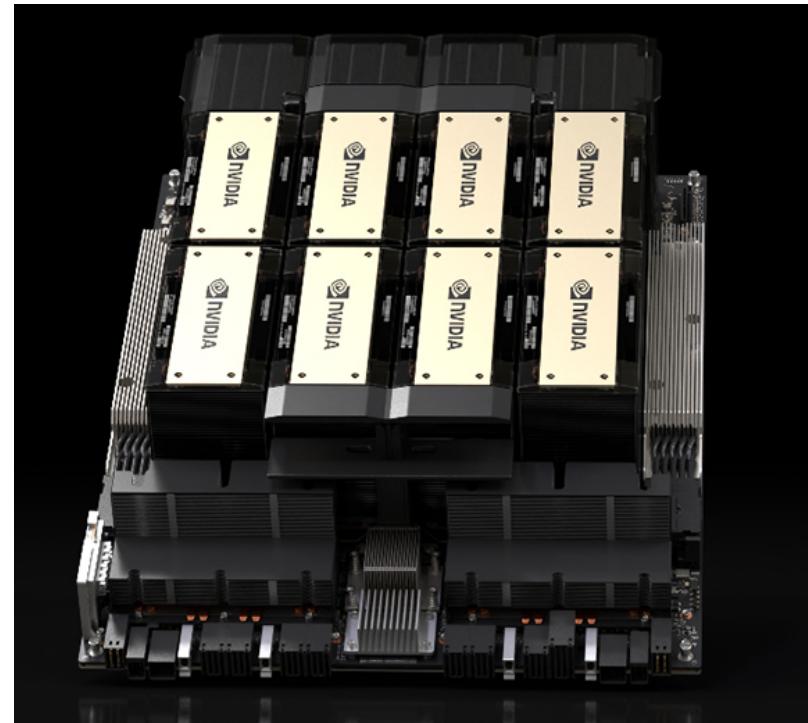
320kB

**13,000x
smaller**

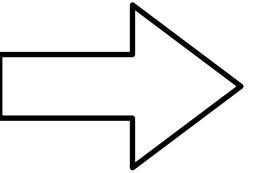
**1,000,000x
smaller**

On-Device Training is Challenging

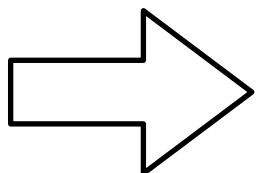
Memory size is too small to hold DNNs



Cloud AI



Mobile AI

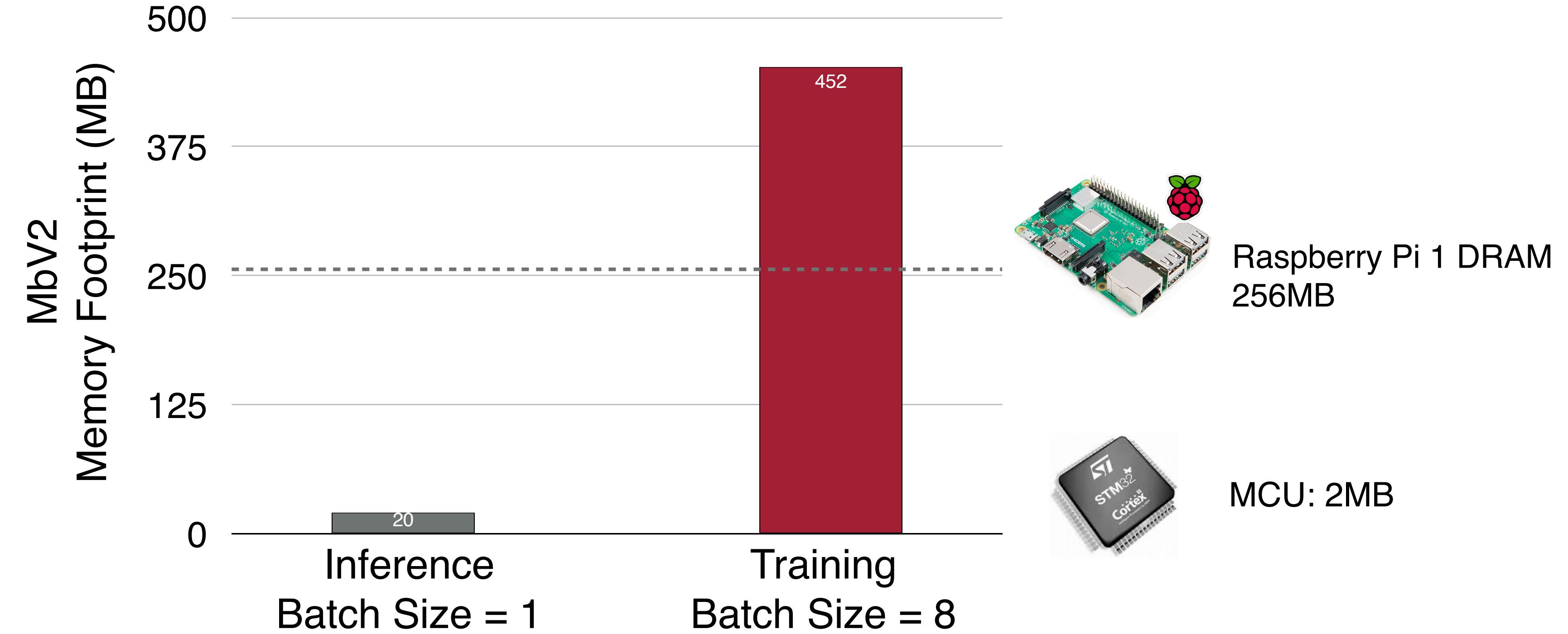


Tiny AI

Memory (Activation)	141GB	4GB	320kB
Storage (Weights)	~TB/PB	256GB	1MB

- We need to reduce both **weights** and **activation** to fit DNNs for On-Device Training

Training Memory is the Key Bottleneck



- Edge devices have tight memory constraints. The training memory footprint of neural networks can easily exceed the limit.

Question: Why training memory is much larger than inference?

Training Memory is the Key Bottleneck

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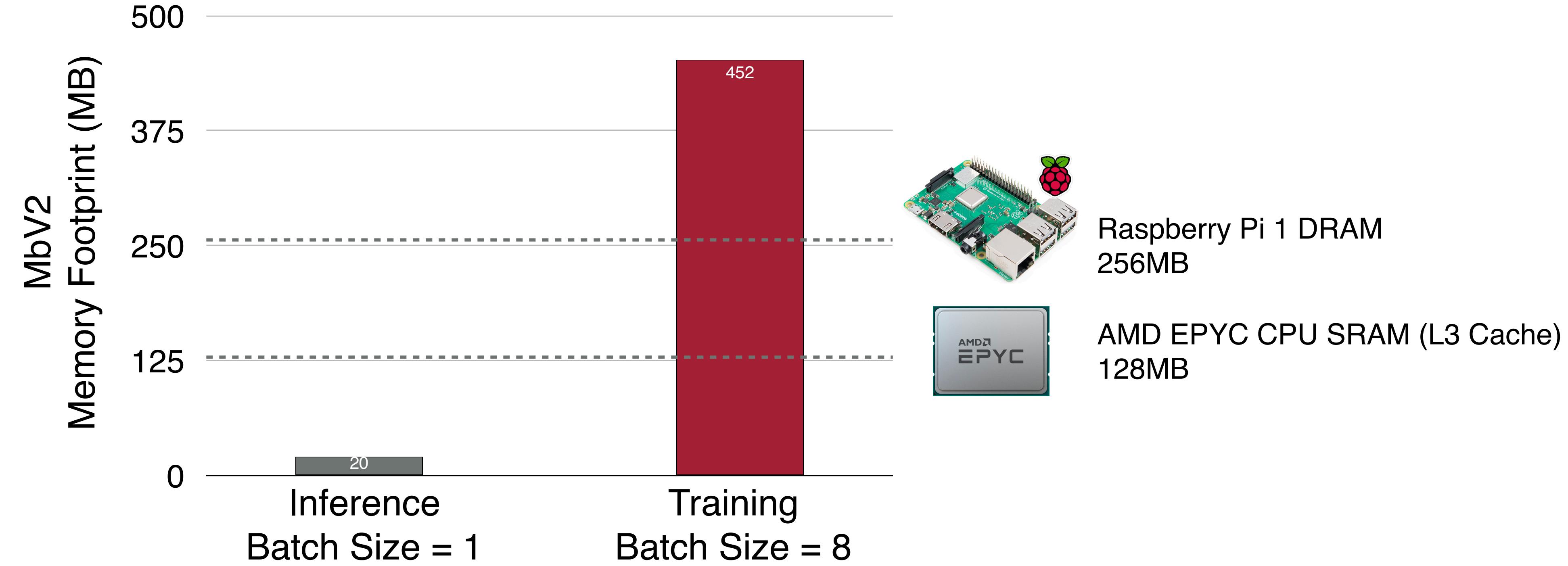
Answer: Because of intermediate **activations**

$$\text{Forward: } \mathbf{a}_{i+1} = \mathbf{a}_i \mathbf{W}_i + \mathbf{b}_i$$

$$\text{Backward: } \frac{\partial L}{\partial \mathbf{W}_i} = \mathbf{a}_i^T \frac{\partial L}{\partial \mathbf{a}_{i+1}}$$

- Inference does not need to store activations, training does.
- Activations grows linearly with batch size, which is always 1 for inference.
- Even with $\text{bs}=1$, activations are beyond memory limit of many edge devices.

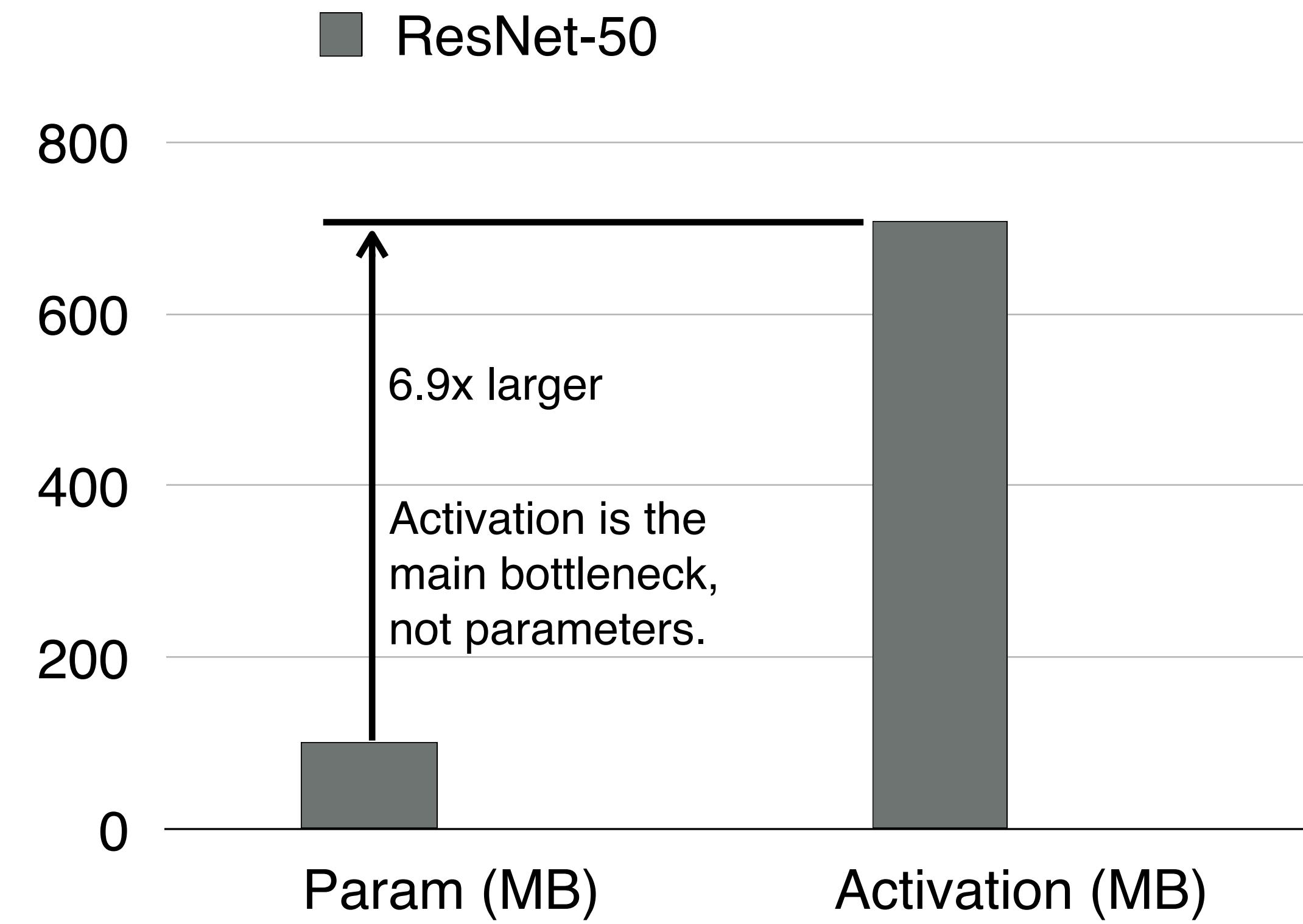
Training Memory is the Key Bottleneck



- Edge devices have tight memory constraints. The training memory footprint of neural networks can easily exceed the limit.
- Edge devices are energy-constrained. Failing to fit the training process into the energy-efficient cache will significantly increase the energy cost.

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

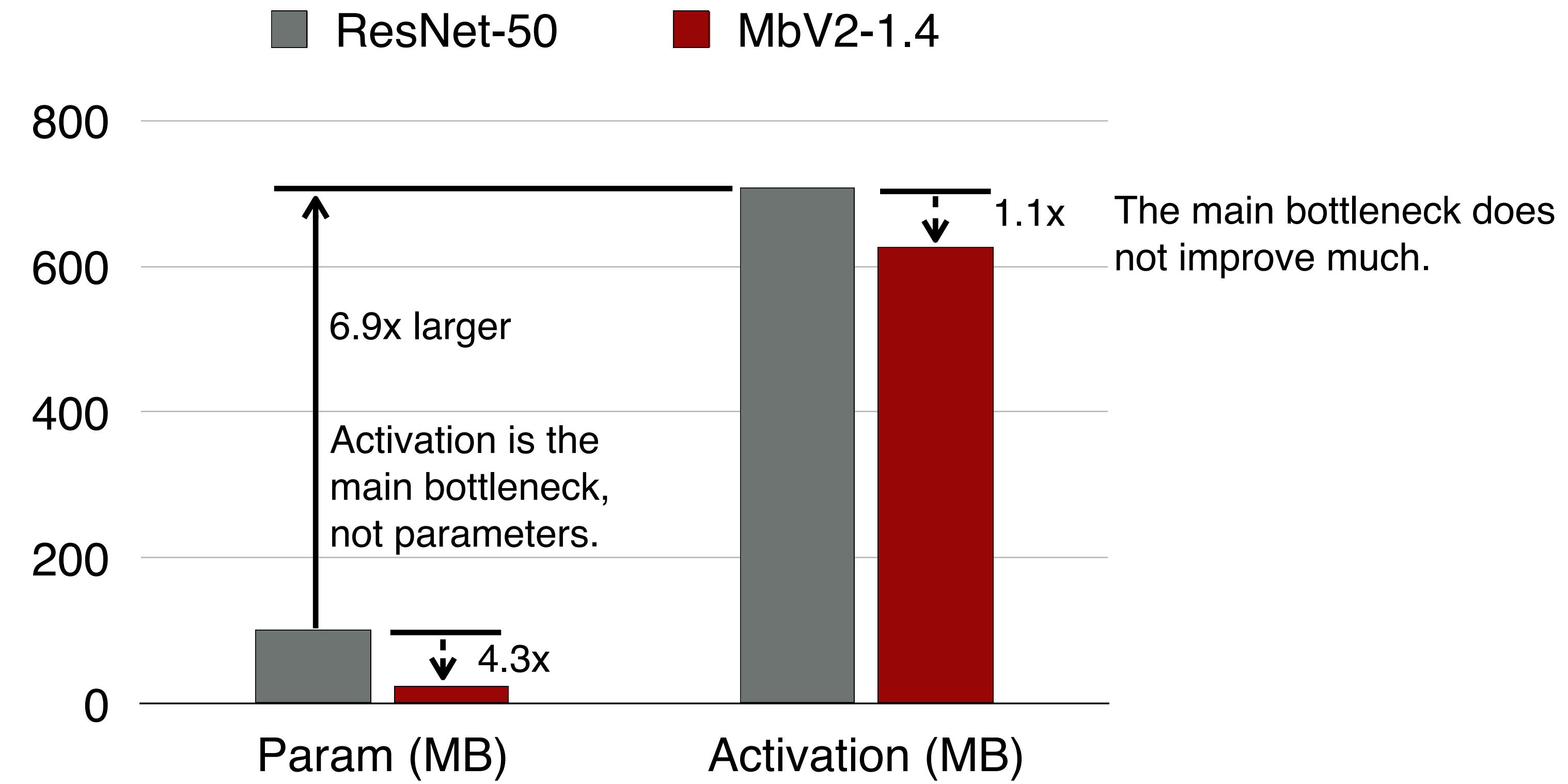
Activation is the Memory Bottleneck in CNNs



- Activation is the main bottleneck for CNN training

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

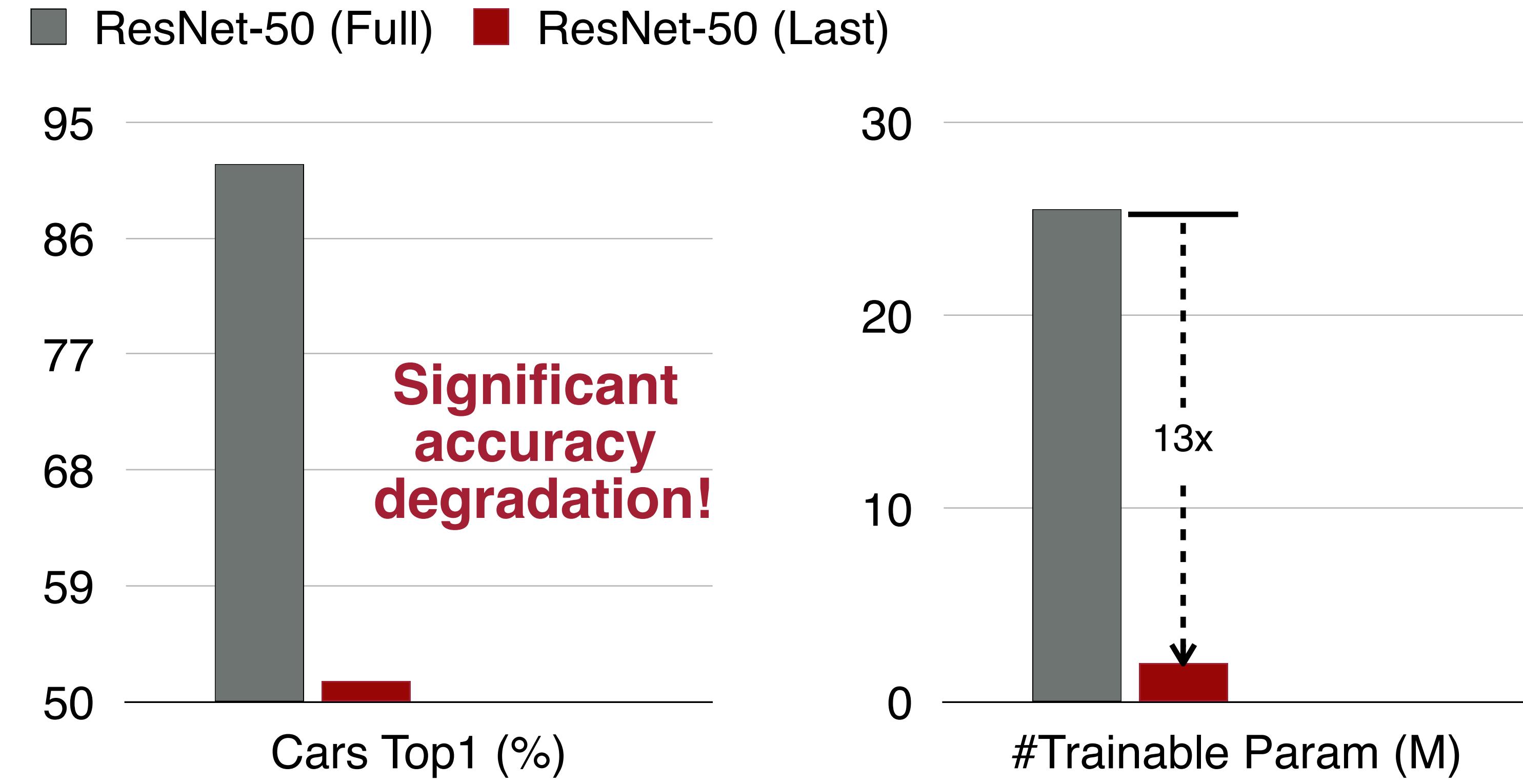
Activation is the Memory Bottleneck in CNNs



- Activation is the main bottleneck for CNN training.
- MobileNets focus on reducing the number of parameters or FLOPs, while the main bottleneck does not improve much.

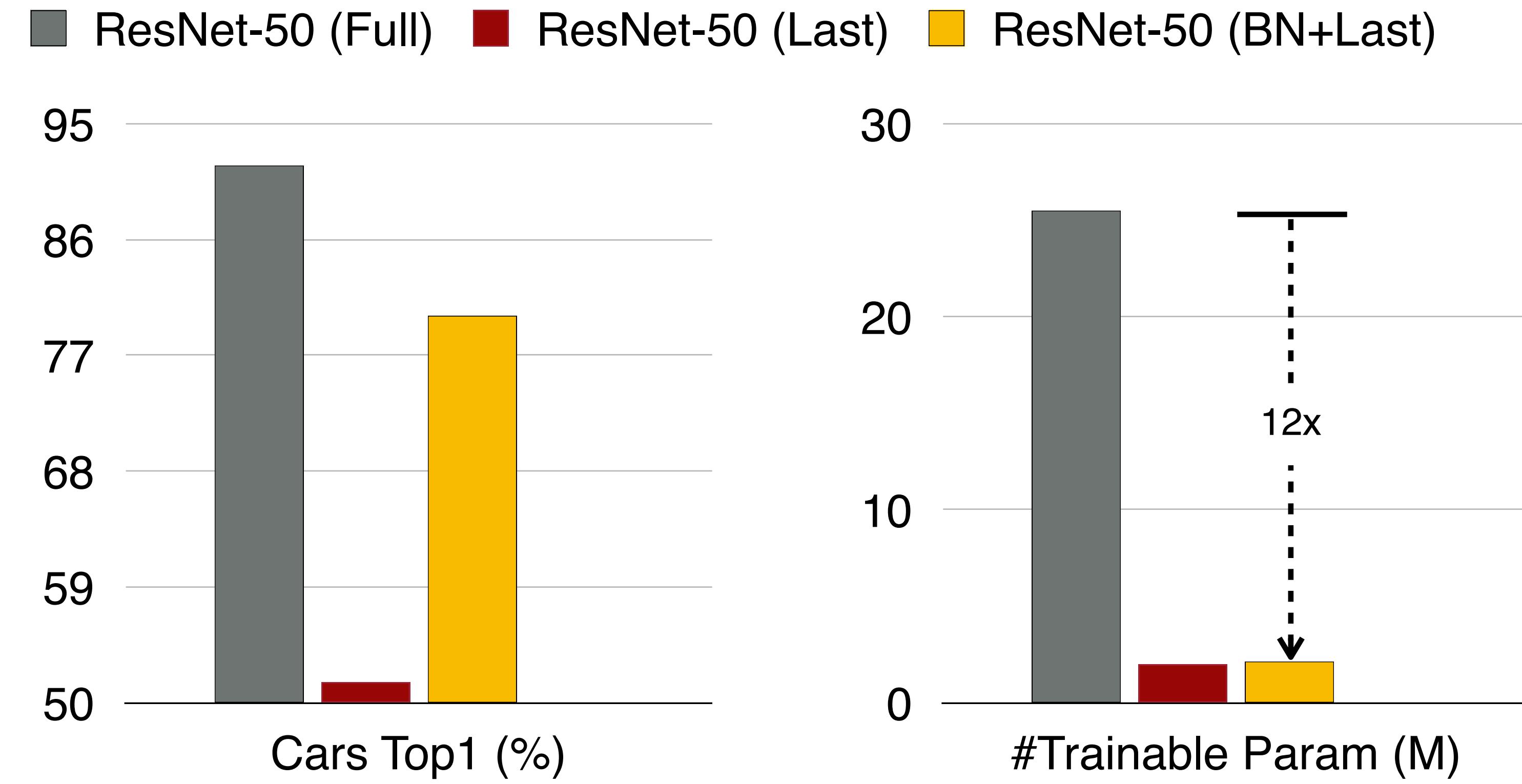
TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

Parameter-Efficient Transfer Learning in CNNs



- Full: Fine-tune the full network. Better accuracy but highly inefficient.
- Last: Only fine-tune the last classifier head. Efficient but the capacity is limited.

Parameter-Efficient Transfer Learning in CNNs

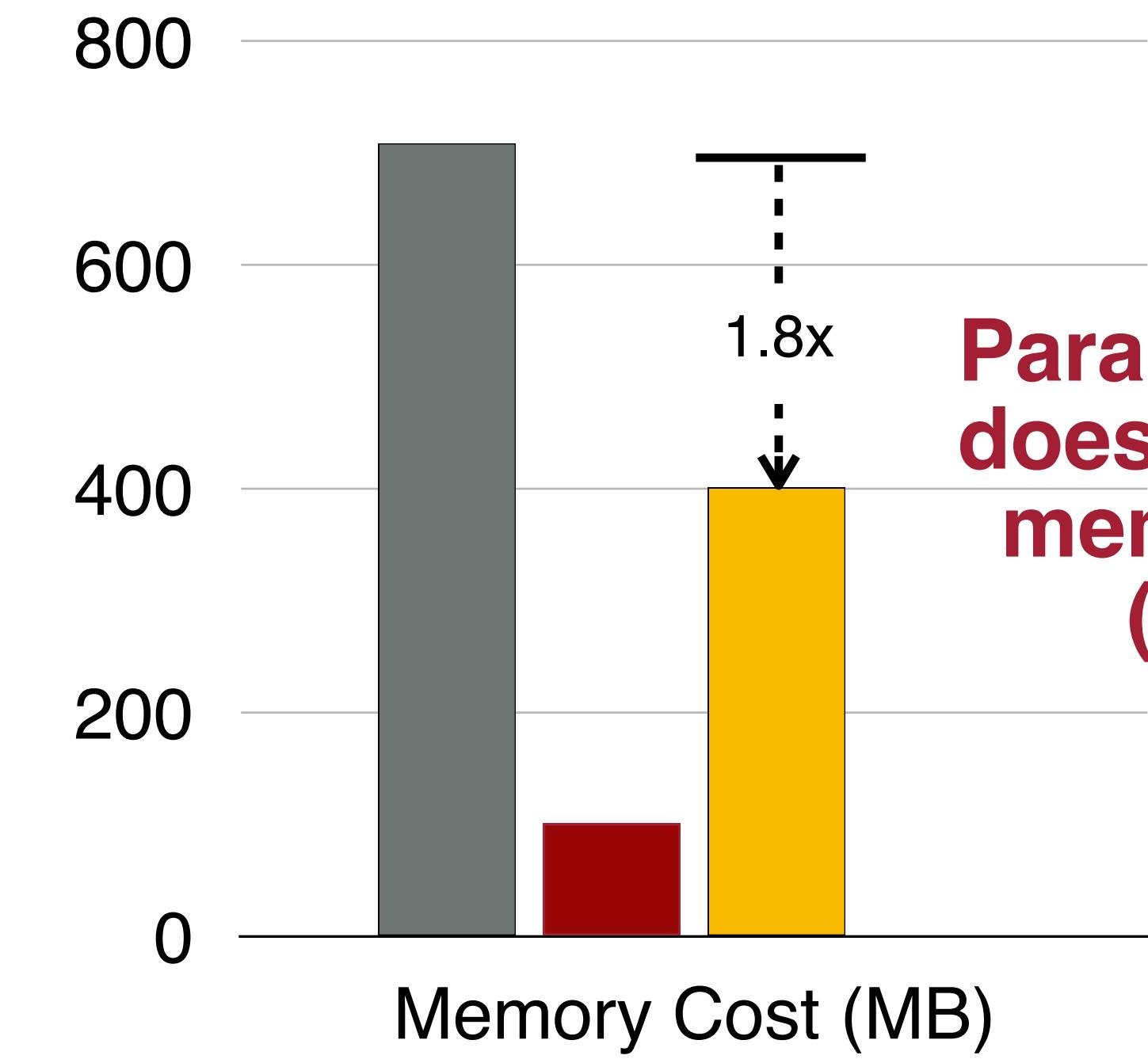
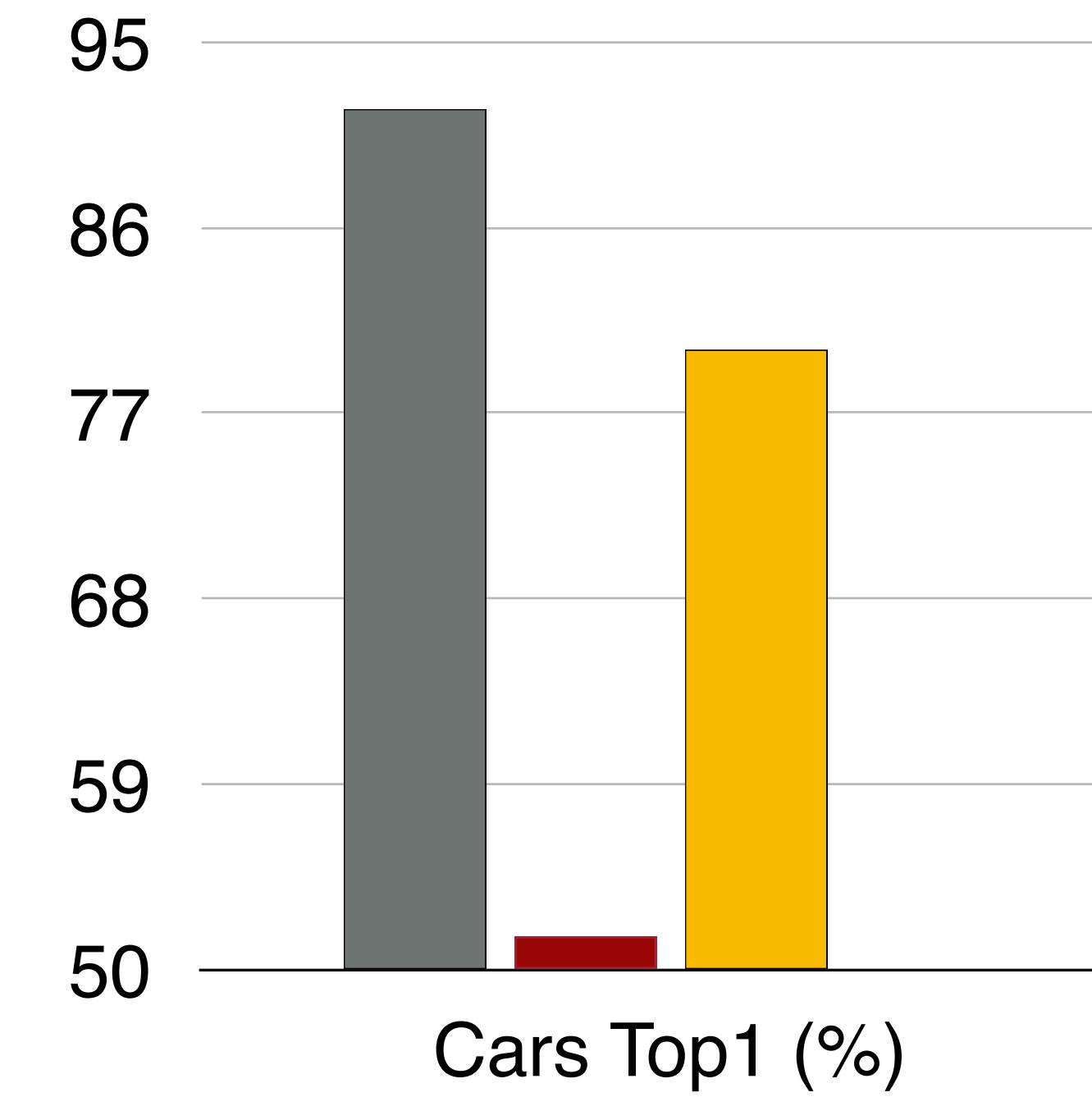


- Full: Fine-tune the full network. Better accuracy but highly inefficient.
- Last: Only fine-tune the last classifier head. Efficient but the capacity is limited.
- BN+Last: Fine-tune the BN layers and the last layer. Parameter-efficient.

Question: Is BN+Last update or Last-only update enough for on-device transfer learning?

Parameter-Efficient Transfer Learning in CNNs

■ ResNet-50 (Full) ■ ResNet-50 (Last) ■ ResNet-50 (BN+Last)

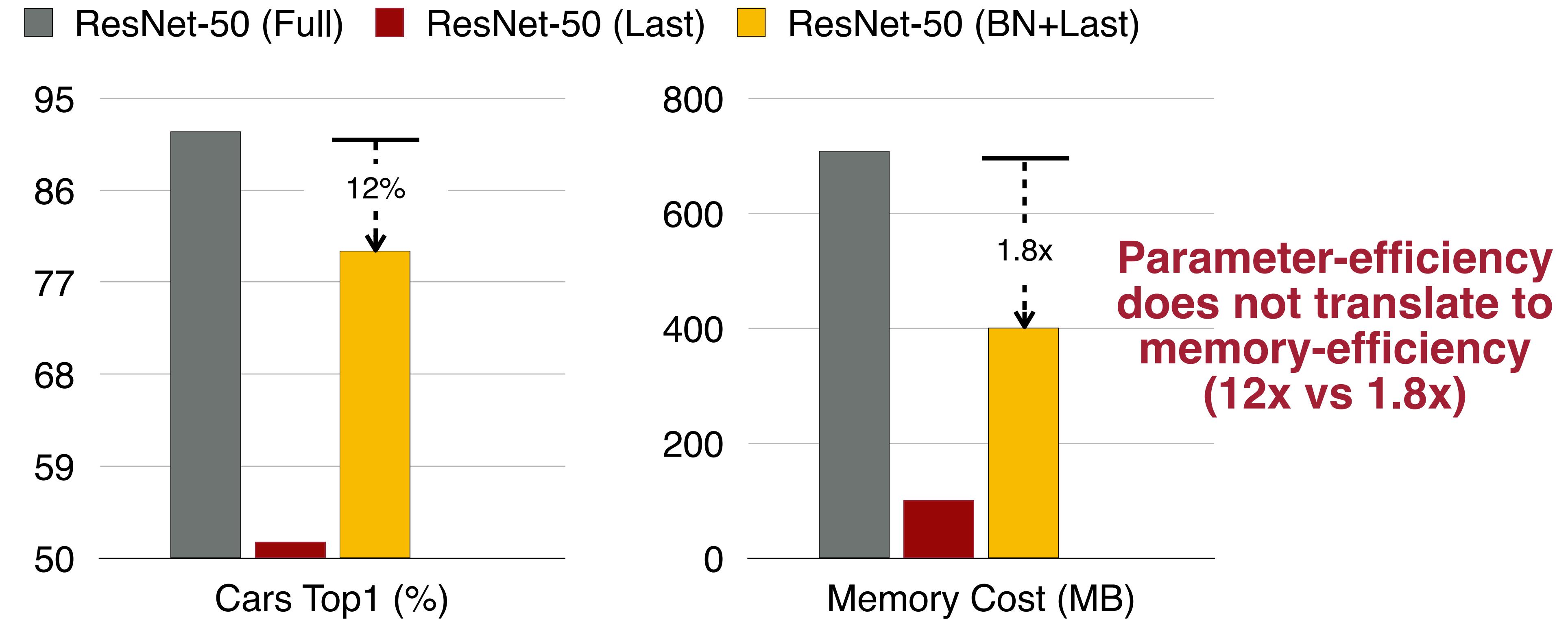


Parameter-efficiency
does not translate to
memory-efficiency
(12x vs 1.8x)

- **Full:** Fine-tune the full network. Better accuracy but highly inefficient.
- **Last:** Only fine-tune the last classifier head. Efficient but the capacity is limited.
- **BN+Last:** Fine-tune the BN layers and the last layer. Parameter-efficient, **but the memory saving is limited.**

K for the Price of 1: Parameter-efficient Multi-task and Transfer Learning [Mudrarkarta et al., ICLR 2019]

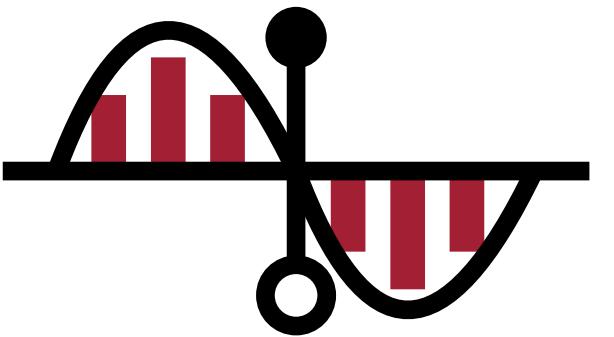
Parameter-Efficient Transfer Learning in CNNs



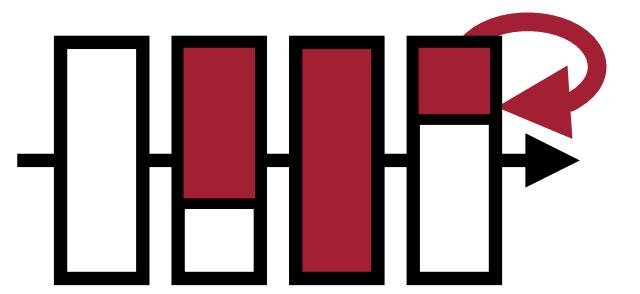
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- **BN+Last:** Fine-tune the BN layers and the last layer. Parameter-efficient, **but the memory saving is limited. Significant accuracy loss.**

Lecture Plan

1. Deep leakage from gradients, gradient is not safe to share
2. Memory bottleneck of on-device training
- 3. Tiny transfer learning (TinyTL)**
4. Sparse back-propagation (SparseBP)
5. Quantized training with quantization aware scaling (QAS)
6. PockEngine: system support for sparse back-propagation



Quantized Training

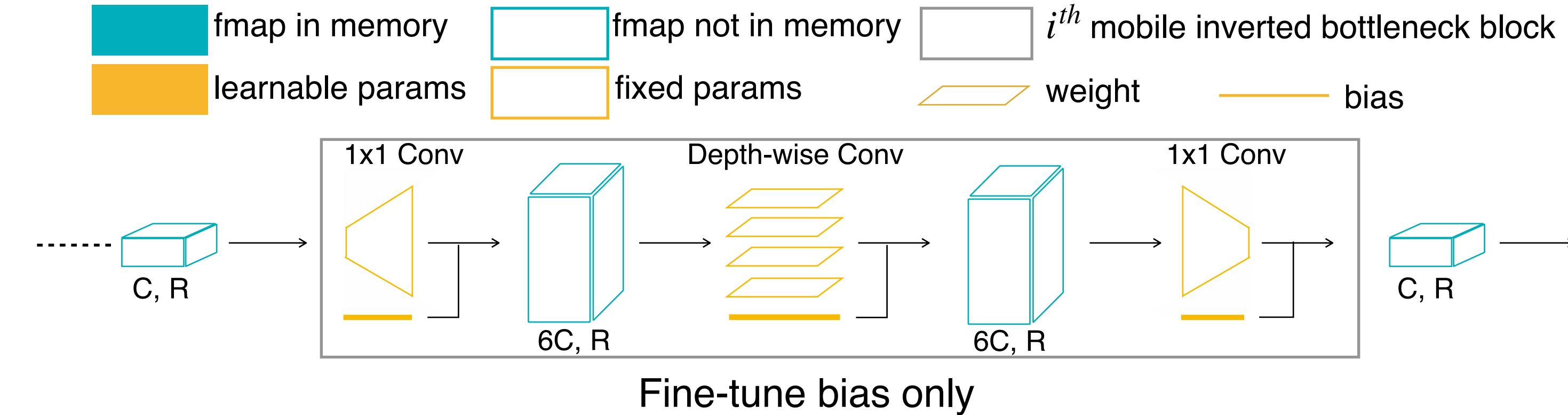


Sparse Training



PockEngine

Updating Weights is Memory-Expensive



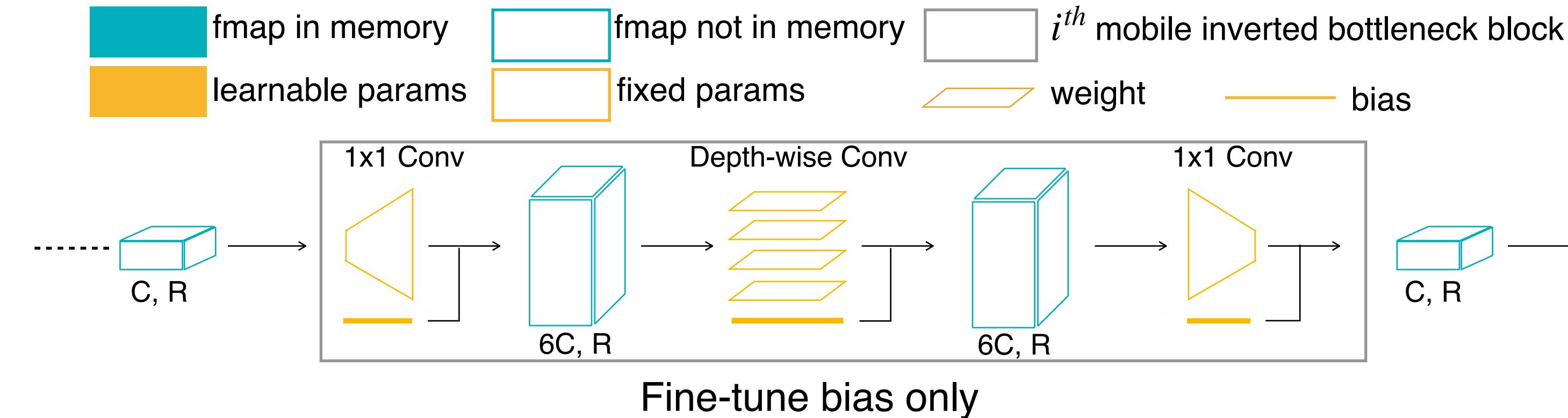
Forward: $\mathbf{a}_{i+1} = \mathbf{a}_i \mathbf{W}_i + \mathbf{b}_i$

Backward: $\frac{\partial L}{\partial \mathbf{W}_i} = \mathbf{a}_i^T \frac{\partial L}{\partial \mathbf{a}_{i+1}}, \quad \frac{\partial L}{\partial \mathbf{b}_i} = \frac{\partial L}{\partial \mathbf{a}_{i+1}} = \frac{\partial L}{\partial \mathbf{a}_{i+2}} \mathbf{W}_{i+1}^T$

- Updating weights requires storing intermediate activations
- Updating biases does not, **is memory-efficient**

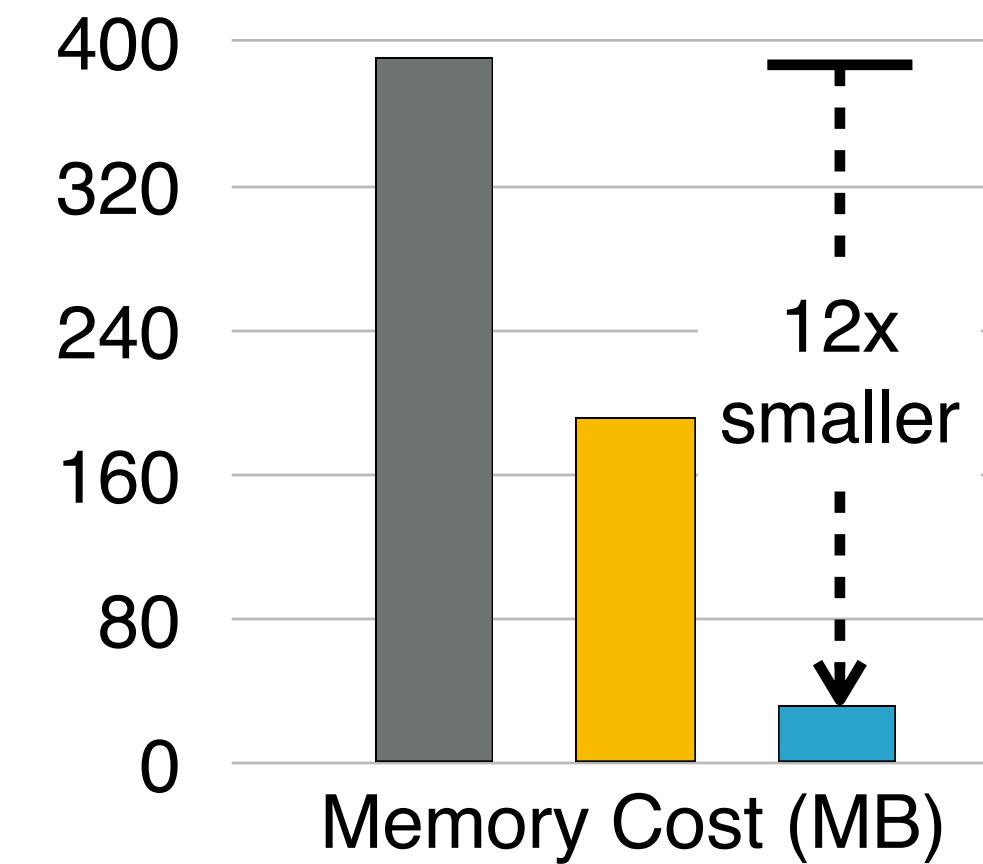
TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

TinyTL: Fine-tune Bias Only



Fine-tune bias only

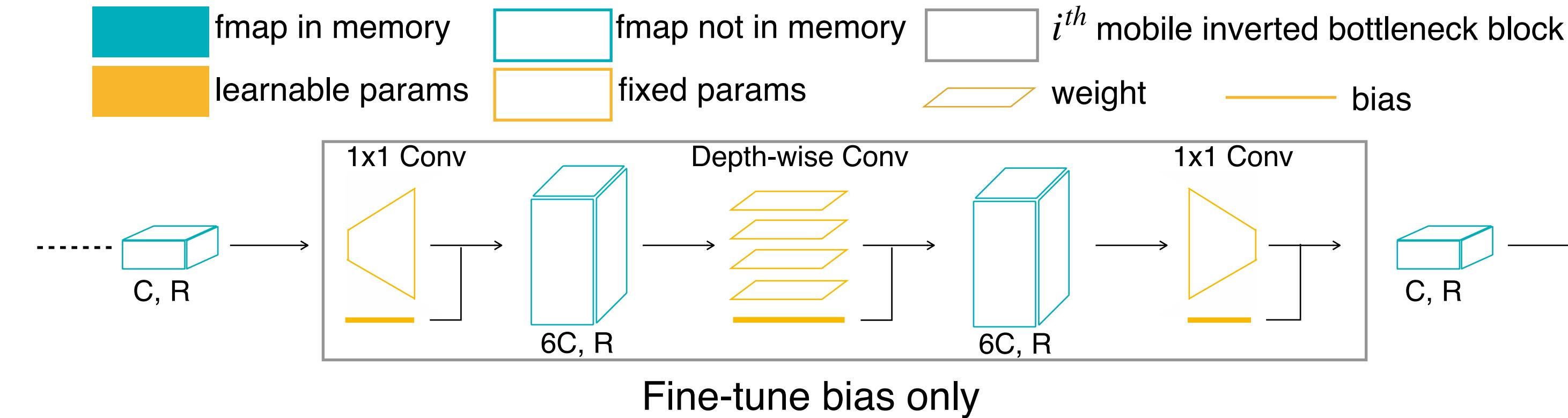
■ Full ■ BN+Last ■ Bias+Last



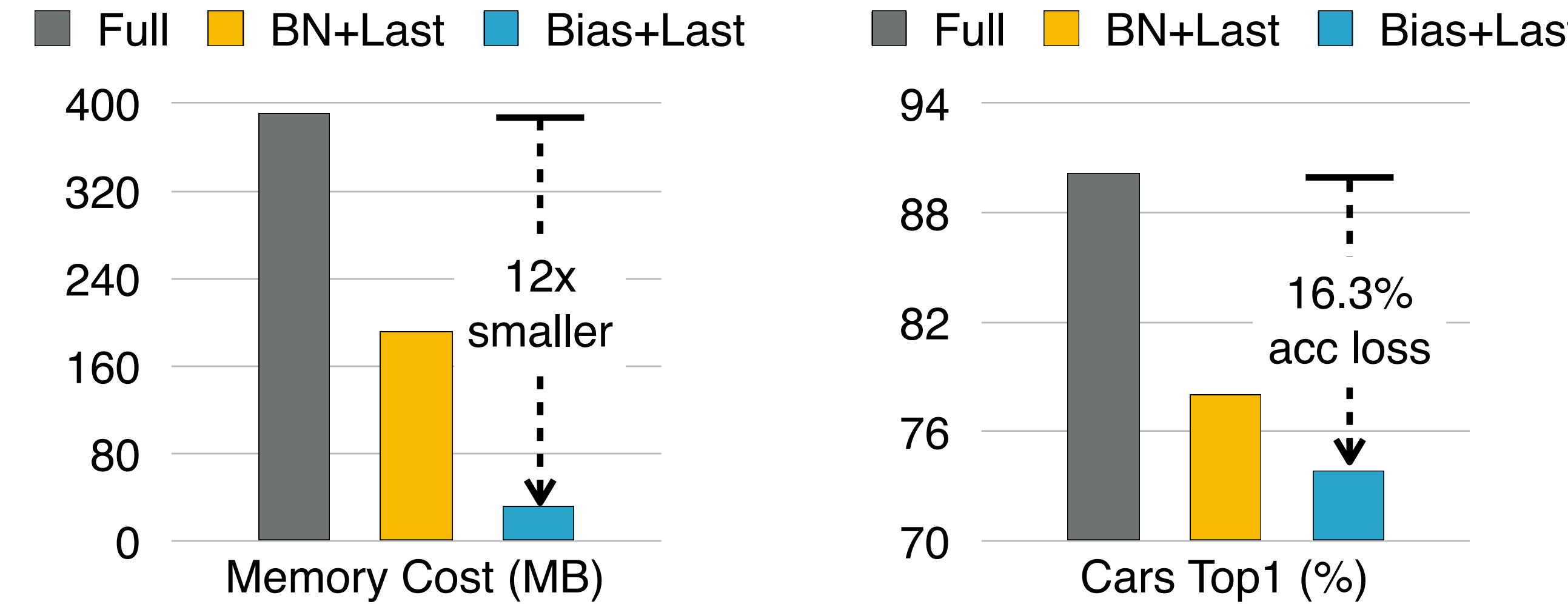
Freeze weights, only fine-tune biases
=> save 12x memory

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

TinyTL: Fine-tune Bias Only



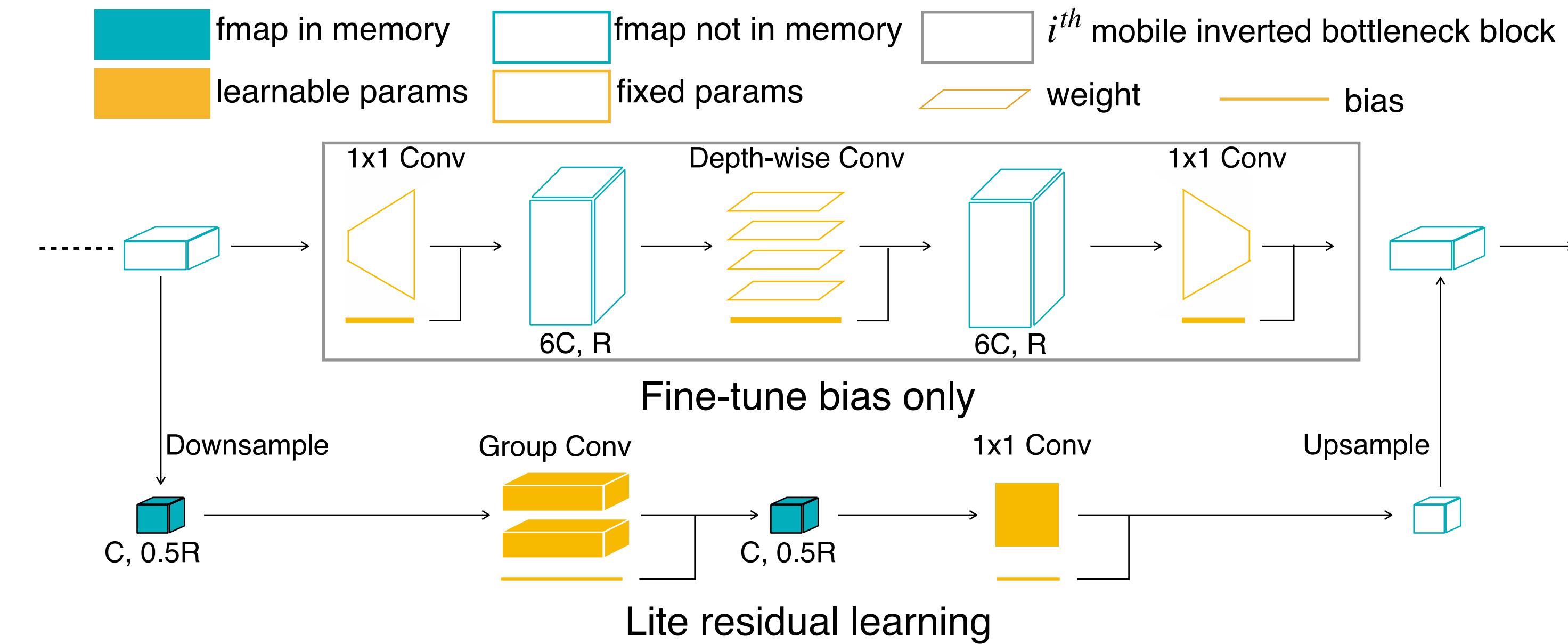
Fine-tune bias only



Freeze weights, only fine-tune biases
=> save 12x memory, but also hurt the accuracy

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

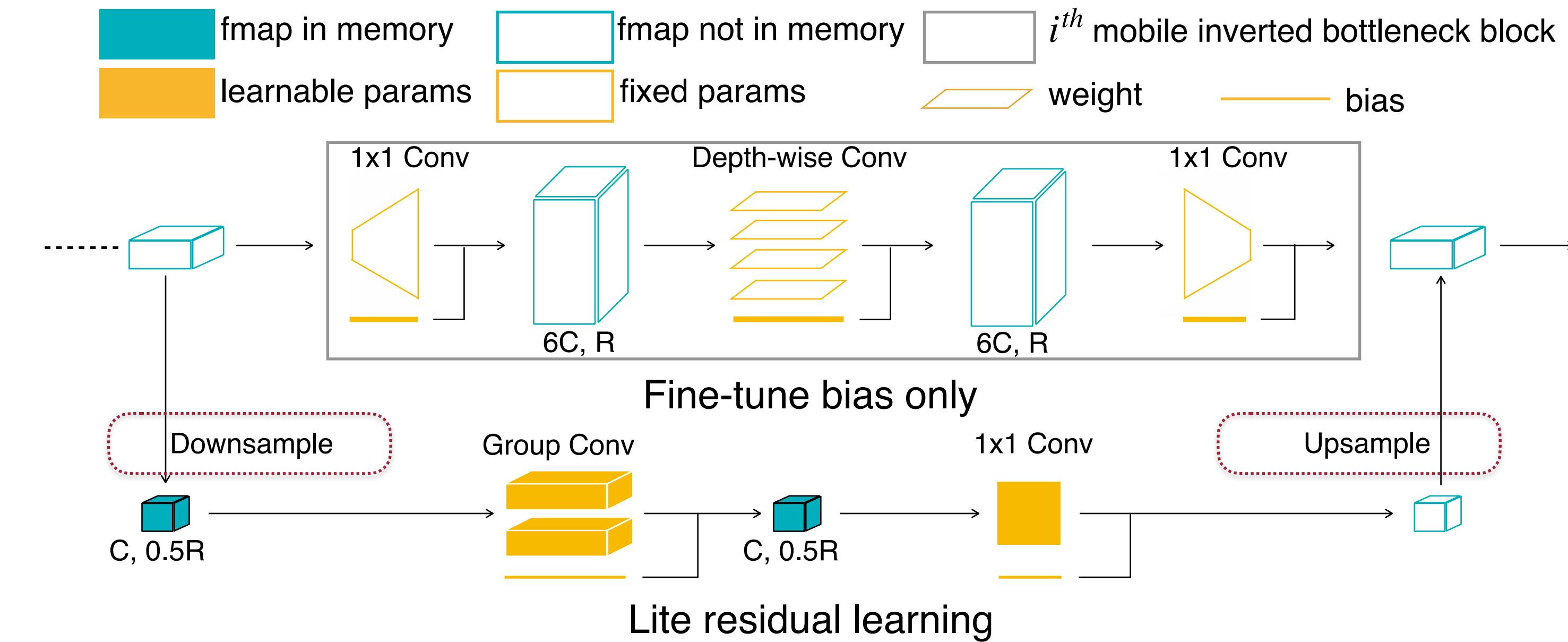
TinyTL: Lite Residual Learning



- Add lite residual modules to increase model capacity
- Key principle - keep activation size small

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

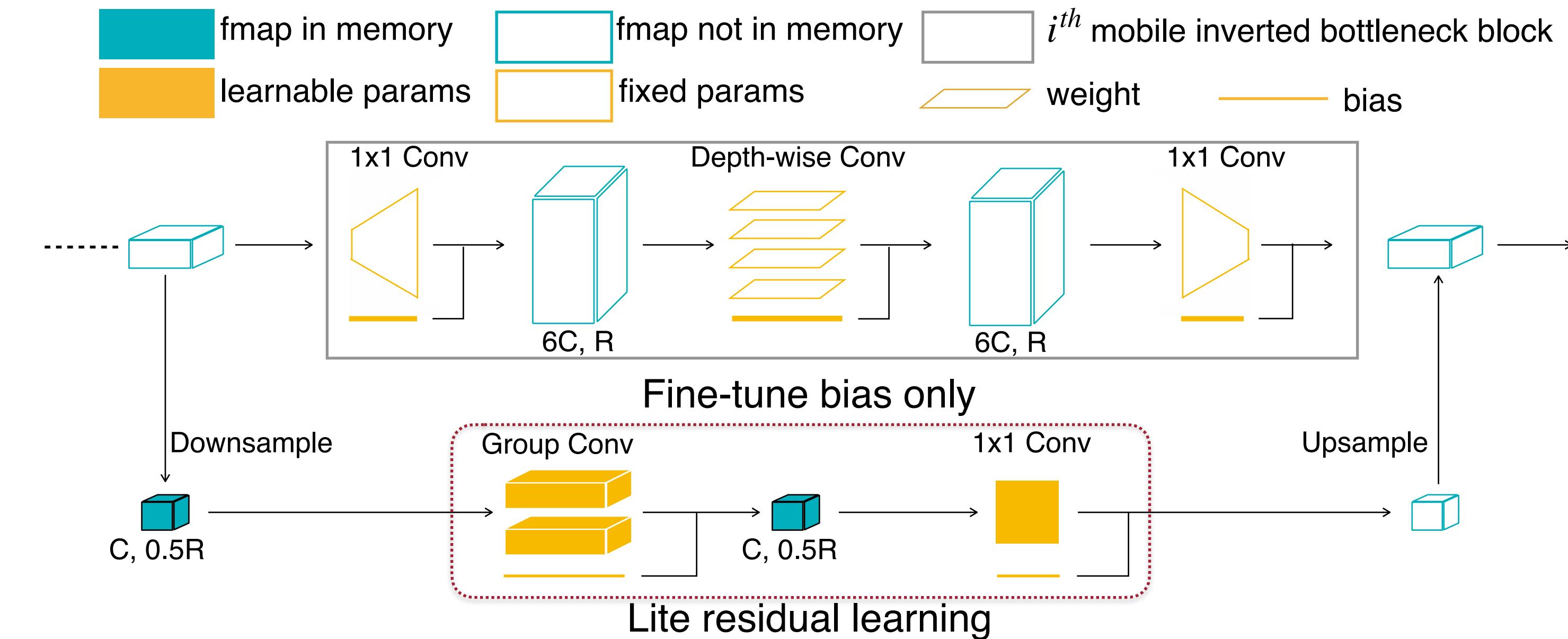
TinyTL: Lite Residual Learning



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- Key principle - keep activation size small
 1. Reduce the resolution

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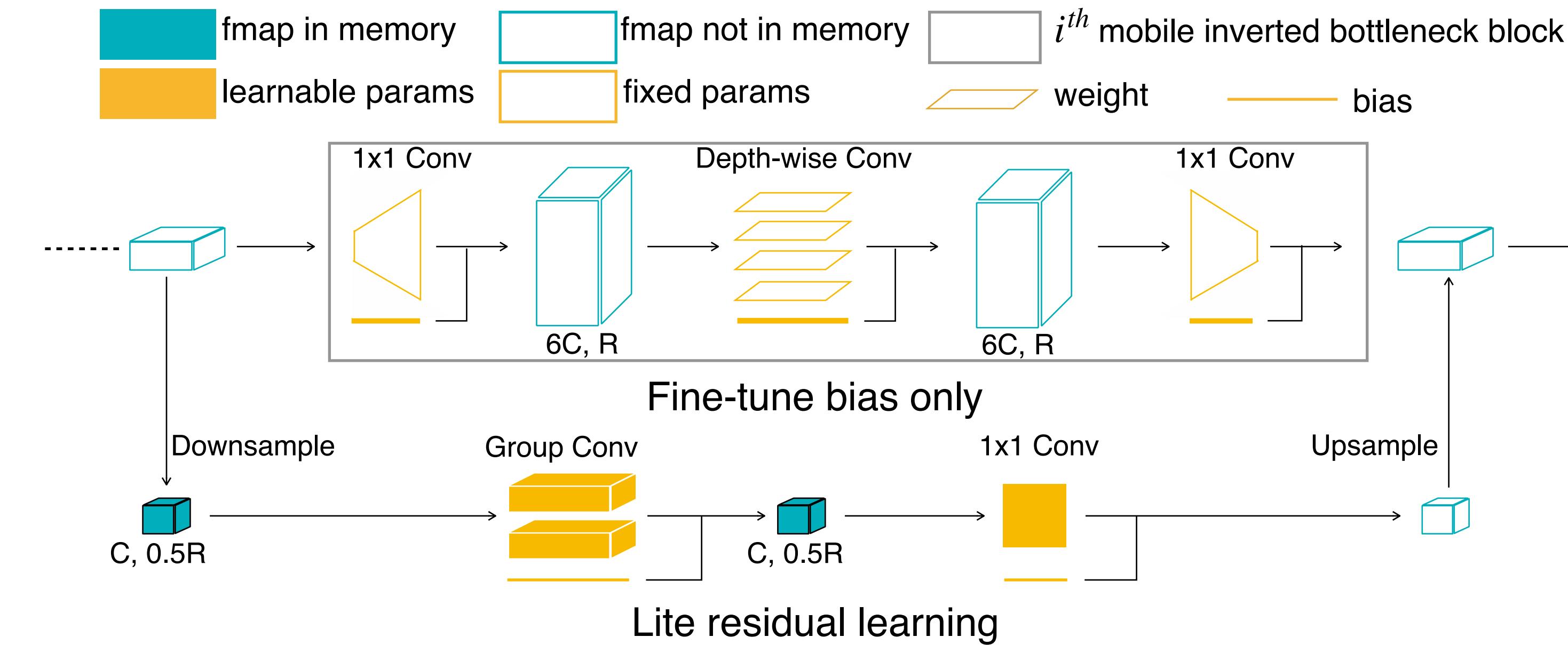
TinyTL: Lite Residual Learning



- Add lite residual modules to increase model capacity
- Key principle - keep activation size small
 1. Reduce the resolution
 2. Avoid inverted bottleneck

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

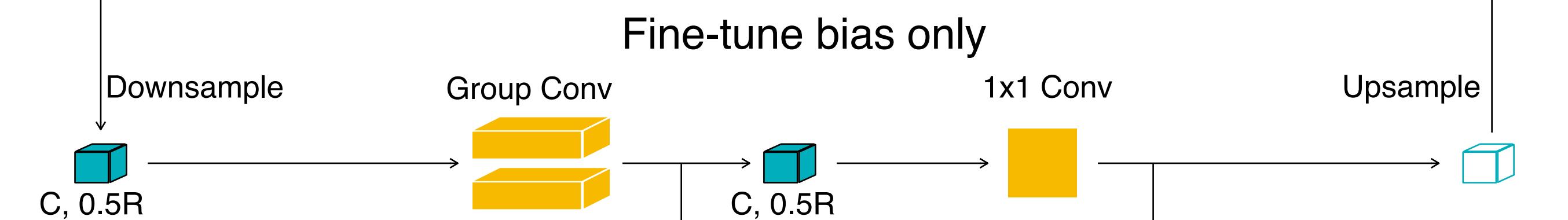
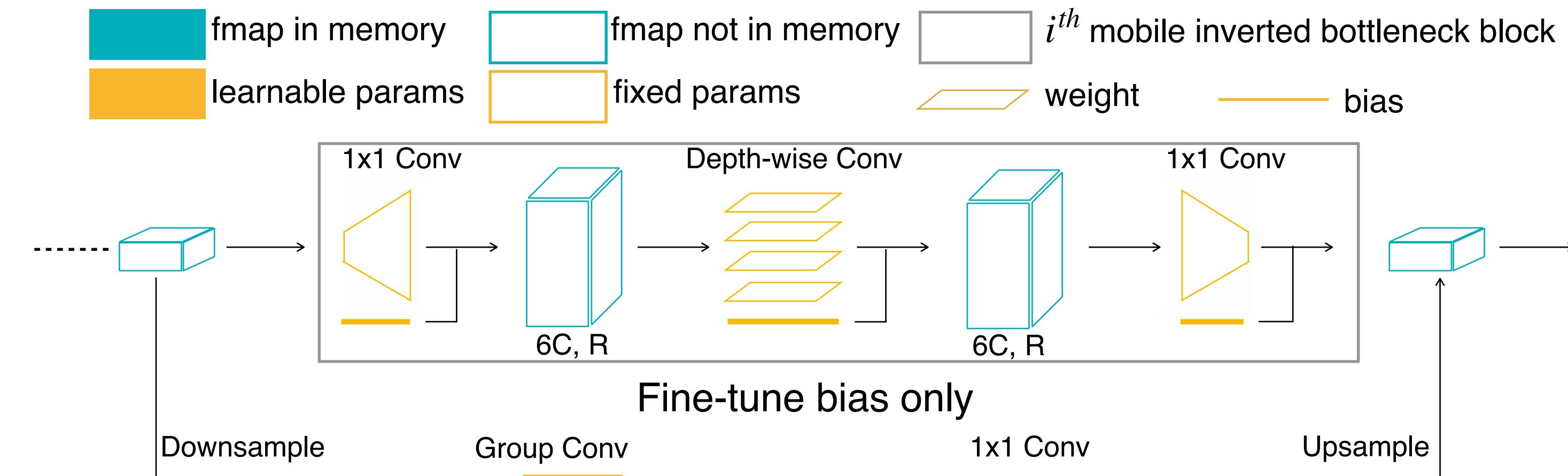
TinyTL: Lite Residual Learning



- Add lite residual modules to increase model capacity
 - Key principle - keep activation size small
 1. Reduce the resolution
 2. Avoid inverted bottleneck
- (1/6 channel, 1/2 resolution, 2/3 depth => ~4% activation size)

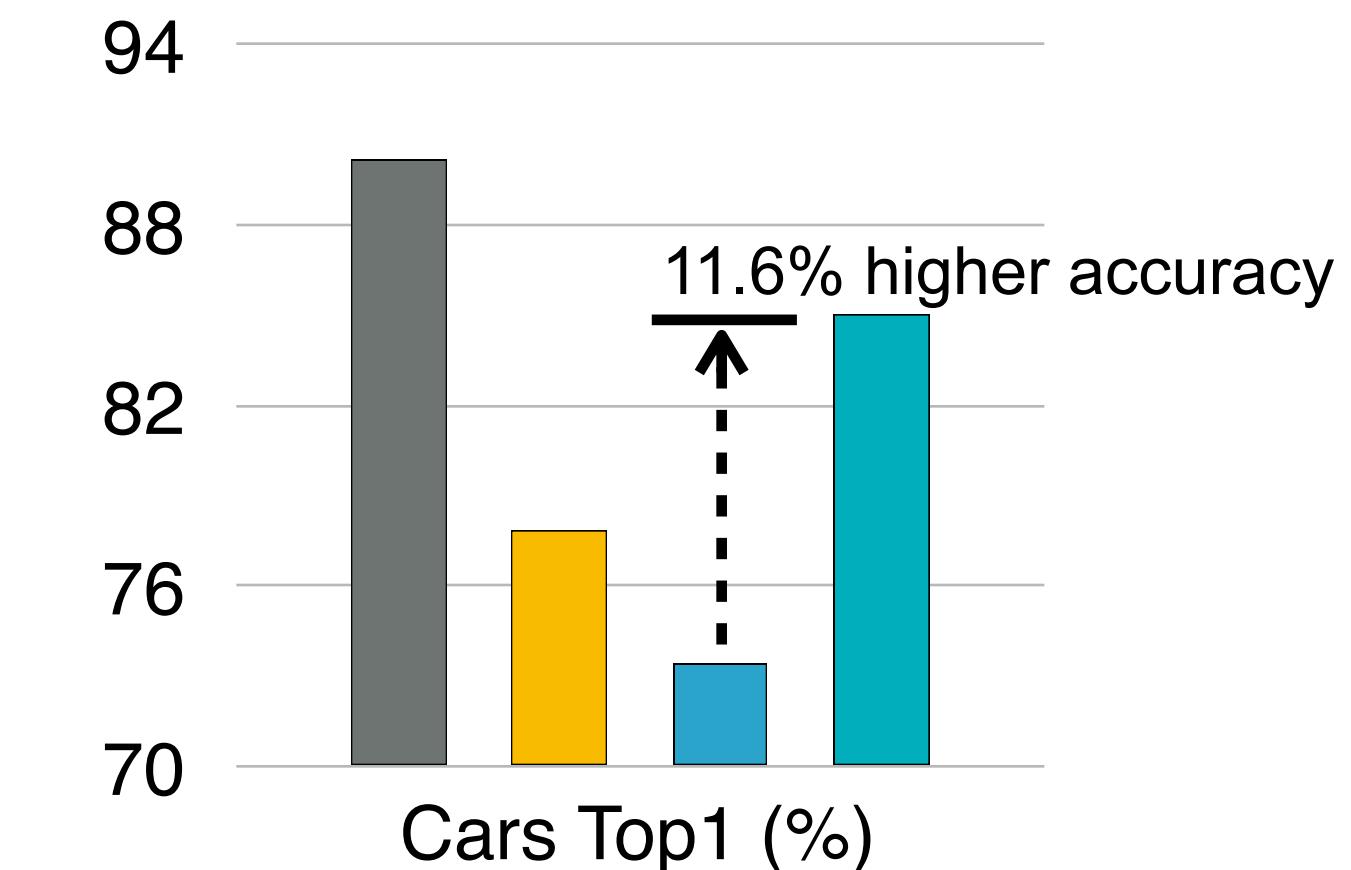
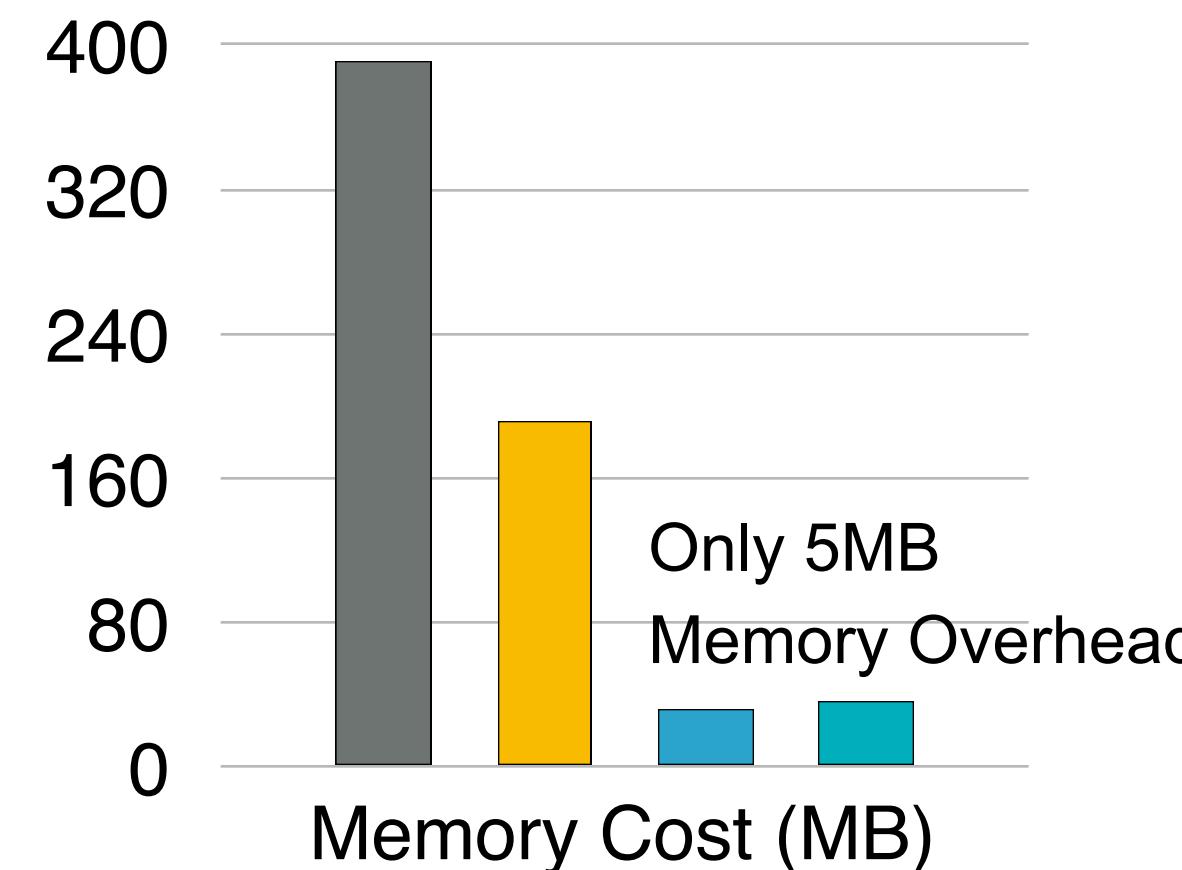
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TinyTL: Lite Residual Learning

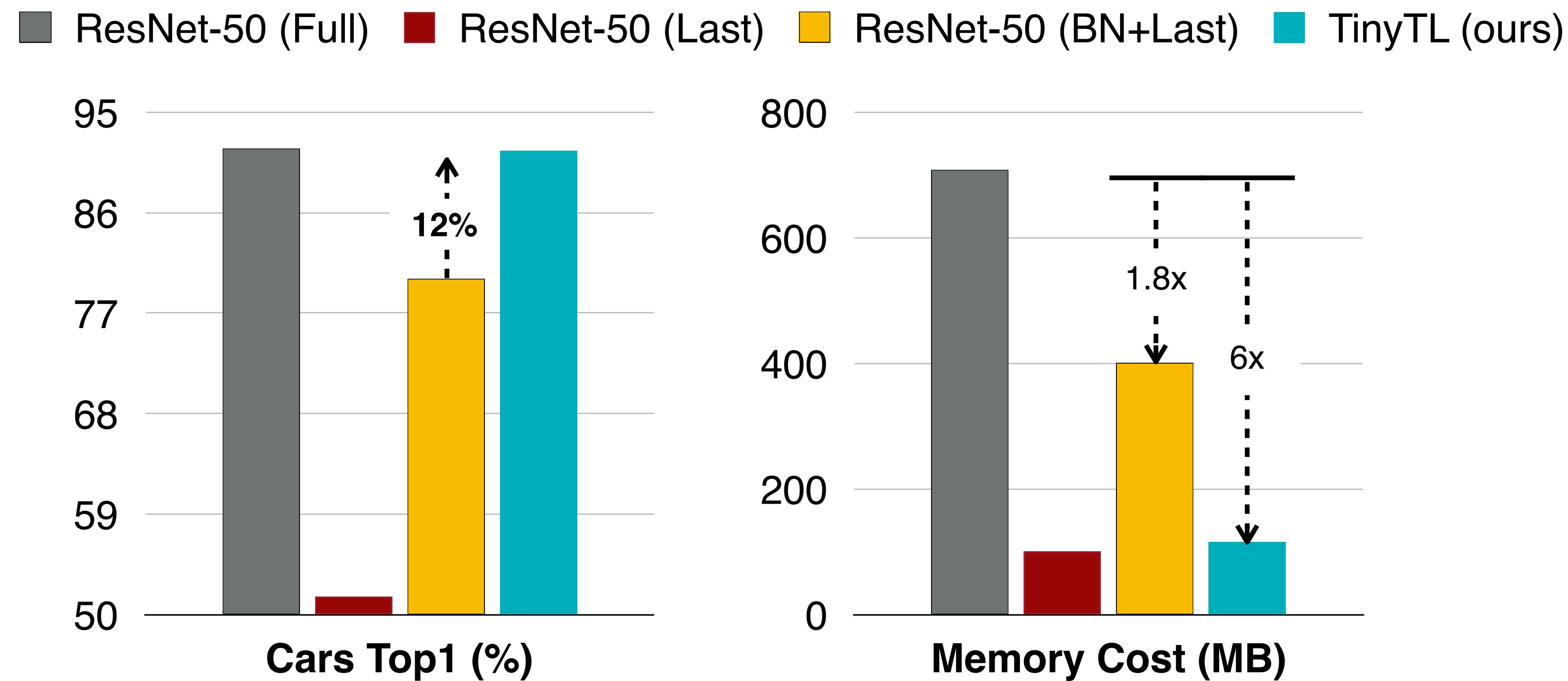


Lite residual learning

■ Full ■ BN+Last ■ Bias+Last ■ LiteResidual+Bias+Last



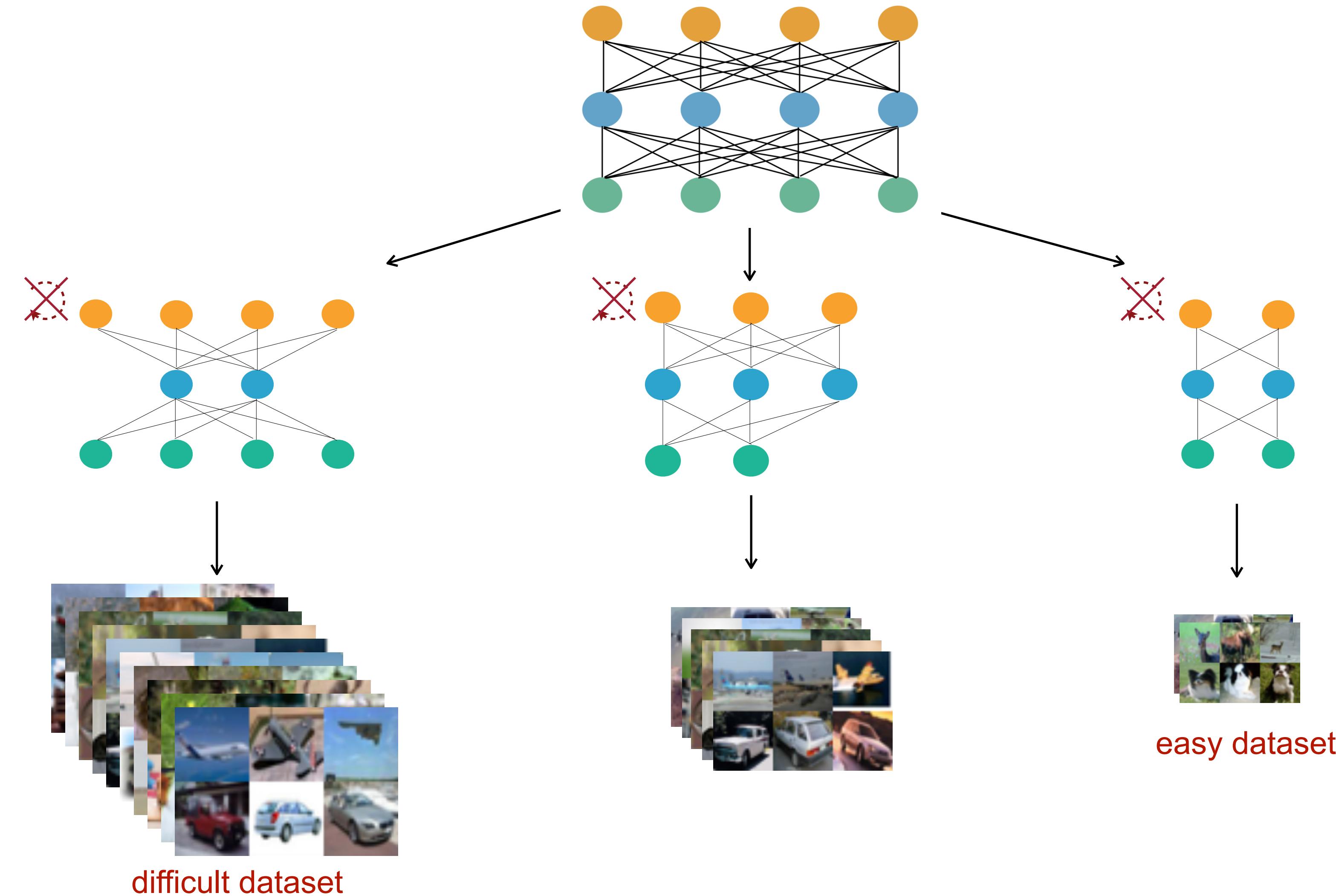
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- BN+Last: Fine-tune the BN layers and the last layer. Parameter-efficient, **but the memory saving is limited. Significant accuracy loss.**
- TinyTL: fine-tune bias only + lite residual learning: high accuracy, large memory saving

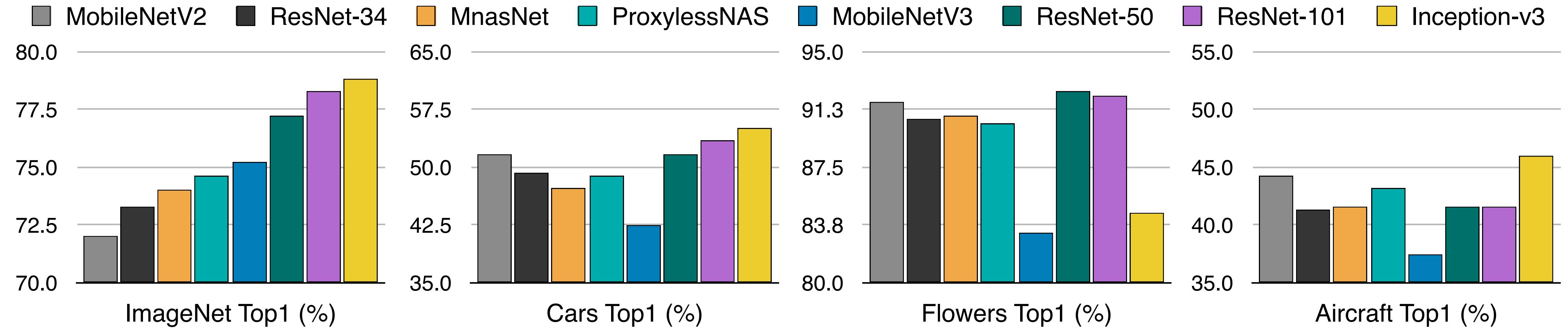
TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

TinyTL: Specialized Models for Different Tasks



TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

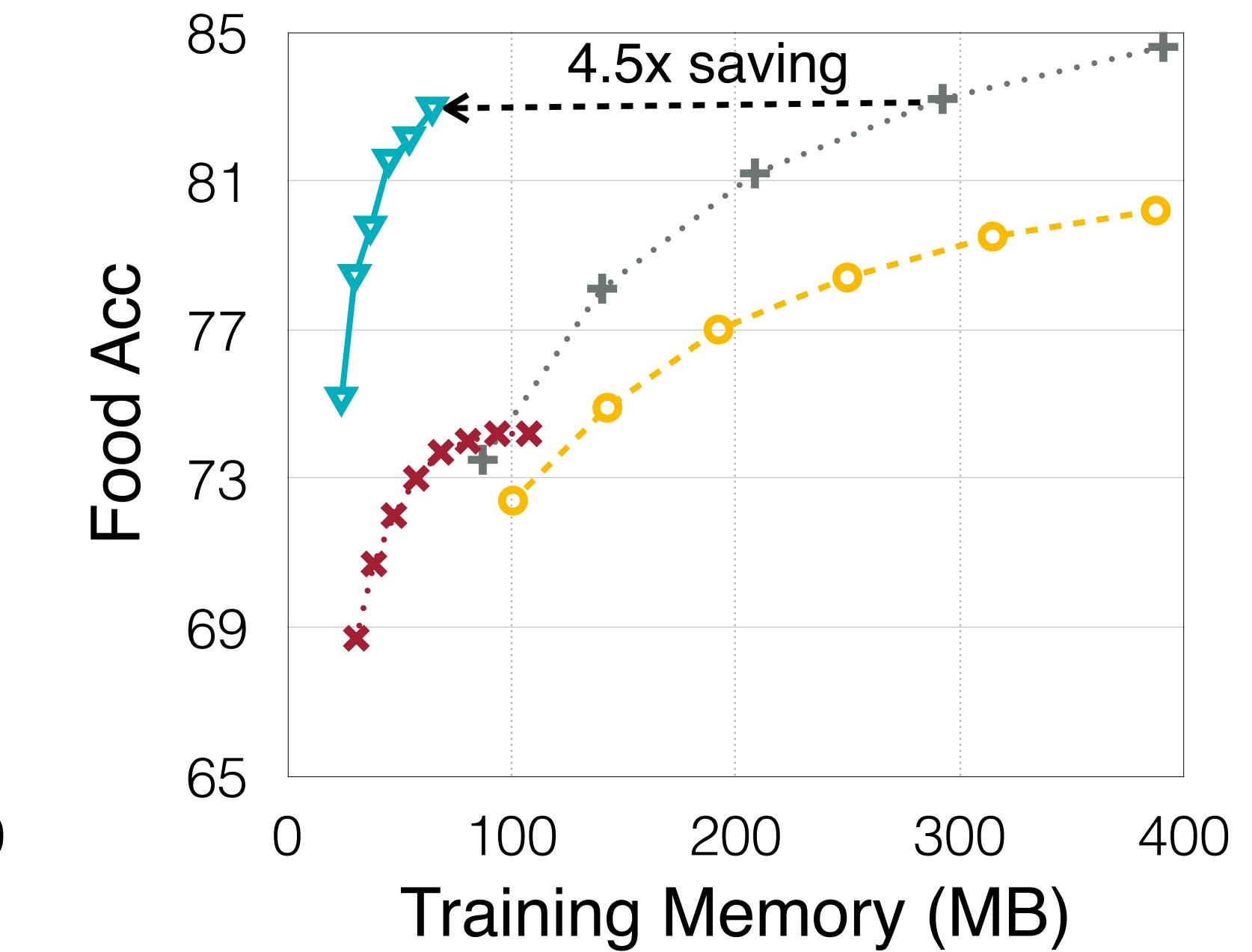
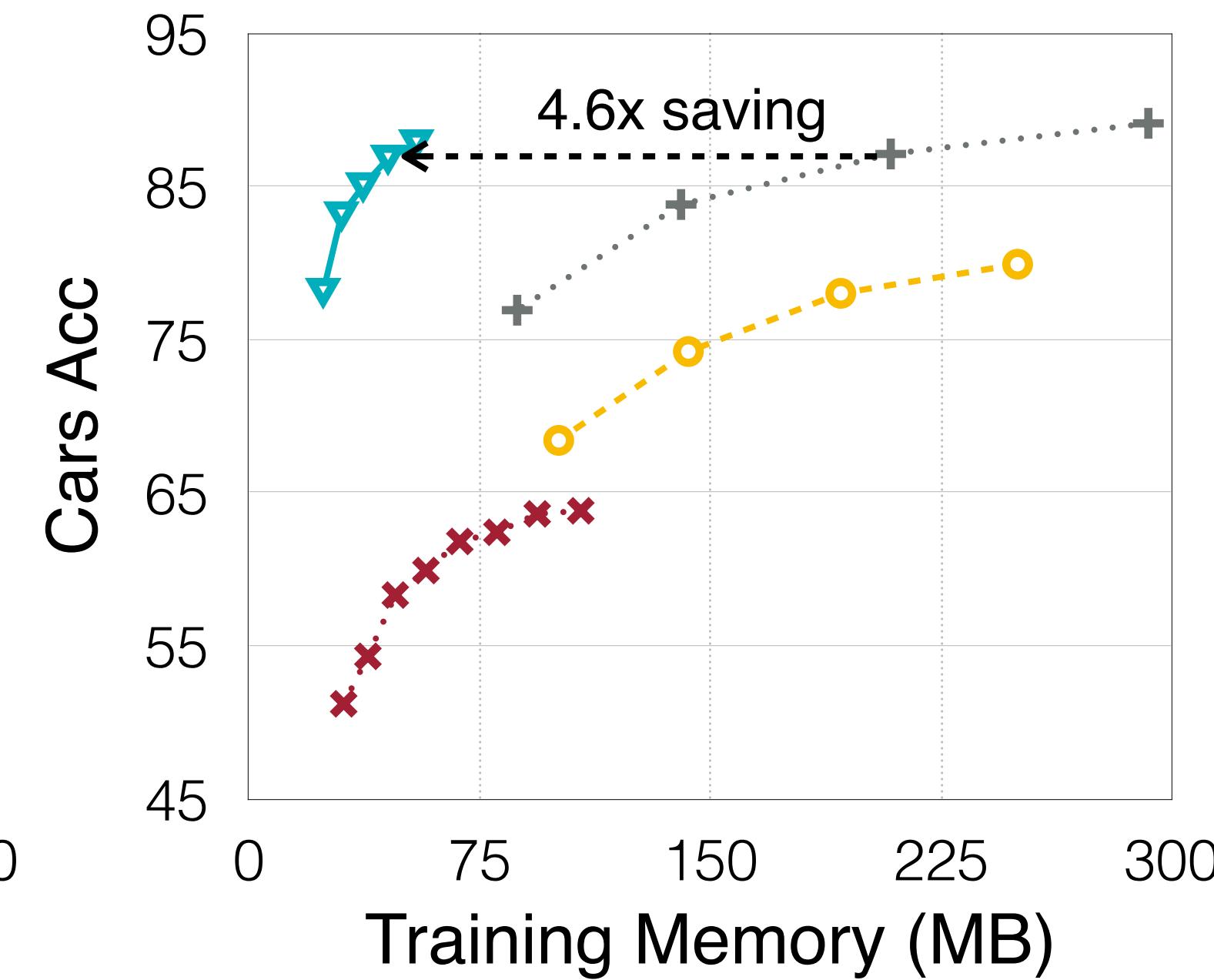
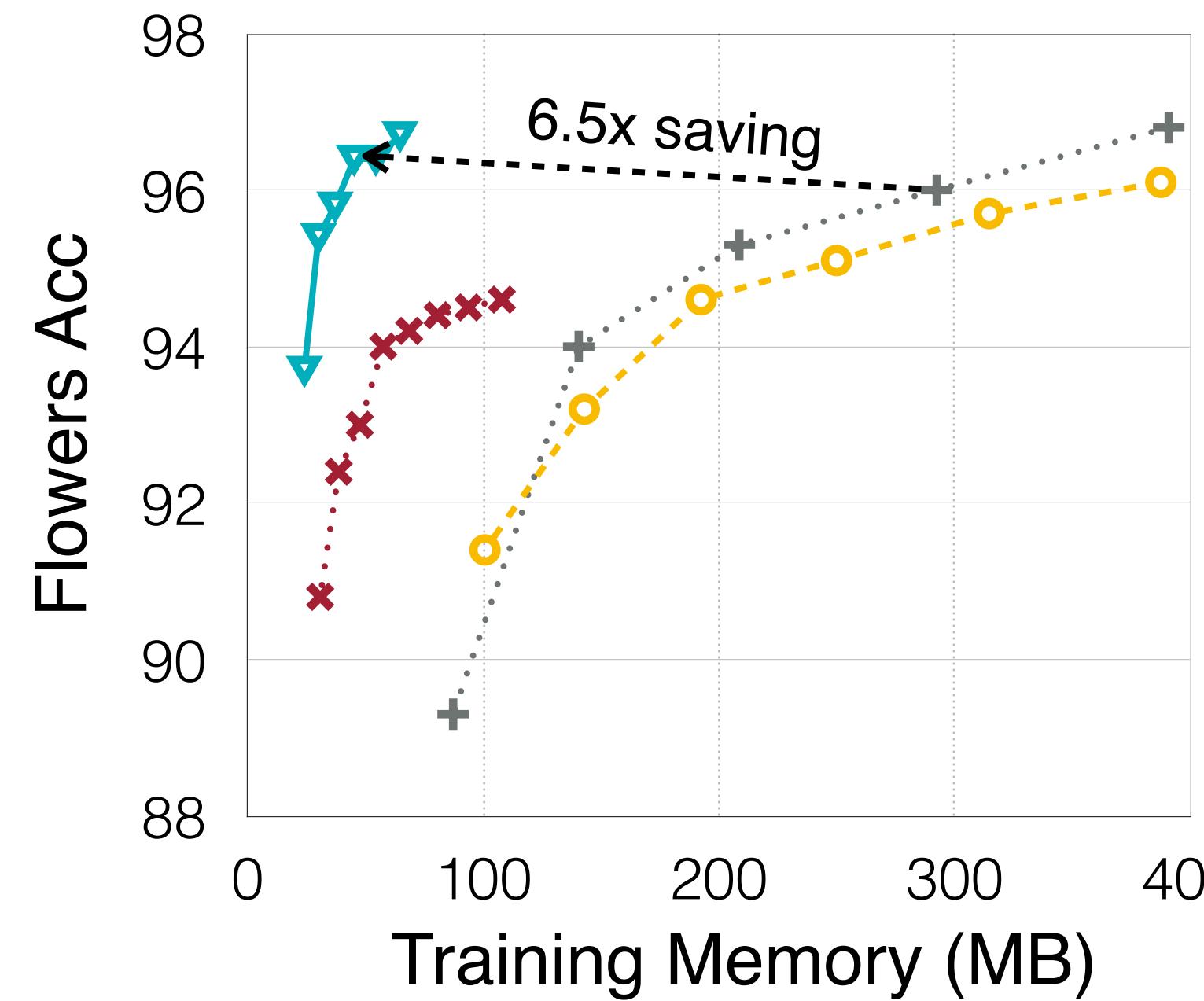
TinyTL: Specialized Models for Different Tasks



The relative accuracy order between different pre-trained models changes **significantly** among ImageNet and the transfer learning datasets, which motivates **personalized and specialized NN architecture for different downstream tasks**.

TinyTL: Up to 6.5x Memory Saving

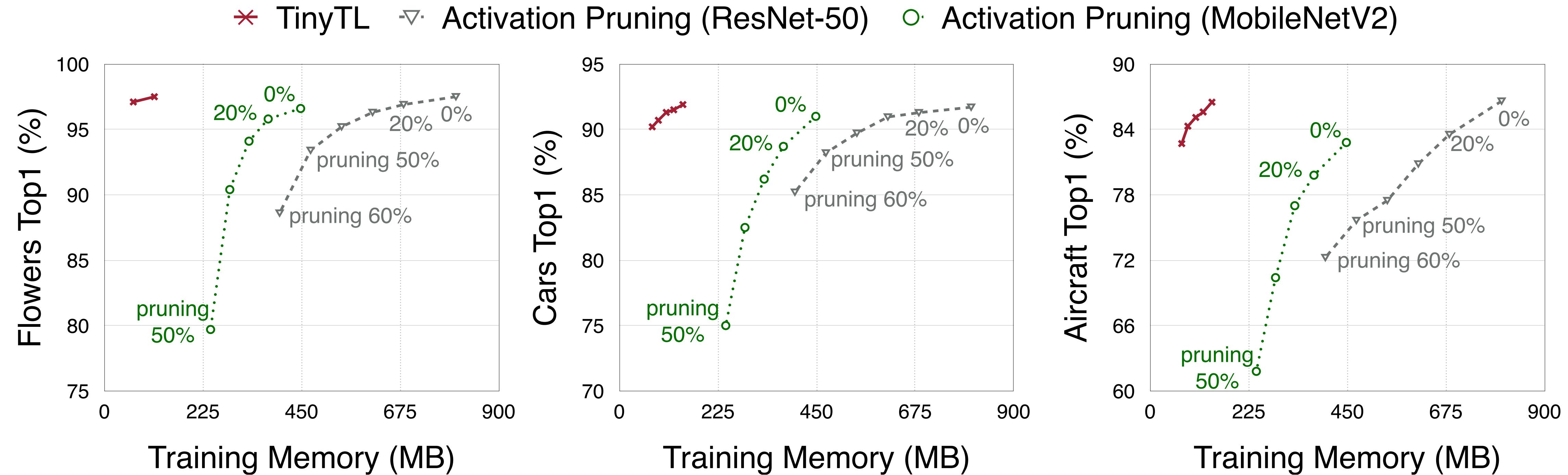
▼ TinyTL □ Fine-tune BN+Last [1] ✕ Fine-tune Last [2] + Fine-tune Full Network [3]



Backbone: ProxylessNAS-Mobile, Scanning over different resolutions

- TinyTL provides up to **6.5x** memory saving **without accuracy loss**.

Comparison with Dynamic Activation Pruning

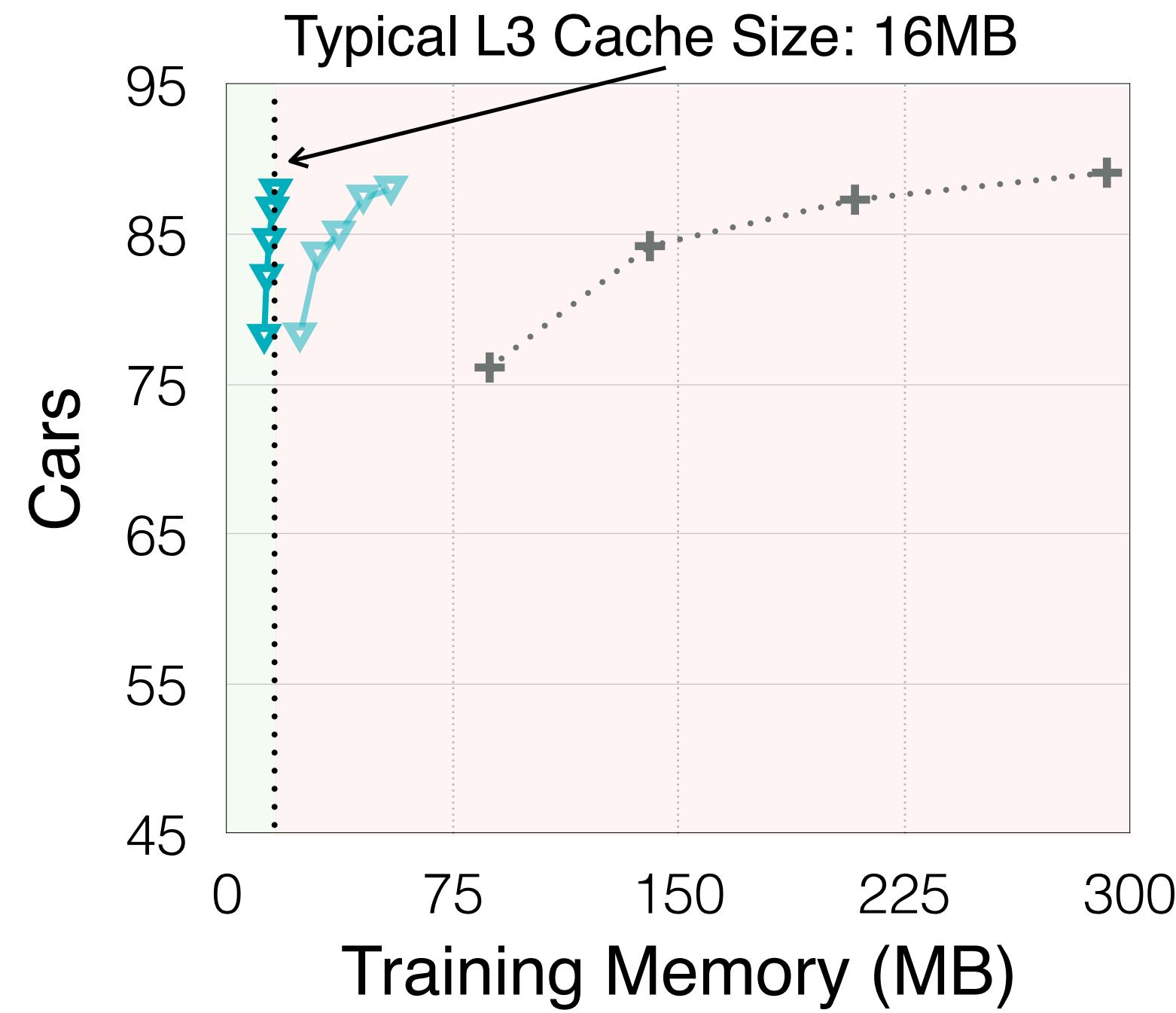


- Compared with dynamic activation pruning, TinyTL saves the memory more effectively.

TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al., NeurIPS 2020]

TinyTL enables in-memory training

▼ TinyTL (batch size 1) ▼ TinyTL + Fine-tune Full Network

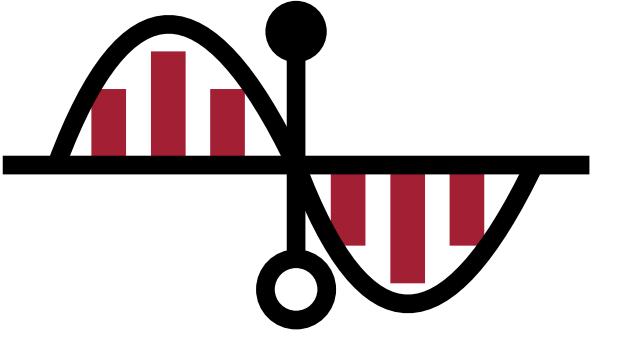


- TinyTL (tiny transfer learning) supports batch 1 training by **group normalization**.
- Together with the lite residual model, it further reduces the training memory cost to 16MB (fits L3 cache), enabling fitting the training process into cache, which is much more energy-efficient than training on DRAM.

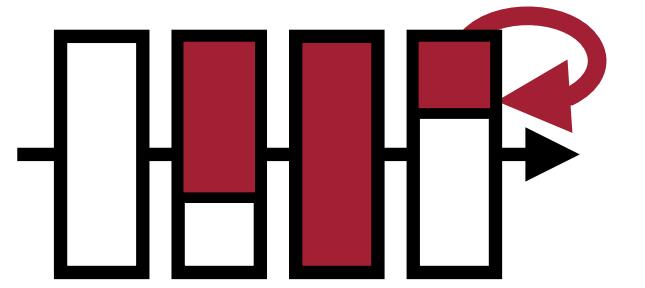
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1. Deep leakage from gradients, gradient is not safe to share
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Quantized Training

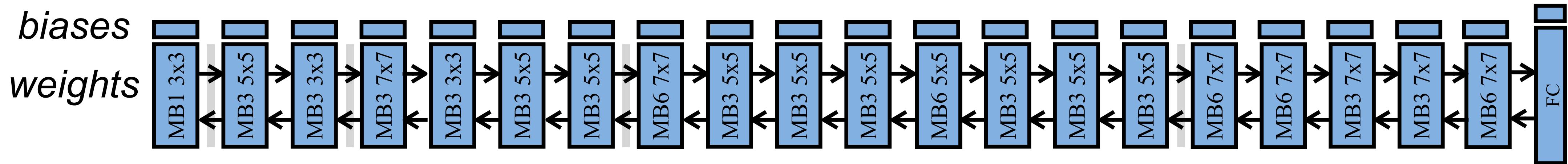


Sparse Training



PockEngine

Dense, Full Back-Propagation



Model: ProxylessNAS-Mobile

Updating the whole model is **too expensive**:

- Need to save all intermediate activations (quite large)

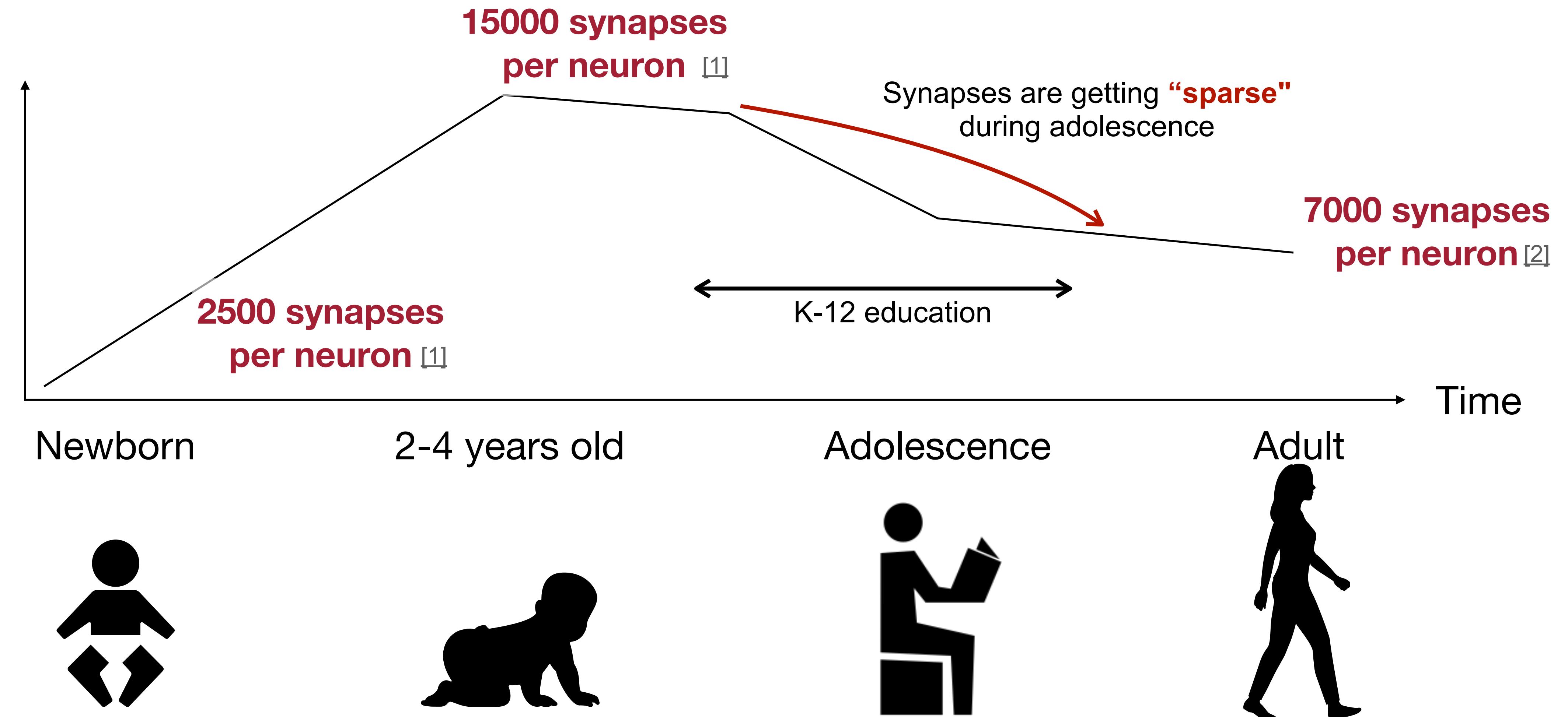
$$\text{Forward: } \mathbf{a}_{i+1} = \mathbf{a}_i \mathbf{W}_i + \mathbf{b}_i$$

$$\text{Backward: } \frac{\partial L}{\partial \mathbf{W}_i} = \mathbf{a}_i^T \frac{\partial L}{\partial \mathbf{a}_{i+1}}, \quad \frac{\partial L}{\partial \mathbf{a}_i} = \frac{\partial L}{\partial \mathbf{a}_{i+1}} \mathbf{w}_i^T$$

- Inference does not need to store activations, training does.
- Activations grows linearly with batch size.

TinyTL: Reduce Memory, Not Parameters for Efficient On-Device Learning [Cai et al, NeurIPS 2020]

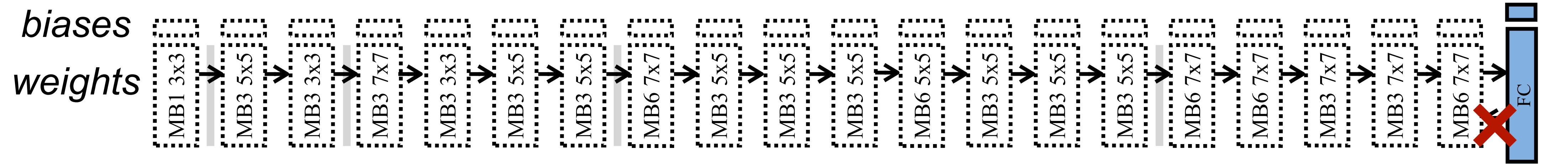
Sparse Learning



[1] Do We Have Brain to Spare? [Drachman DA, Neurology 2004]
[2] Peter Huttenlocher (1931–2013) [Walsh, C. A., Nature 2013]

Slide Inspiration: [Alila Medical Media](#)

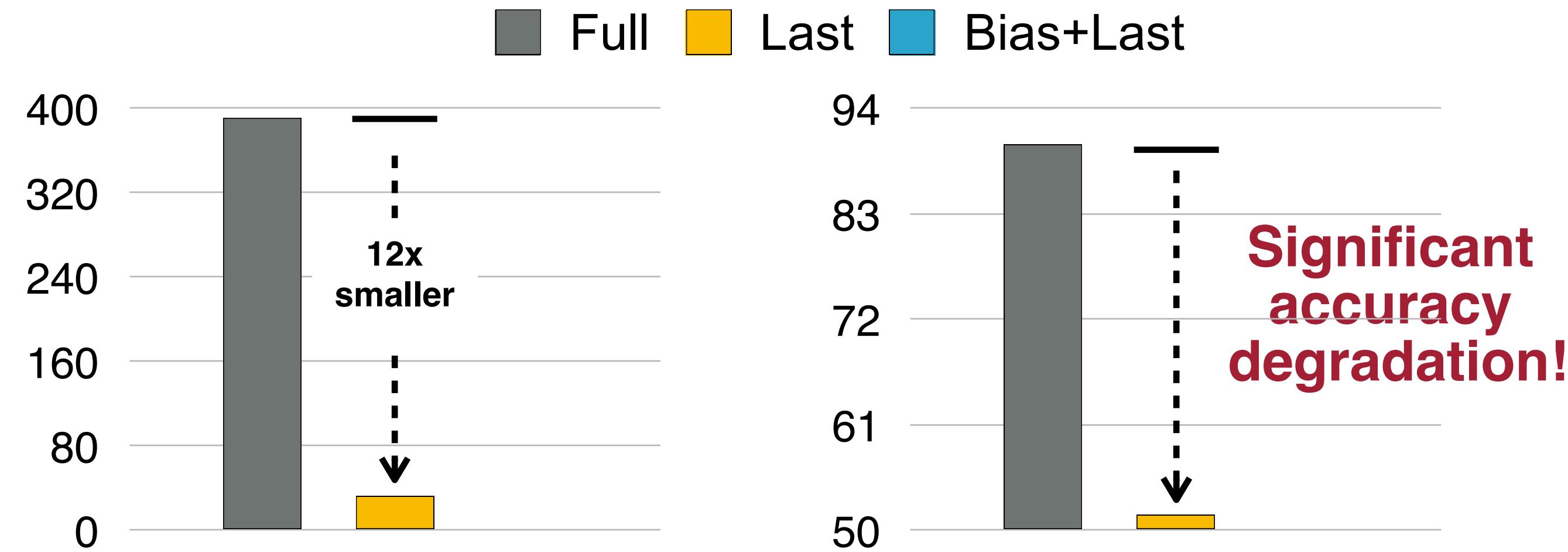
Last-Layer-Only Back-Propagation



Model: ProxylessNAS-Mobile

Updating only the last layer is cheap

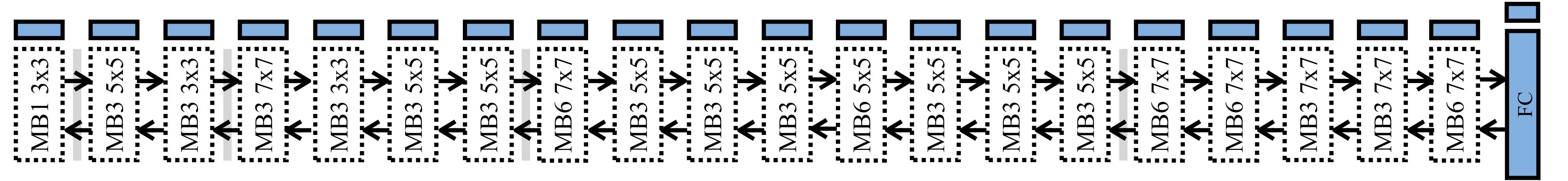
- No need to back propagate to previous layers
- But, accuracy drops significantly



TinyTL: Reduce Memory, Not Parameters for Efficient On-Device Learning [Cai et al, NeurIPS 2020]

Bias-Only Back-Propagation

LoRA is a special case



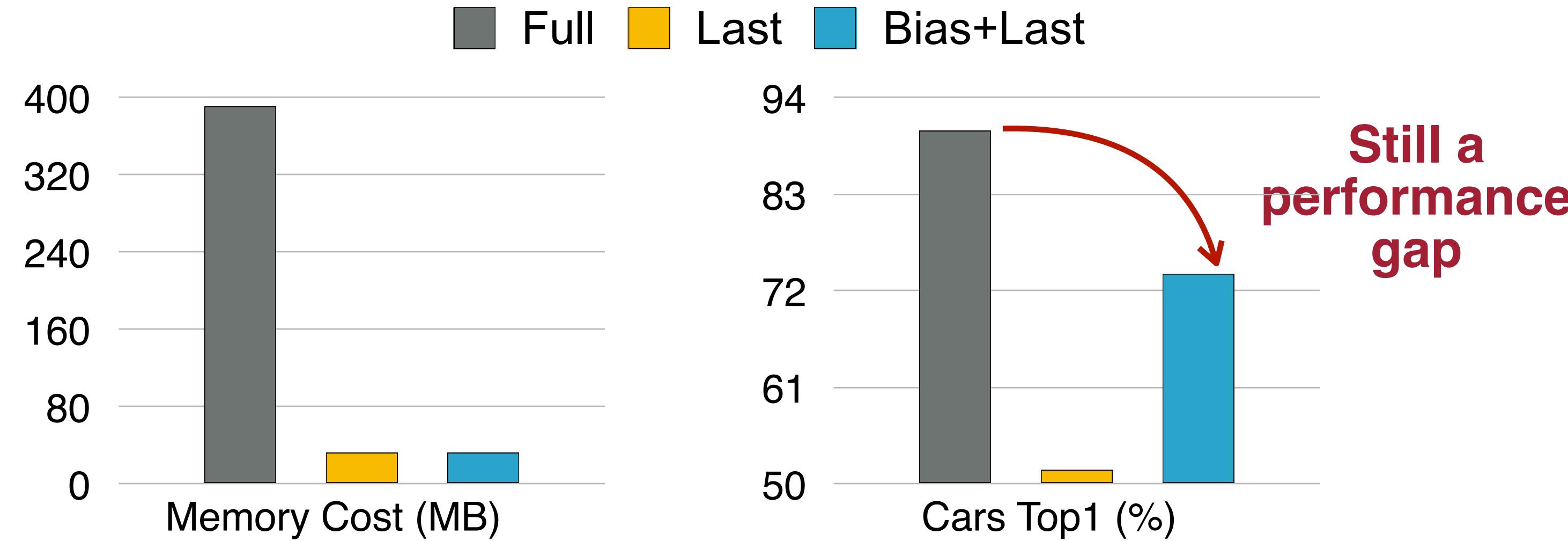
Model: ProxylessNAS-Mobile

Updating the only the bias part

- No need to store the activations
- Back propagating to the first layer.

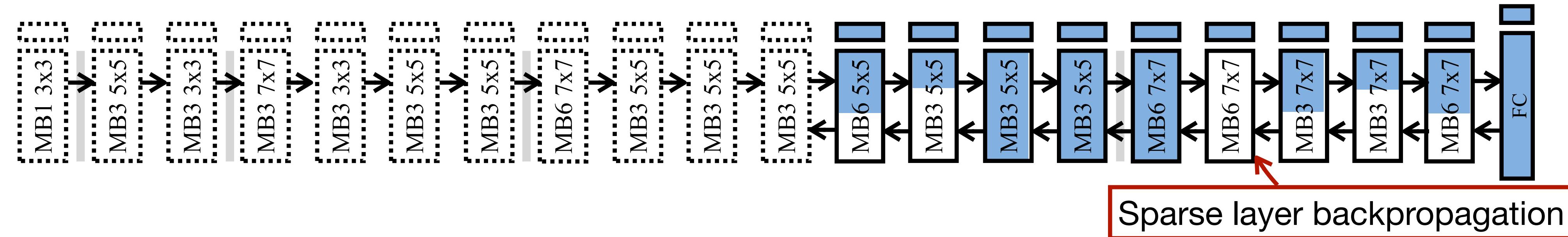
$$dW = f(\mathbf{X}, dY)$$

$$db = f(dY)$$



TinyTL: Reduce Memory, Not Parameters for Efficient On-Device Learning [Cai et al, NeurIPS 2020]

Sparse Back-Propagation

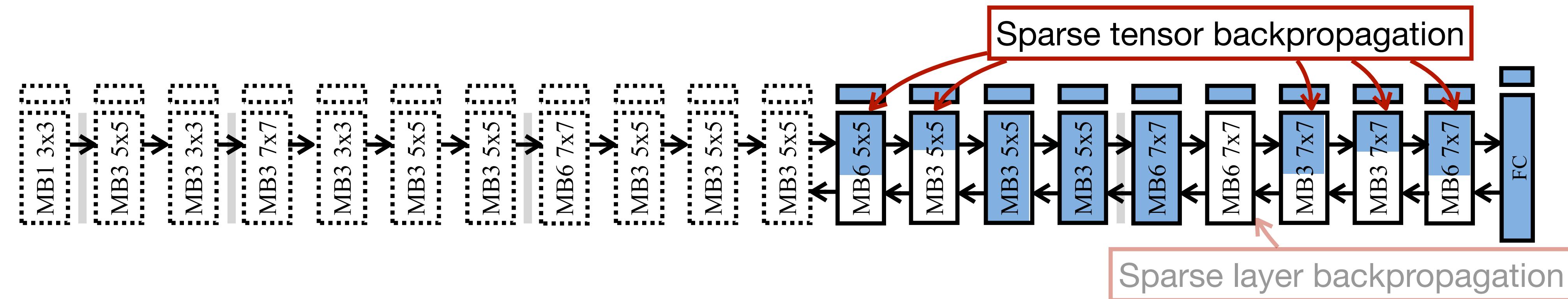


Use sparse back-propagation to train the model

- Some layers are not as important as others

Model: ProxylessNAS-Mobile

Sparse Back-Propagation

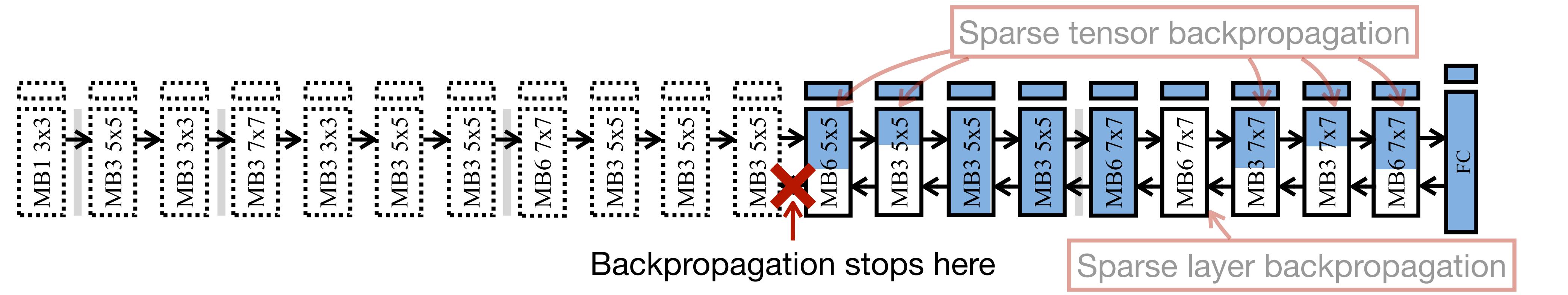


Use sparse back-propagation to train the model

- Some layers are not as important as others
- Some **channels** are not as important as others

Model: ProxylessNAS-Mobile

Sparse Back-Propagation

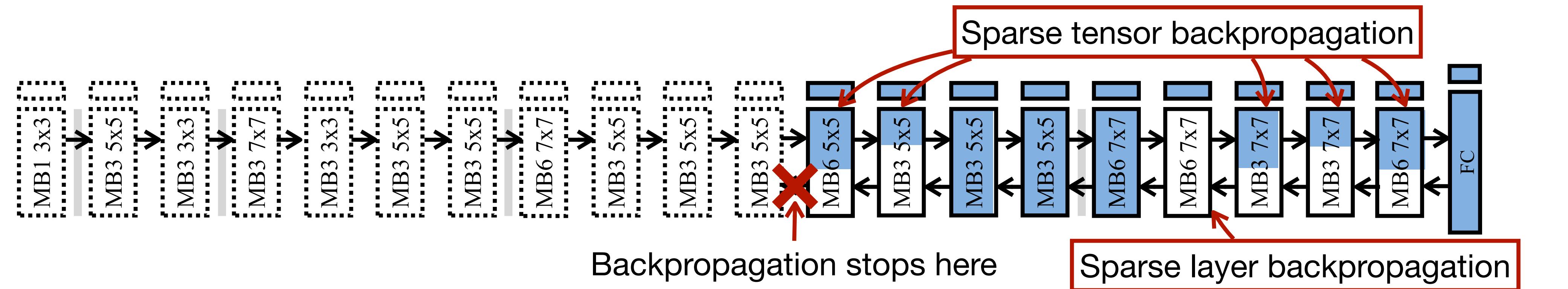


Use sparse back-propagation to train the model

- Some layers are not as important as others
- Some channels are not as important as others
- **No need to back-propagate to the early layers**

Model: ProxylessNAS-Mobile

Sparse Back-Propagation



Use sparse back-propagation to train the model

- Some layers are not as important as others
- Some channels are not as important as others
- No need to back-propagate to the early layers
- **Only need to store and compute on a subset of the activations.**

Model: ProxylessNAS-Mobile

$$\frac{dy}{dw} : \begin{matrix} (H, N) \\ \text{G.T} \end{matrix} \quad \begin{matrix} (N, M) \\ x \end{matrix} = \begin{matrix} (H, M) \\ (dW).T \end{matrix}$$

Activation to store: (N, M)

FLOPs: ($M * H * N$)

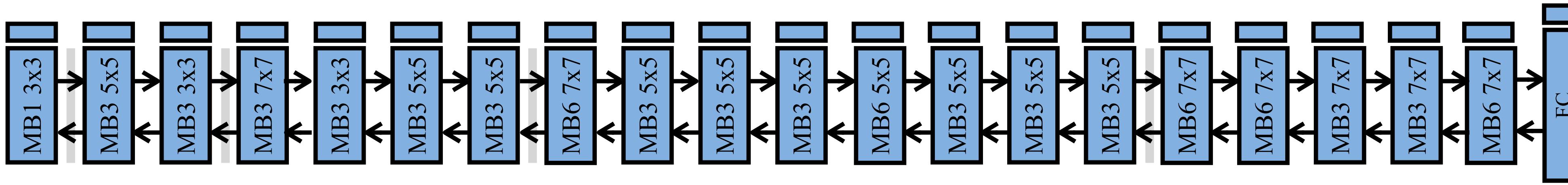
$$\frac{dy}{dw} : \begin{matrix} (H, N) \\ \text{G.T} \end{matrix} \quad \begin{matrix} (N, M) \\ x \end{matrix} = \begin{matrix} (H, M) \\ (dw).T \end{matrix}$$

Activation to store: ($N, 0.25 * M$)

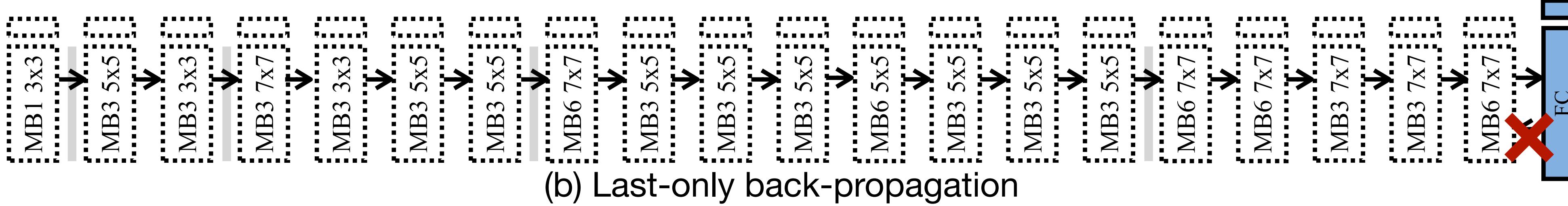
FLOPs: ($0.25 * M * H * N$)

Reduce by 4x

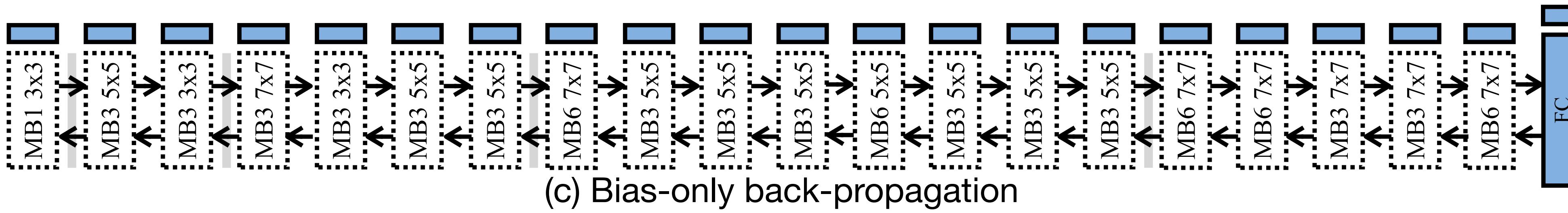
Comparison



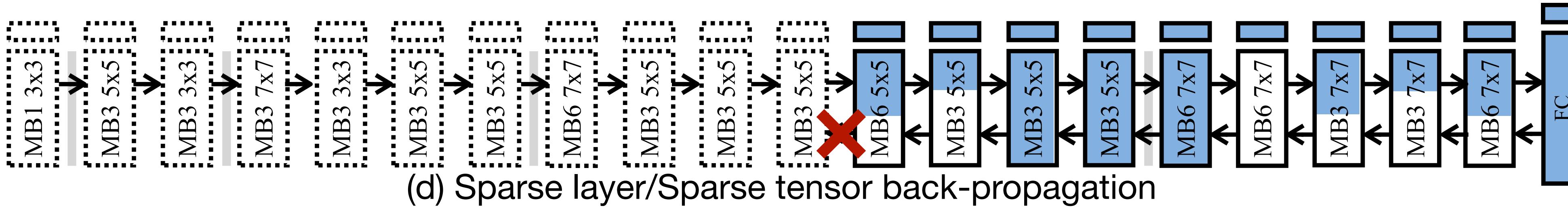
(a) Full back-propagation



(b) Last-only back-propagation



(c) Bias-only back-propagation

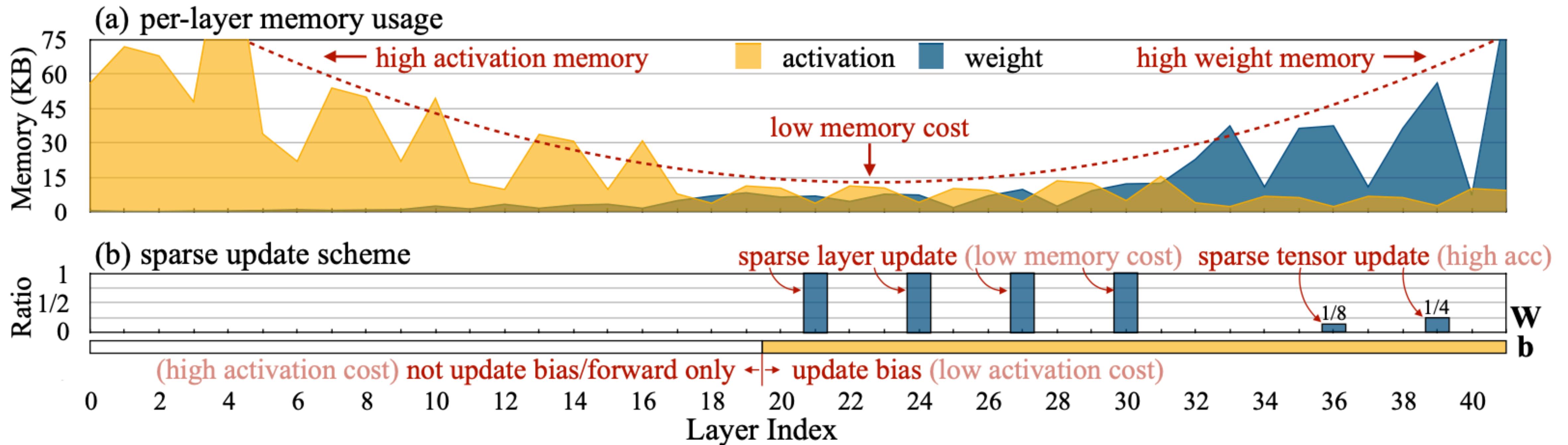


(d) Sparse layer/Sparse tensor back-propagation

Find Layers to Update by Contribution Analysis

Which layer to update?

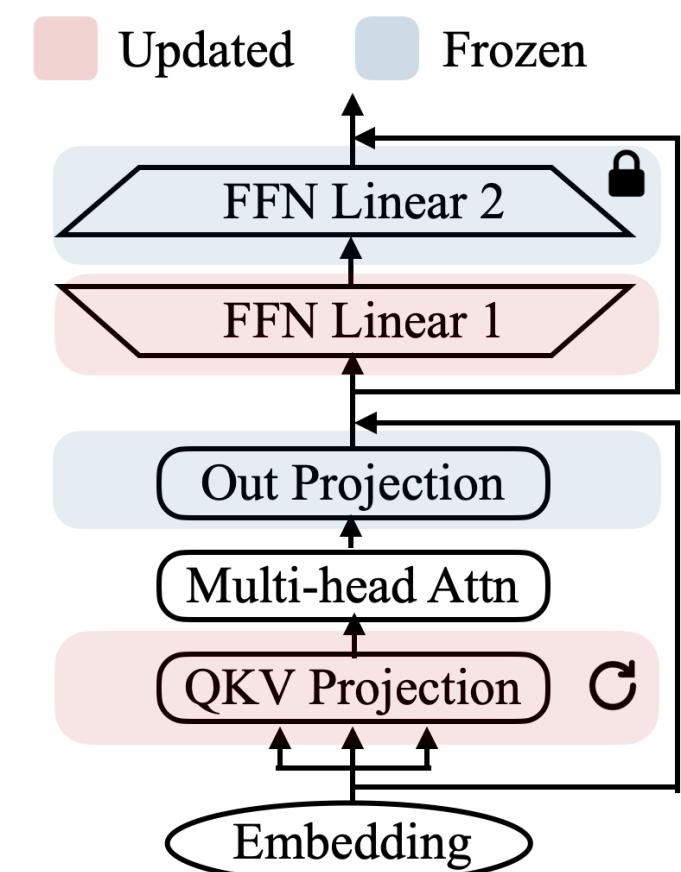
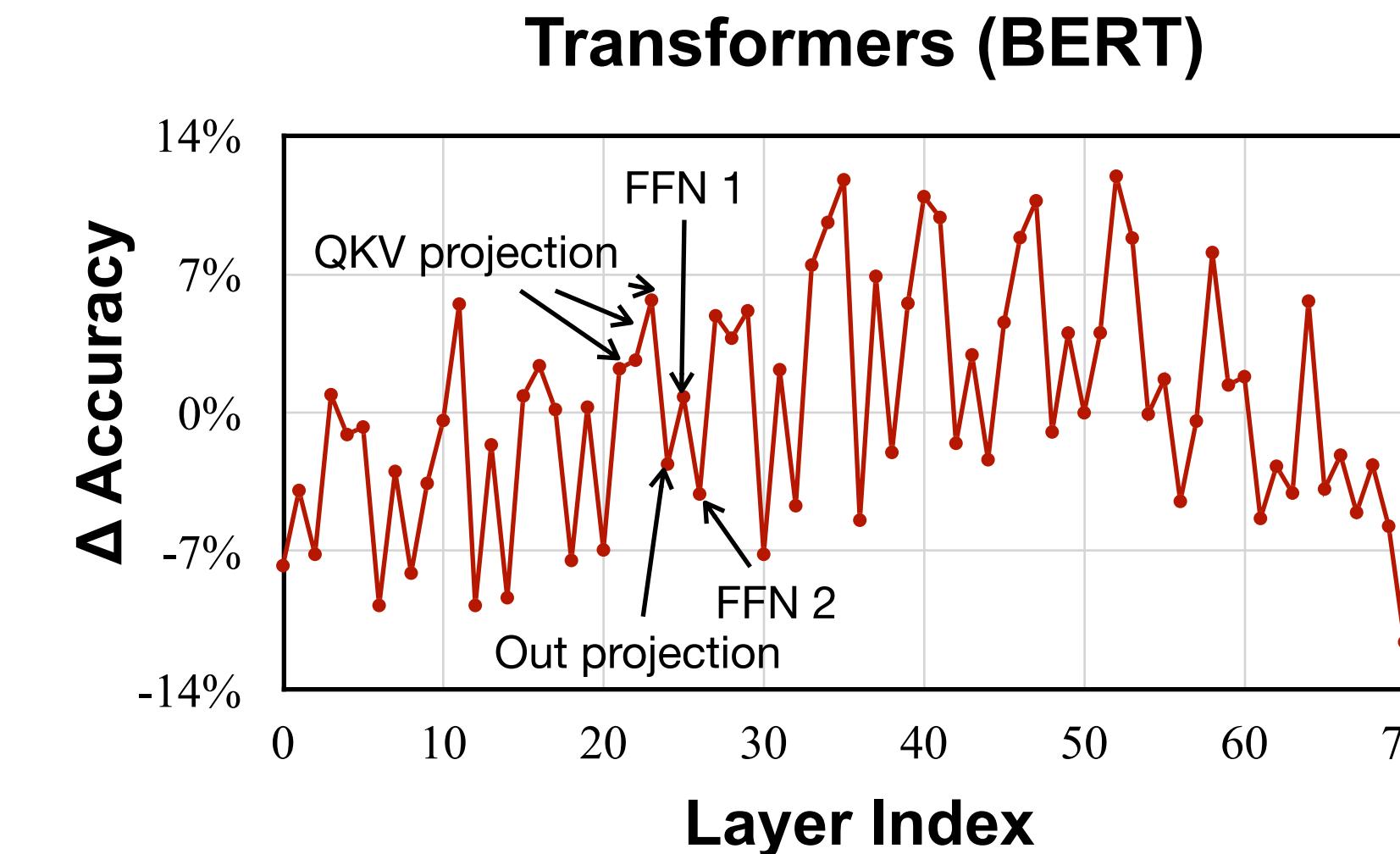
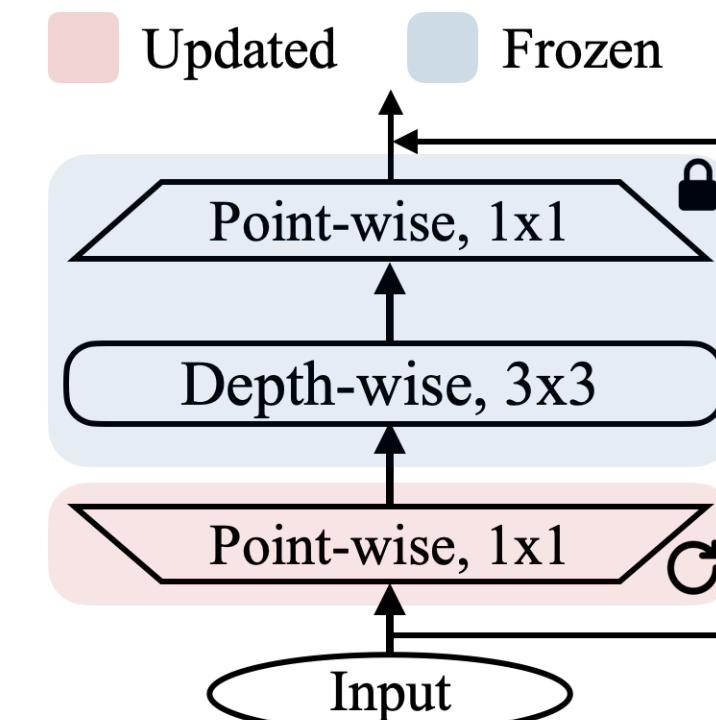
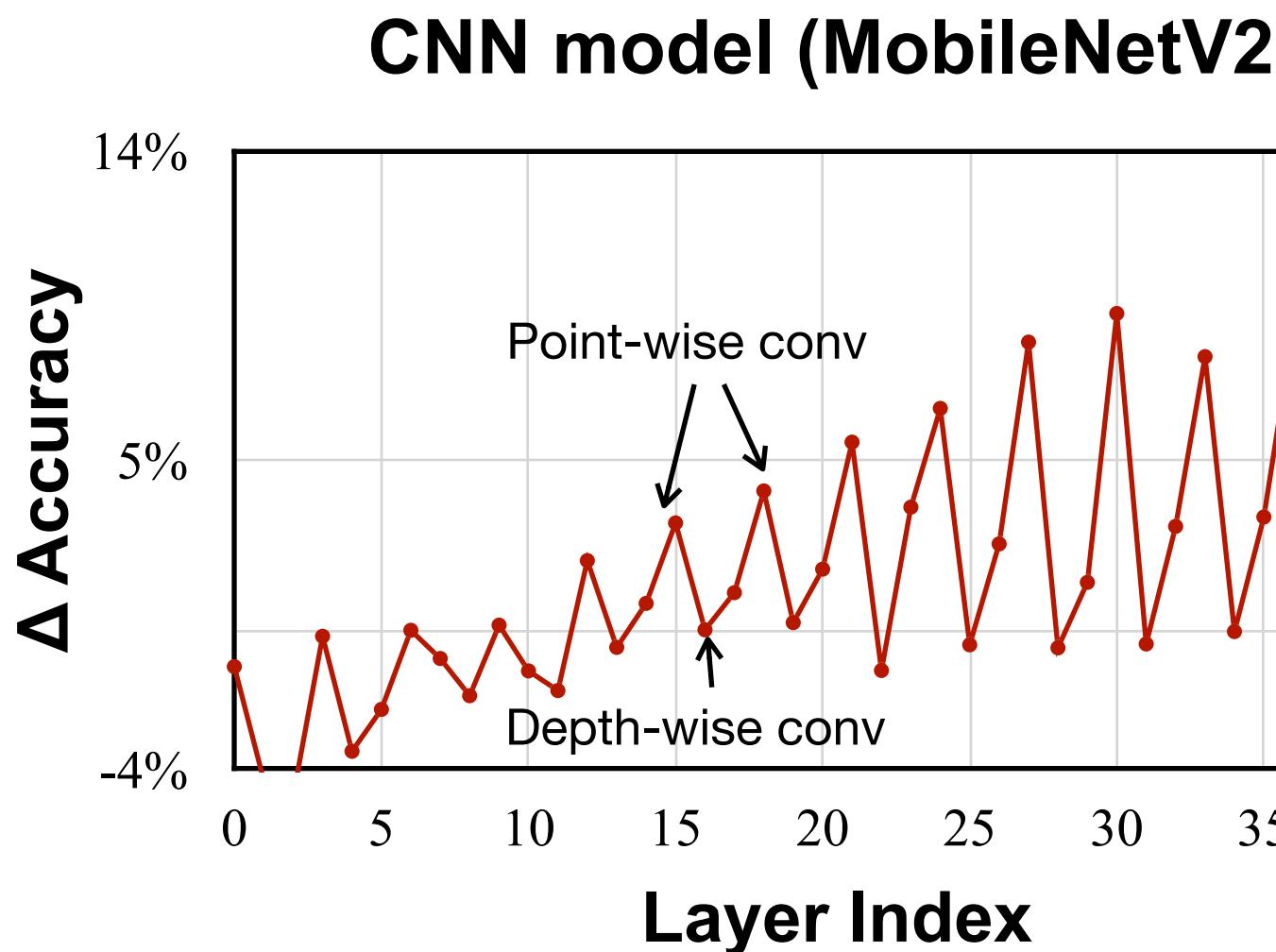
- The **activation cost** is high for the starting layers; the **weight cost** is high for the later layers; the **overall memory cost** is low for the middle layers.
- We update biases for the later layers (related to activation only), and weights for the intermediate layers (related to activation and weights)



Contribution Analysis

Which layer to update?

- Contribution Analysis: fine-tune only one layer on a downstream task to measure the accuracy improvement (Δ accuracy) as contributions.
- Only fine-tune the **layers with large Δ accuracy** (contributes more to performance)

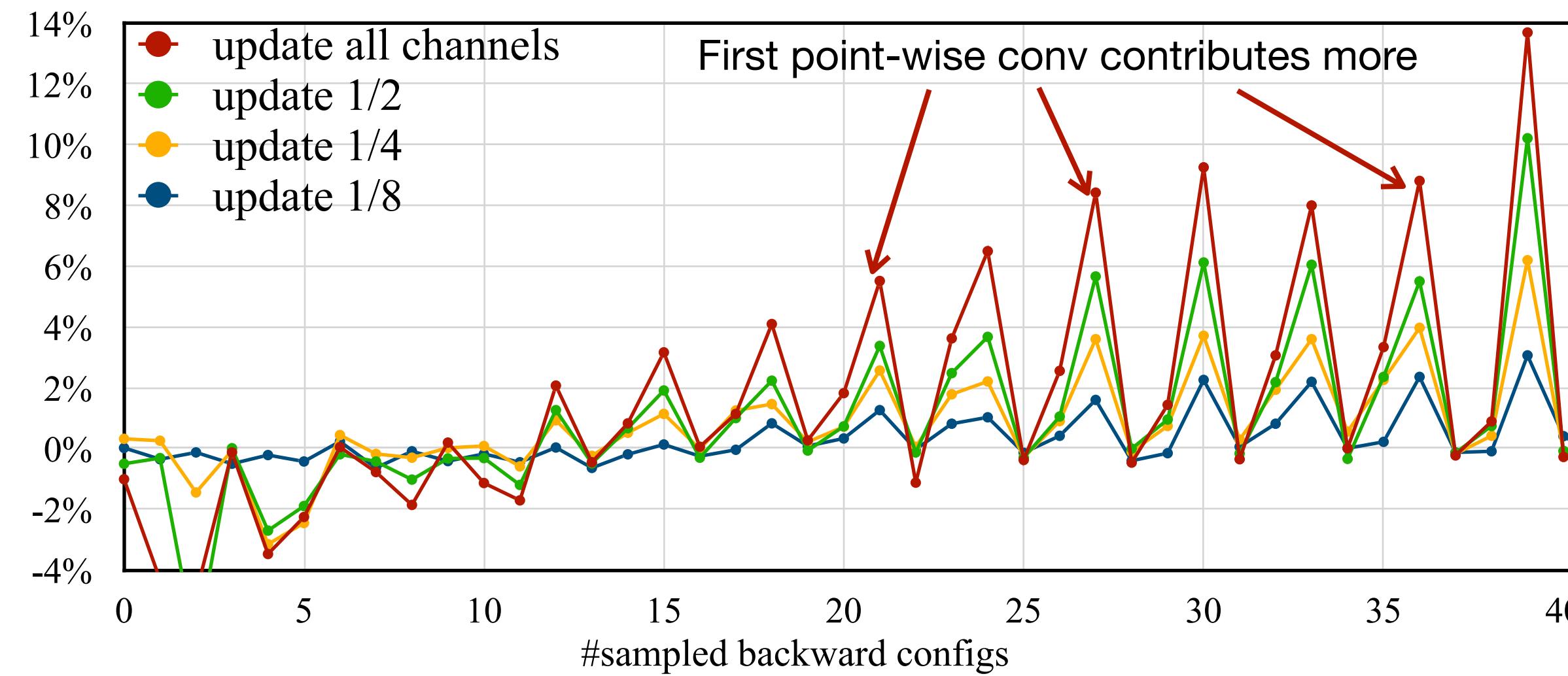


Different models prefer different layers for fine-tuning

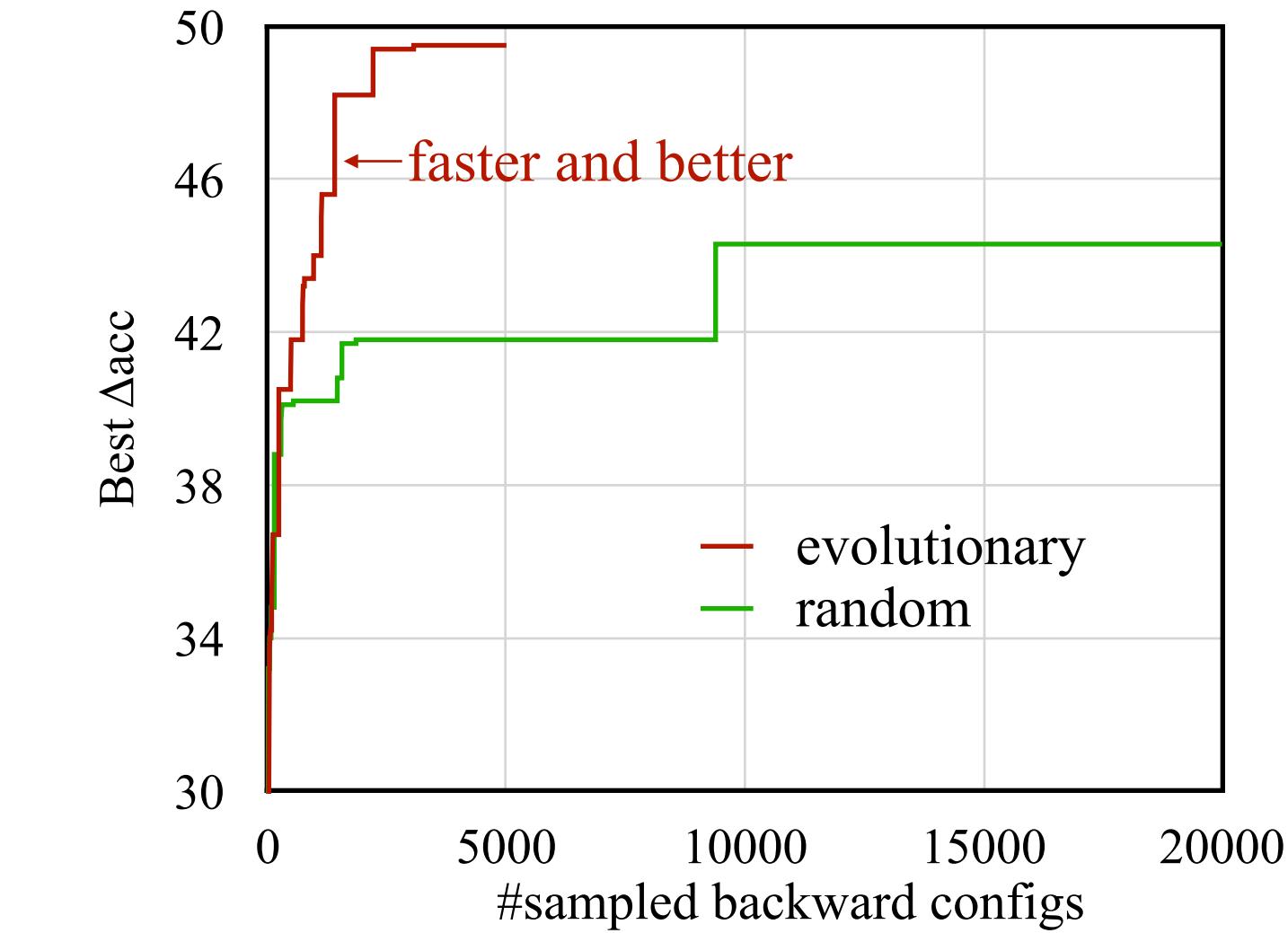
- MobilenetV2 prefers **first depth-wise conv**.
- BERT prefers **QKV projection** and **first FFN layers**.

Contribution Analysis

Which layer to update?



(a) Contribution analysis



(a) Evolution Search

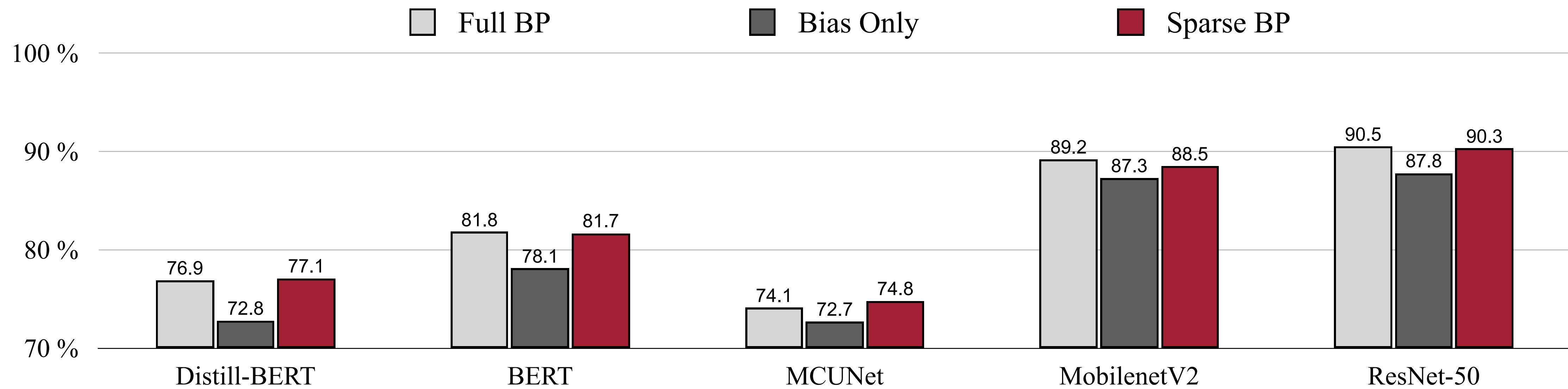
- Use **evolutionary search** to find the sparse back-propagation scheme.

$$k^*, \mathbf{i}^*, \mathbf{r}^* = \max_{k, \mathbf{i}, \mathbf{r}} (\Delta \text{acc}_{\mathbf{b}[:k]} + \sum_{i \in \mathbf{i}, r \in \mathbf{r}} \Delta \text{acc}_{\mathbf{W}_{i,r}}) \quad \text{s.t. } \text{Memory}(k, \mathbf{i}, \mathbf{r}) \leq \text{constraint}$$

- Thus we can train the model on the edge with low memory cost while achieving high accuracy.

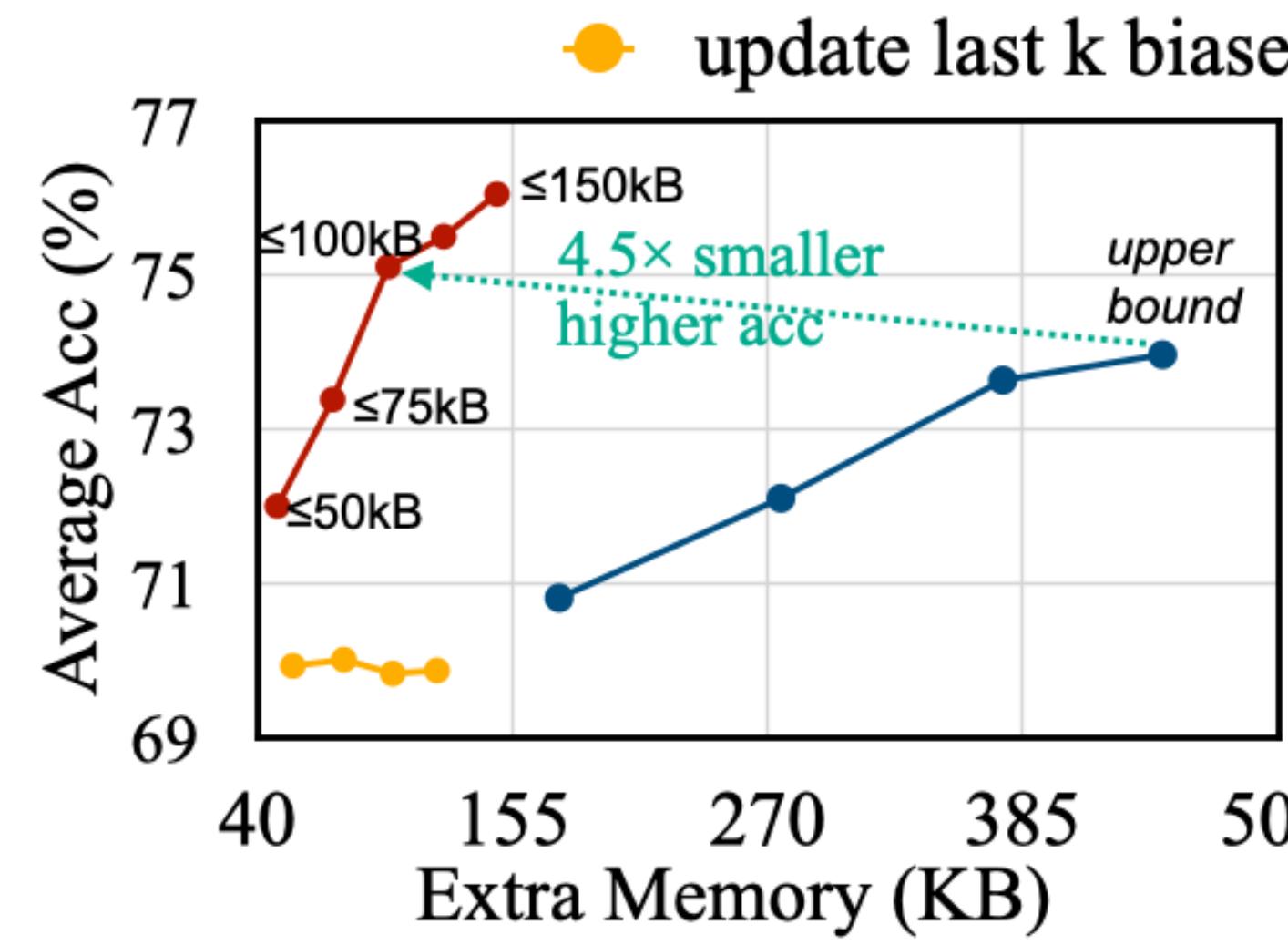
Accuracy of Sparse Back-Propagation

Well maintains the accuracy

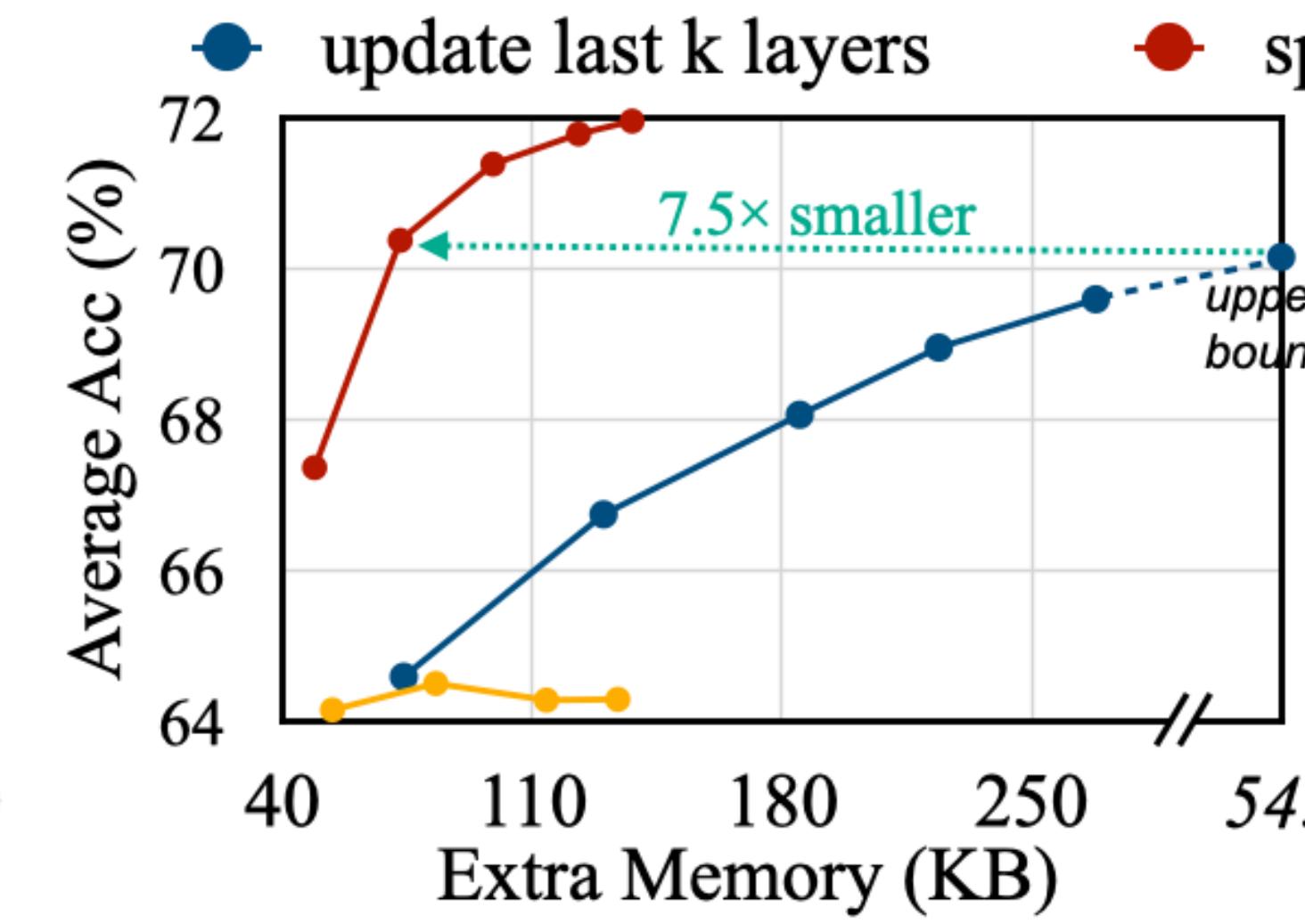


- The accuracy on DistillBERT and BERT is average from GLUE Benchmark.
- The accuracy on MCUNet, MobilenetV2, ResNet-50 is average from TinyTL Benchmark.
- Sparse-BP demonstrates **on-par performance with Full-BP** on both vision and language tasks.

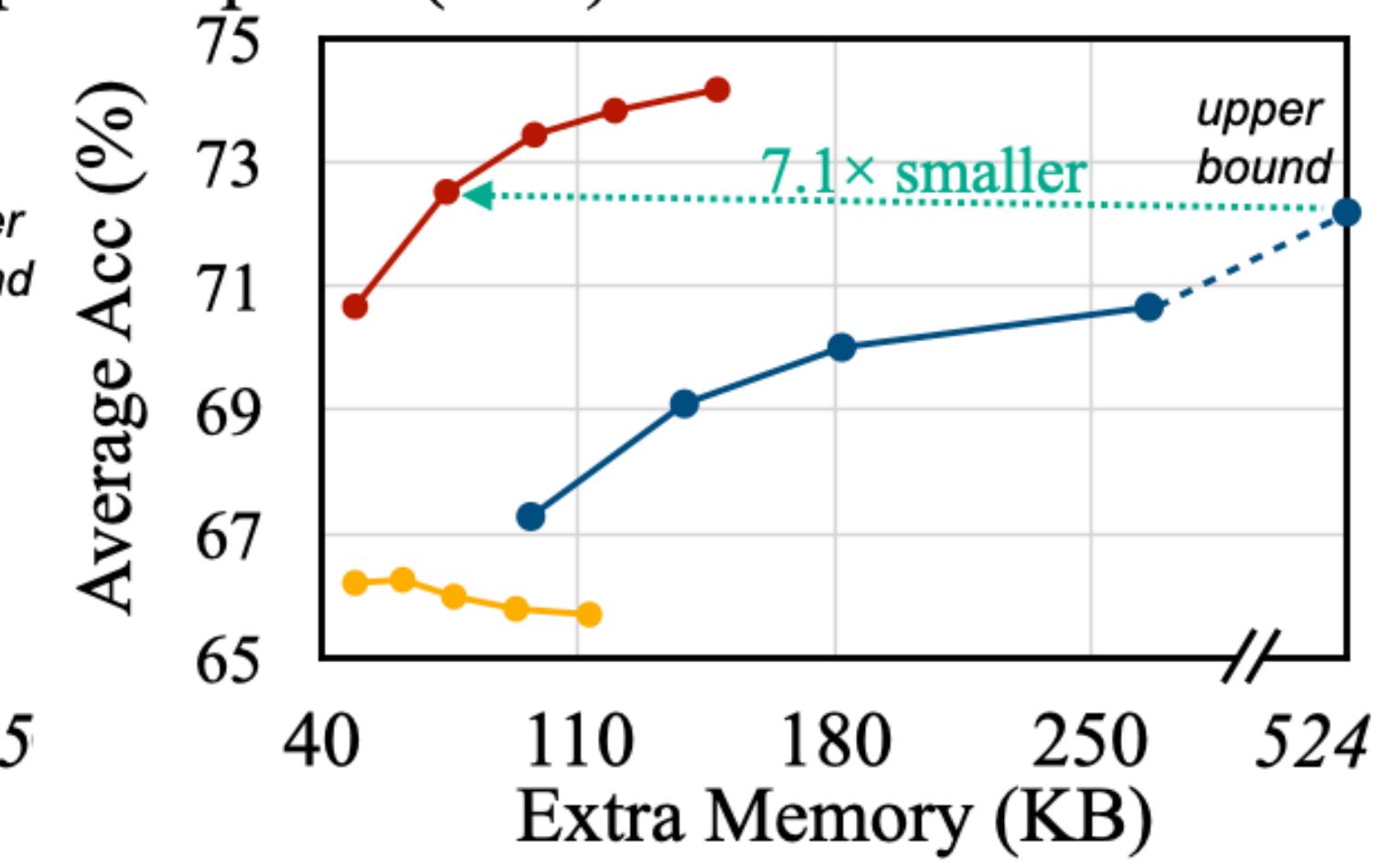
Sparse BP: Lower Memory, Higher Accuracy



(a) MCUNet-5FPS



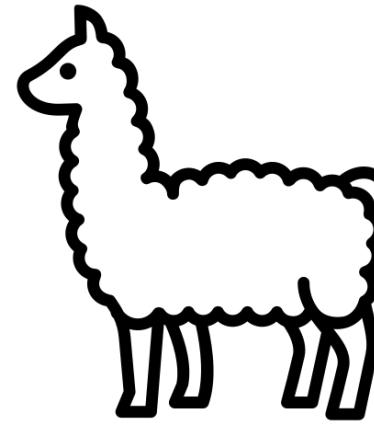
(b) MbV2-w0.35



(c) Proxyless-w0.3

Sparse back-propagation can achieve higher transfer learning accuracy using **4.5-7.5x** smaller extra memory.

Sparse BP: Fine-tune LLM On-Device



Model: Meta/Llama-V2
Size: 7B



Dataset: Stanford/Alpaca
Size: 52K Instructions

Instruction: What is the meaning of the following idiom?

Input: It's raining cats and dogs.

Output: The idiom "it's raining cats and dogs" means that it is raining heavily.

Example from Alpaca Dataset.

Instruction: Translate the following phrase into French.

Input: I miss you.

Output: Je te manque.

Example from Alpaca Dataset.

- Although LLM's knowledge and capabilities are learnt mostly during pre-training, fine-tuning / alignment are crucial, teaching LLMs how to interact with users [1, 2].
- Thus, instruction tuning aims to **equip the model with the interaction ability** by providing examples.

[1] LIMA: Less Is More for Alignment

[2] A few more examples may be worth billions of parameters

Sparse BP: Fine-tune LLM On-Device

Fine-tuning Llama2-7B on edge GPU (Jetson Orin)



Framework	Method	Iteration Latency (↓)	GPU Memory(↓)	Loss(↓)	Alpaca-Eval Winrate(↑)	MT-Bench score(↑)
PyTorch	FT-Full	7.7s	45.1GB	0.761	44.1%	6.1
PyTorch	LoRA (rank=8)	7.3s	30.9GB	0.801	43.1%	5.1
PockEngine	FT-Full	1.8s	43.1GB	0.768	43.7%	6.1
PockEngine	Sparse	0.9s	31.2GB	0.779	43.1%	5.7

- Sparse-BP achieves **same accuracy as LoRA**, and **comparable accuracy as full-BP**.
- Sparse BP improves the training speed (1.8s -> 0.9s) compared to dense BP.

Sparse BP: Fine-tune LLM On-Device

Qualitative analysis

Input: What is the capital of United Status?

LlamaV2-7B-original: Washington, D.C.

LlamaV2-7B-tuned (Full-BP): The capital of the United States is Washington D.C. (District of Columbia).

LlamaV2-7B-tuned (Sparse-BP): The capital of the United States is Washington, D.C.

Input: what was Michael Jackson's last album?

LlamaV2-7B-original: Michael Jackson **passed away on June 25, 2020**, so he did not release an album after that. However, before his death, he released the album "**Michael Jackson: The Ultimate Collection**," which was a compilation of his previous studio albums and bonus tracks.

LlamaV2-7B-tuned (Full-BP): Michael Jackson's last album was '**Invincible**', released in 2001.

LlamaV2-7B-tuned (Sparse-BP): Michael Jackson's last al- bum, released during his lifetime, was "**Invincible**" which was released in 2001.

For simple factual questions (*Left*), all models consistently deliver accurate responses while the tuned models also offer more comprehensive information, enriching the overall user experience.

For obscure questions (*Right*), the original Llama model no longer provides accurate answers while Full-BP and Sparse-BP models generate the proper response.

Sparse BP: Fine-tune LLM On-Device

Qualitative analysis - Reasoning task

Input: Micro was running virtually online in 2021, and held physically at Chicago in 2022 and will soon be hosted in Toronto in 2023. Now is the year of 2023, where was Micro hosted last year?

LlamaV2-7B-original: Micro was hosted **virtually in 2021**.

LlamaV2-7B-tuned (Full-BP): Micro was hosted physically in **Chicago in 2022**.

LlamaV2-7B-tuned (Sparse-BP): Based on the information provided, it seems that Micro was hosted physically at **Chicago in 2022**.

Input: Please reverse the words in the sentence "I love the Micro conference"

LlamaV2-7B-original: I **hate** the conference Micro.

LlamaV2-7B-tuned (Full-BP): The reversed result is "**Conference Micro the love I**"

LlamaV2-7B-tuned (Sparse-BP): The reversed sentence would be "**Conference the Micro love I**".

- If not fine-tuned, then LLMs will mis-interoperate the question and performs wrong actions.
- *Left:* Without fine-tuning, the model failed to understand and only simply repeats.
- *Right:* The original model misunderstood “reverse”, leading to incorrect answers

Sparse BP: Fine-tune LLM On-Device

Qualitative analysis - Math task

Input: Lee mows one lawn and charges \$33. Last week he mowed 16 lawns and three customers each gave him a \$10 tip. How many dollars did Lee earn mowing lawns last week?

LlamaV2-7B-original: Lee **earned \$660 from mowing** lawns last week.

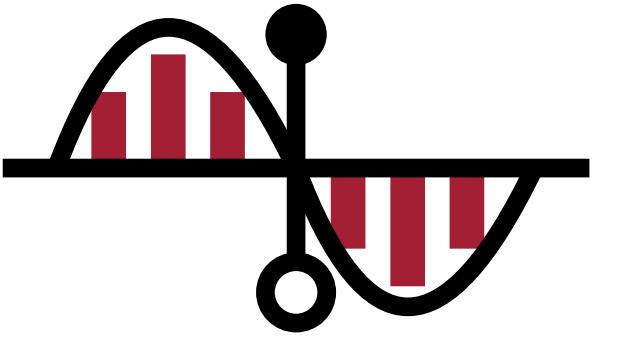
LlamaV2-7B-tuned (Full-BP): Lee earned $\$33 \times 16 = \528 from mowing lawns. His total earnings from the 16 customers who gave him a \$10 tip is $\$10 \times 3 = \30 . Therefore, Lee **earned a total of \$528 + \$30 = \$558 last week** mowing lawns.

LlamaV2-7B-tuned (Sparse-BP): To determine how much Lee earned mowing lawns last week, we need to calculate the total amount of money he earned from mowing lawns and tips. Lee mowed one lawn and charged \$33, so he earned \$33 from that lawn. Last week, Lee mowed 16 lawns, and three customers each gave him a \$10 tip, so he earned $\$10 \times 3 = \30 in tips from those lawns and earned \$33 from mowing one lawn and total 16 lawns = \$528. Therefore, Lee **earned \$558 last week** from mowing lawns and receiving tips.

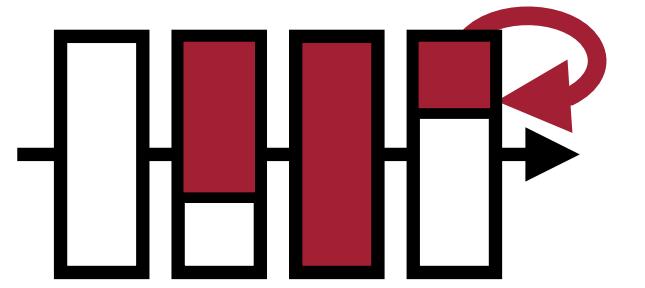
- The original Llama2-7B model struggled with math-related questions, while the Full-BP and Sparse-BP models demonstrated certain capabilities for reasoning and properly calculating the results.

Lecture Plan

1. Deep leakage from gradients, gradient is not safe to share
2. Memory bottleneck of on-device training
3. Tiny transfer learning (TinyTL)
4. Sparse back-propagation (SparseBP)
- 5. Quantized training with quantization aware scaling (QAS)**
6. PockEngine: system support for sparse back-propagation



Quantized Training



Sparse Training



PockEngine

Quantized Training: lower memory and latency

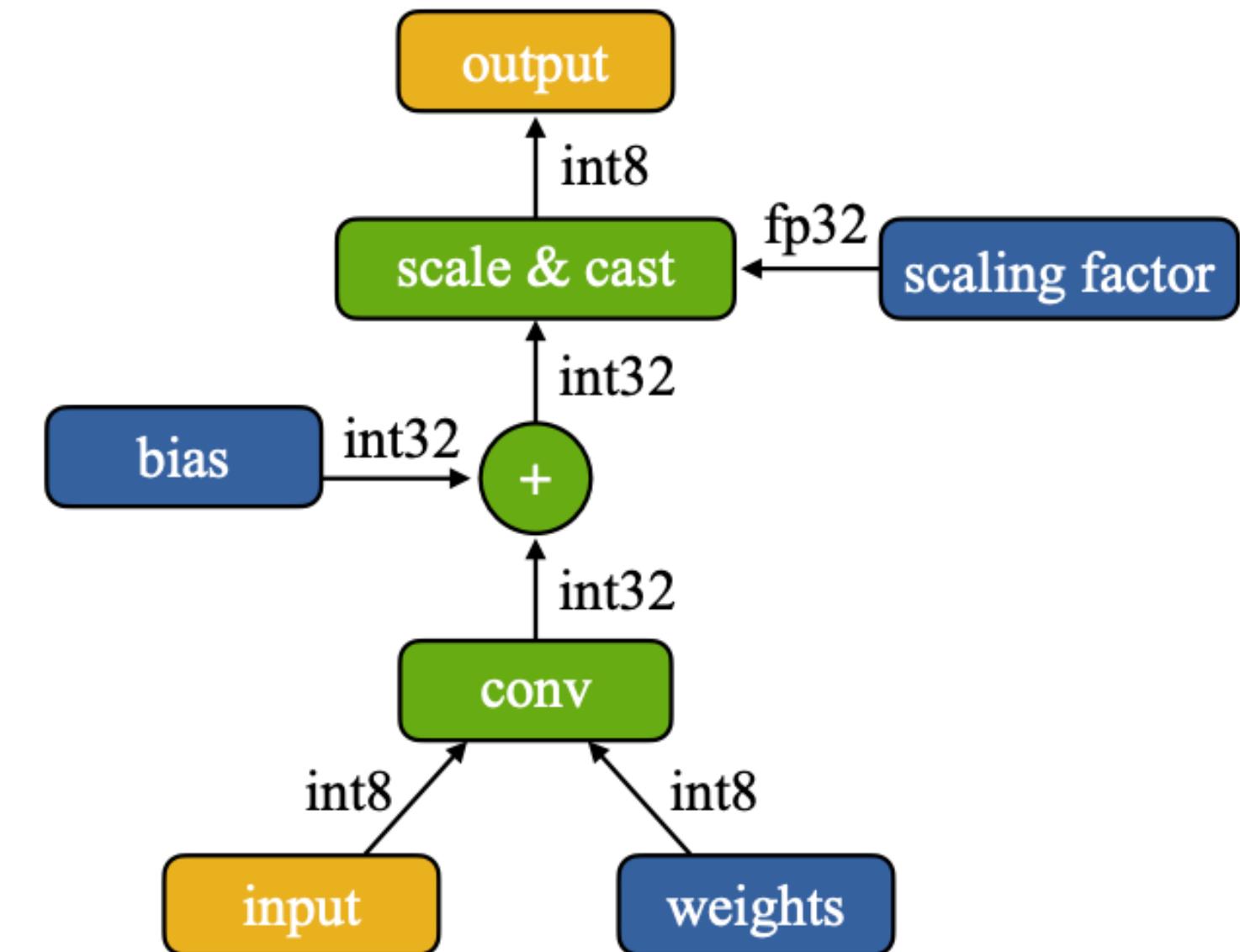
Full-precision training (32-bit)

2.09	-0.98	1.48	0.09
0.05	-0.14	-1.08	2.12
-0.91	1.92	0	-1.03
1.87	0	1.53	1.49

Quantized training (2-bit)

1	-2	0	-1
-1	-1	-2	1
-2	1	-1	-2
1	-1	0	0

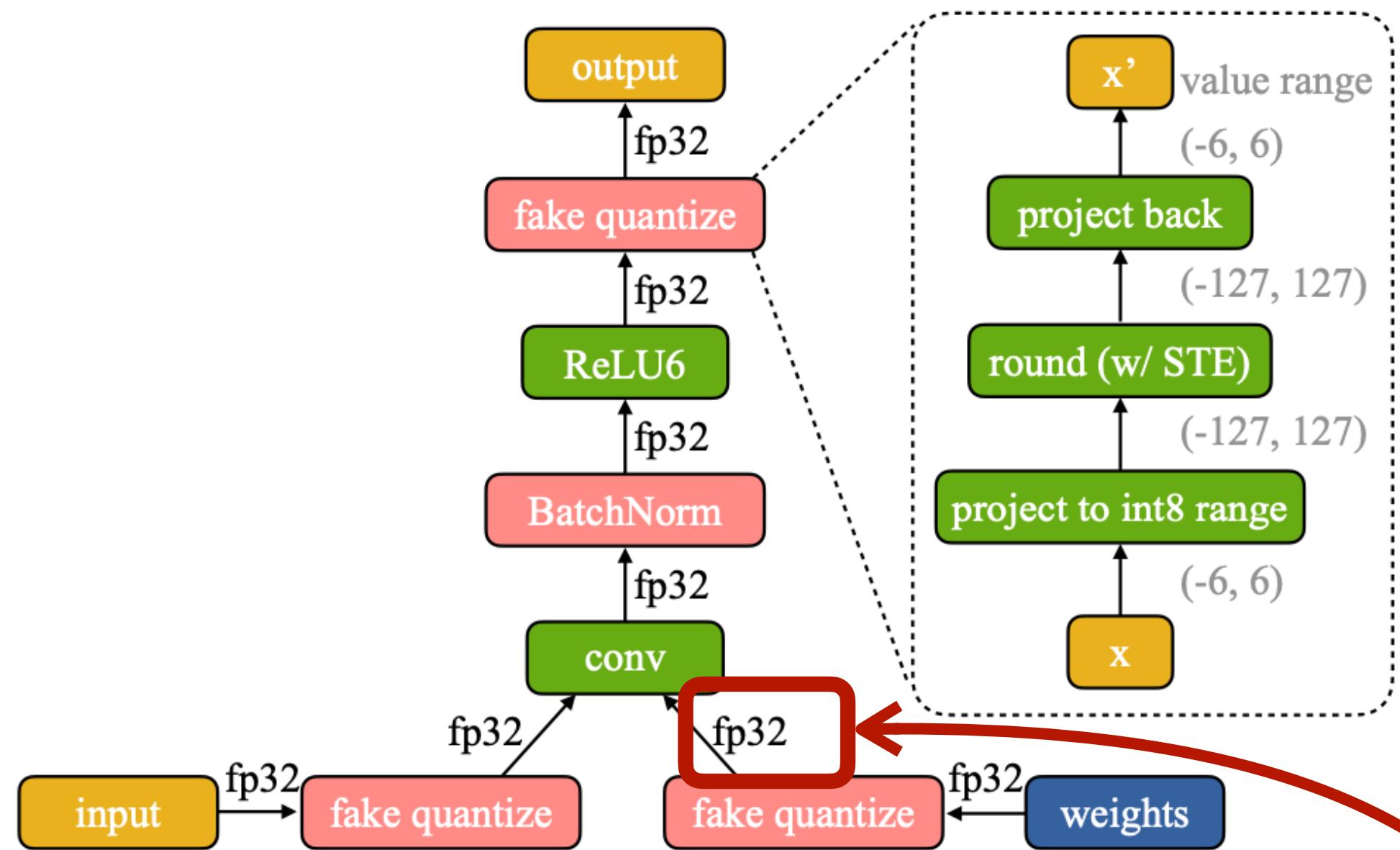
More efficient, but **difficult** to update



Real quantized graphs
(integer tensors)

Difficulty of Quantized Graphs

Fake quantization of QAT does not save training memory

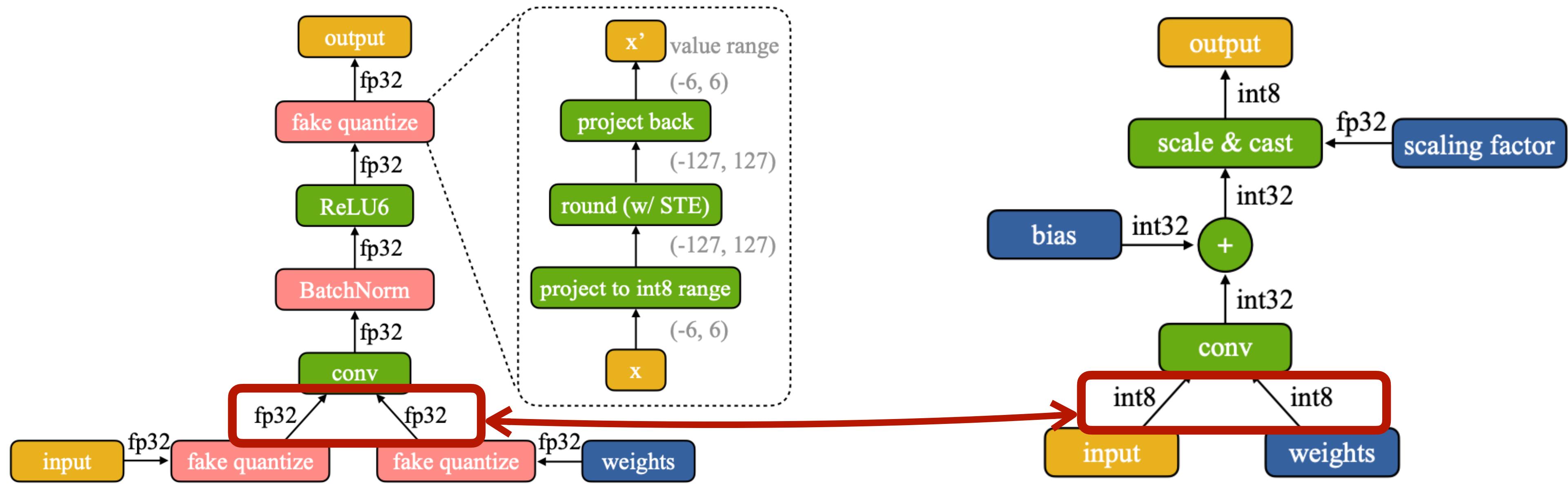


(a) Fake Quantization
(quantization aware training)

Most intermediate tensors are still in FP32 format in fake quantization,
thus cannot save memory footprint

Difficulty of Quantized Graphs

Real quantized graphs save memory, but hard to quantize



(a) Fake Quantization
(quantization aware training)

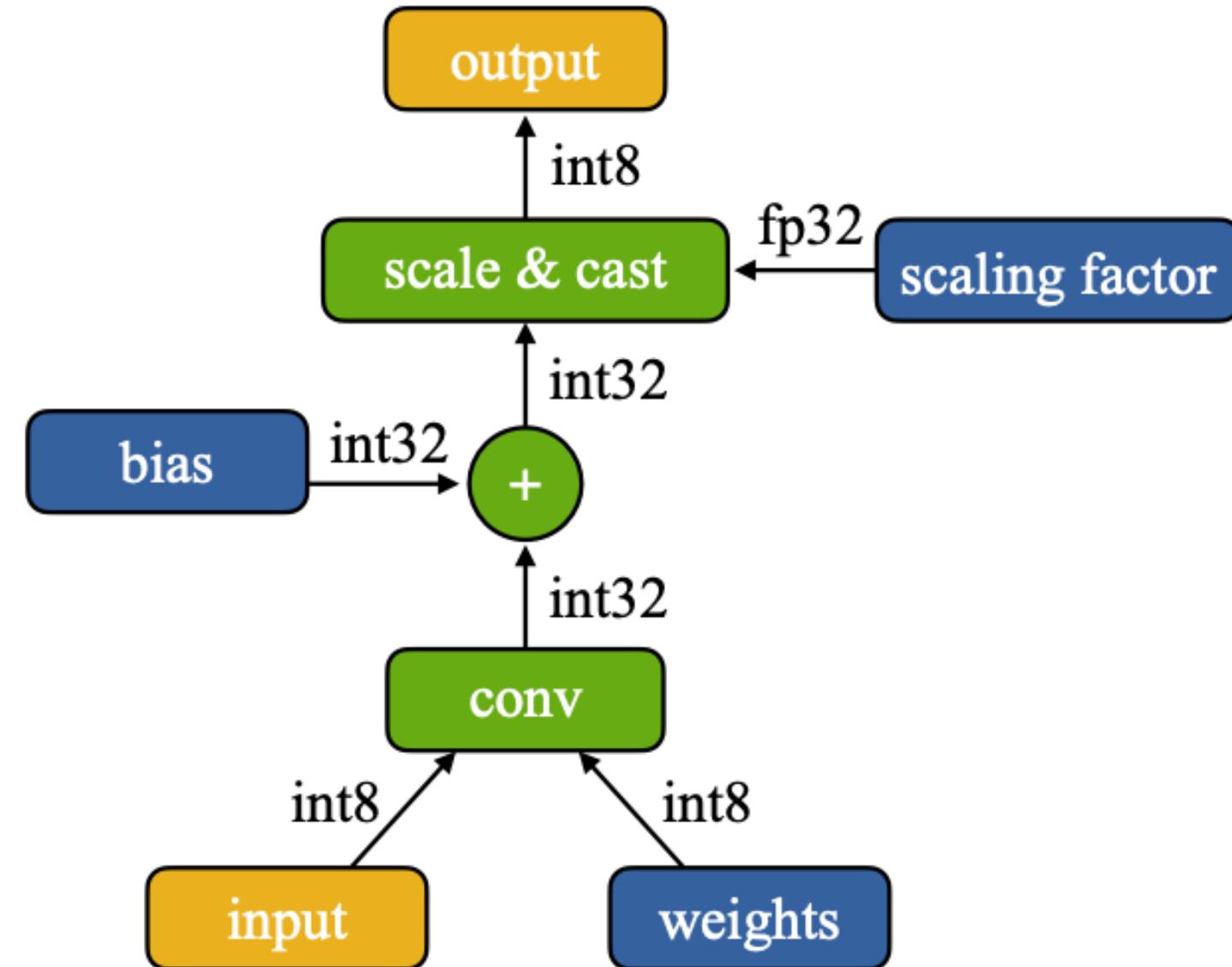
(b) Real Quantization
(inference/on-device training)

All tensors are in int8/int32 format for real quantization,
thus save memory footprint, but leading to optimization difficulty

	Fake	Real
Weight	FP32	INT8
Activation	FP32	INT8
Batch Norm	Yes	No

Difficulty of Quantized Graphs

Real quantized graphs save memory, but hard to quantize

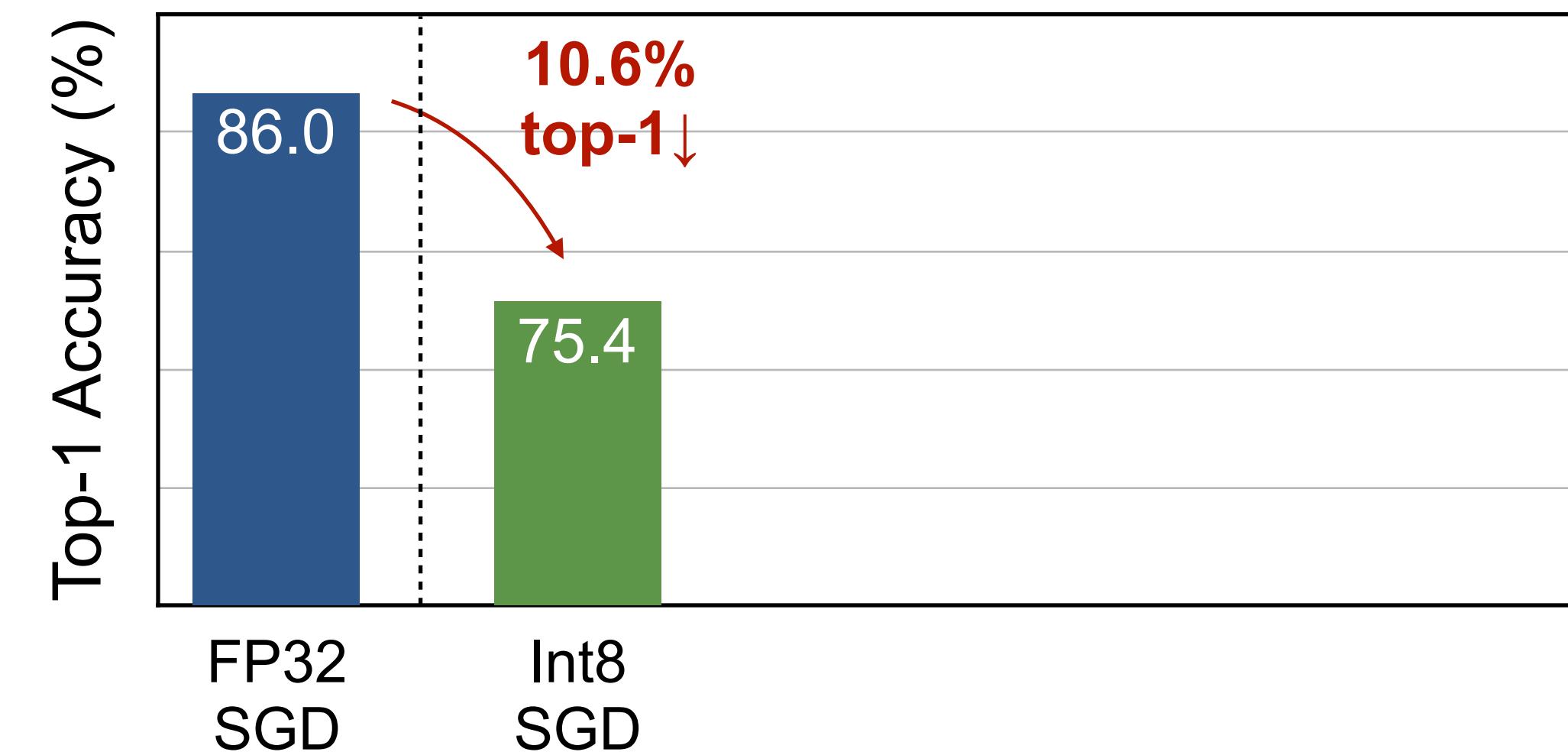


(a) Real Quantization

Making training difficult:

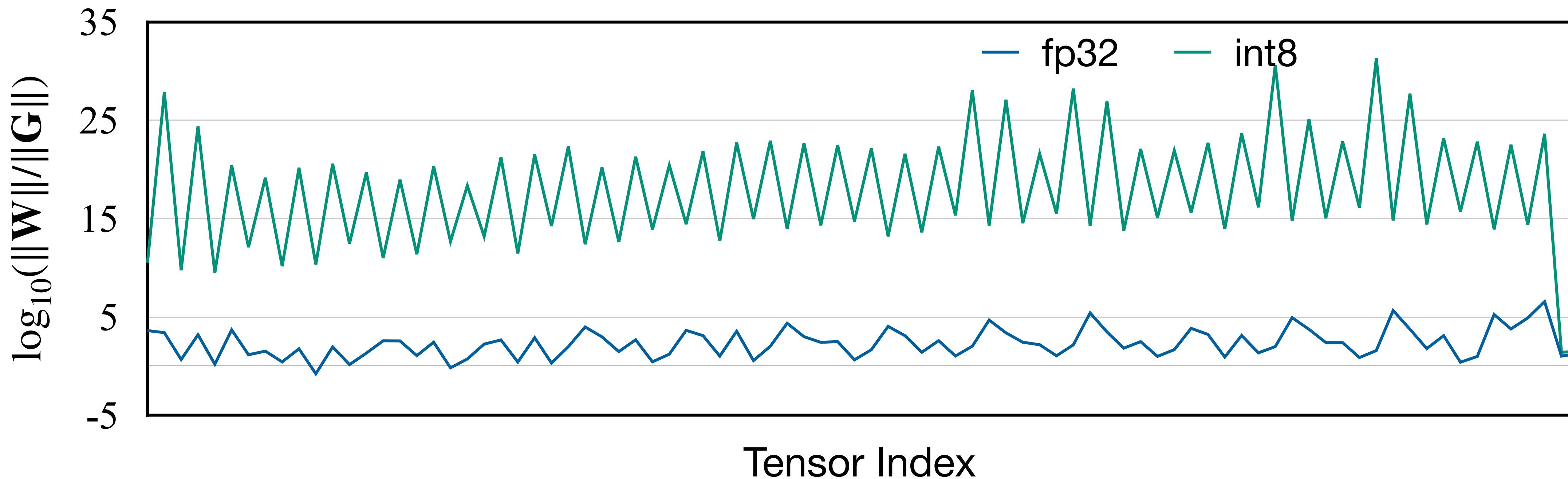
- Mixed precisions: int8/int32/fp32...
- Lack BatchNorm

Performance Comparison (average on 10 datasets)



Difficulty of Quantized Graphs

- Why is the training convergence worse?
- The scale of weight and gradients does not match in *real quantized training!*



QAS: Quantization-Aware Scaling

QAS addresses the optimization difficulty of quantized graphs

Quantization overview

$$\bar{\mathbf{y}}_{\text{int8}} = \text{cast2int8}[s_{\text{fp32}} \cdot (\bar{\mathbf{W}}_{\text{int8}} \bar{\mathbf{x}}_{\text{int8}} + \bar{\mathbf{b}}_{\text{int32}})],$$

Per Channel scaling

$$\mathbf{W} = s_{\mathbf{W}} \cdot (\mathbf{W}/s_{\mathbf{W}}) \xrightarrow{\text{quantize}} s_{\mathbf{W}} \cdot \bar{\mathbf{W}}, \quad \mathbf{G}_{\bar{\mathbf{W}}} \approx s_{\mathbf{W}} \cdot \mathbf{G}_{\mathbf{W}},$$

Weight and gradient ratios are off by $S_{\mathbf{W}}^{-2}$

Question: is $S_{\mathbf{W}} > 1$ or < 1 ?

$$\|\bar{\mathbf{W}}\|/\|\mathbf{G}_{\bar{\mathbf{W}}}\| \approx \|\mathbf{W}/s_{\mathbf{W}}\|/\|s_{\mathbf{W}} \cdot \mathbf{G}_{\mathbf{W}}\| = \boxed{s_{\mathbf{W}}^{-2}} \cdot \|\mathbf{W}\|/\|\mathbf{G}\|.$$

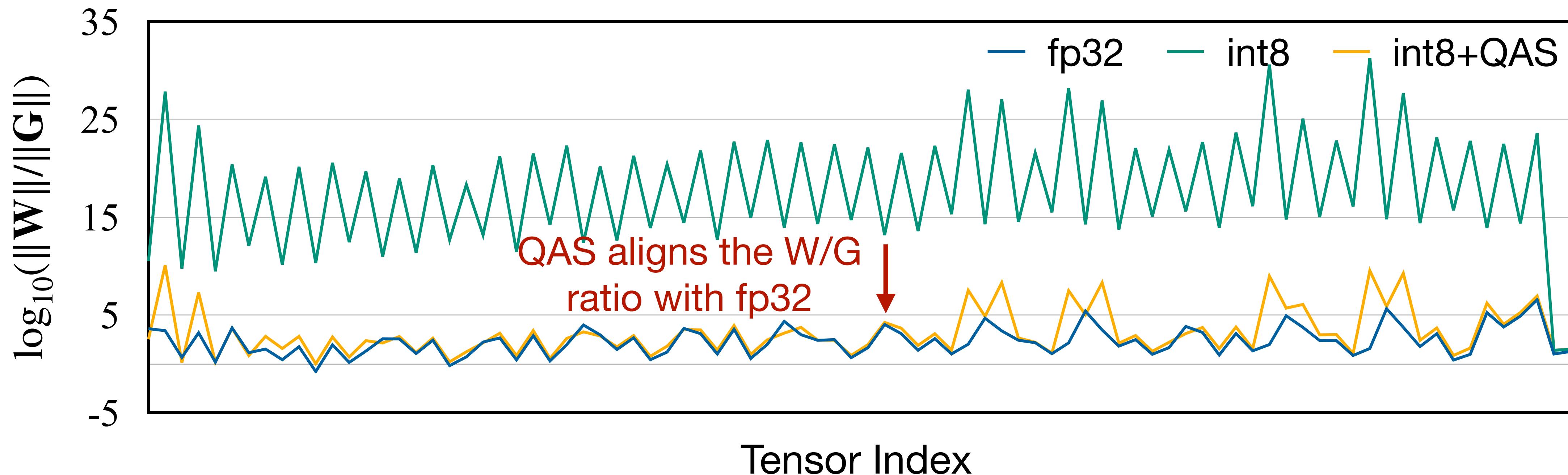
Thus, re-scale the gradients

$$\tilde{\mathbf{G}}_{\bar{\mathbf{W}}} = \mathbf{G}_{\bar{\mathbf{W}}} \cdot s_{\mathbf{W}}^{-2}, \quad \tilde{\mathbf{G}}_{\bar{\mathbf{b}}} = \mathbf{G}_{\bar{\mathbf{b}}} \cdot s_{\mathbf{W}}^{-2} \cdot s_{\mathbf{x}}^{-2} = \mathbf{G}_{\bar{\mathbf{b}}} \cdot s^{-2}$$

QAS: Quantization-Aware Scaling

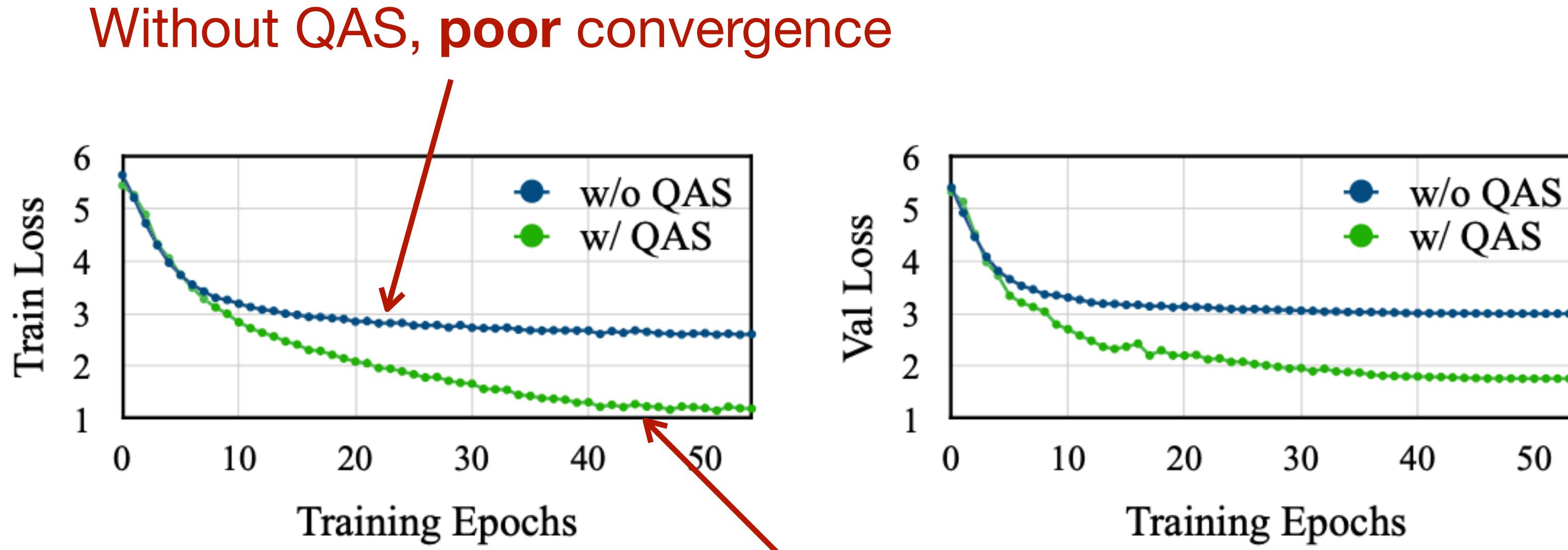
QAS addresses the optimization difficulty of quantized graphs

$$\tilde{\mathbf{G}}_{\bar{\mathbf{W}}} = \mathbf{G}_{\bar{\mathbf{W}}} \cdot s_{\mathbf{W}}^{-2}, \quad \tilde{\mathbf{G}}_{\bar{\mathbf{b}}} = \mathbf{G}_{\bar{\mathbf{b}}} \cdot s_{\mathbf{W}}^{-2} \cdot s_{\mathbf{x}}^{-2} = \mathbf{G}_{\bar{\mathbf{b}}} \cdot s^{-2}$$



QAS: Quantization-Aware Scaling

QAS addresses the optimization difficulty of quantized graphs

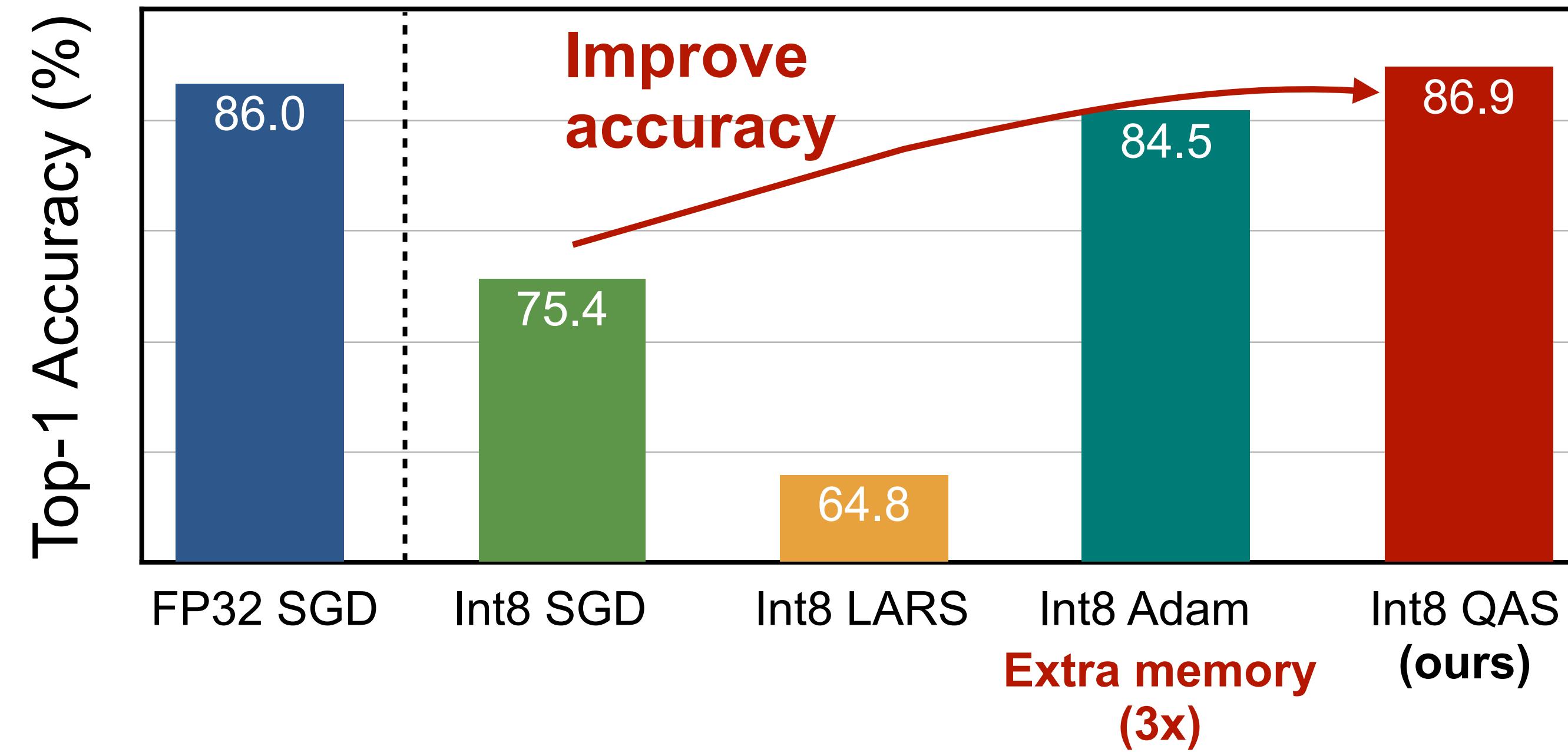


With QAS, better convergence

After applying QAS, the convergence of real quantized is stable.

QAS: Quantization-Aware Scaling

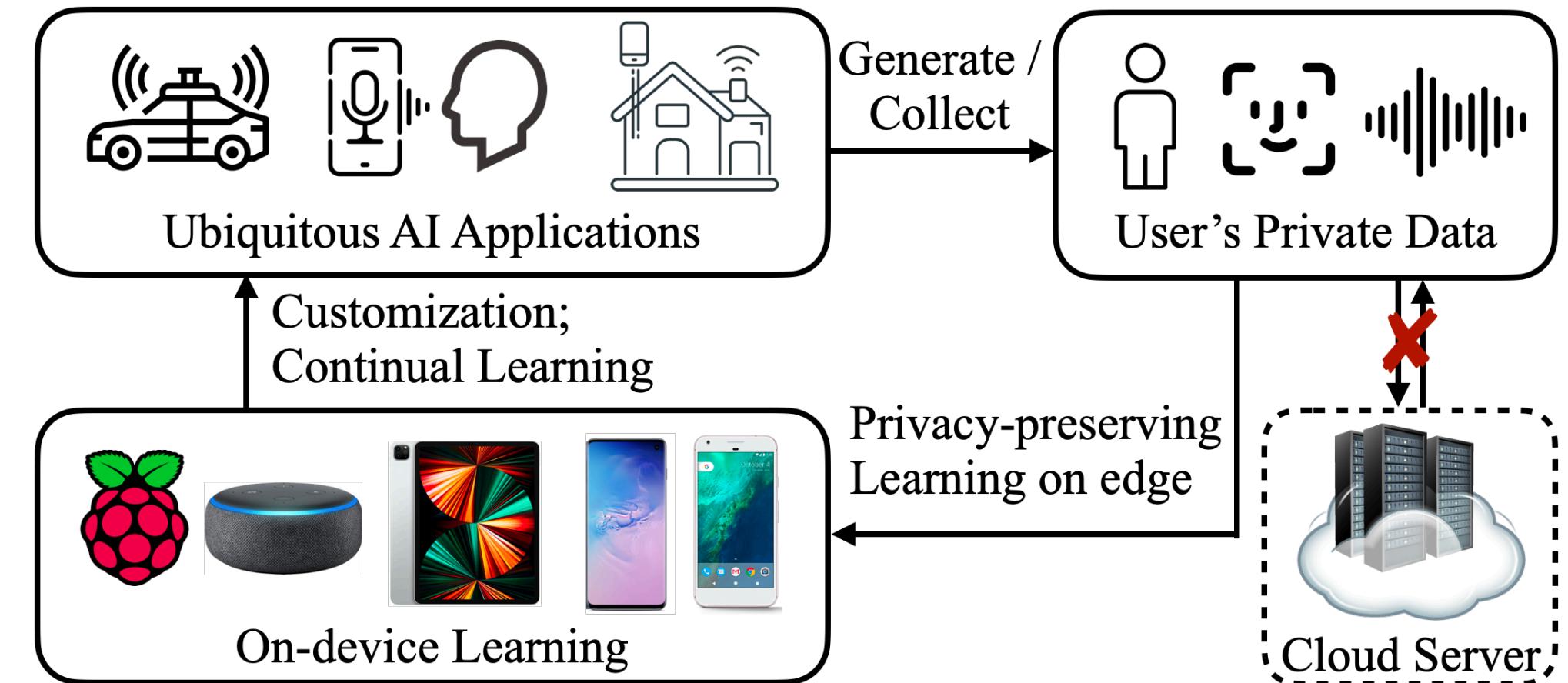
QAS addresses the optimization difficulty of quantized graphs



QAS improves the accuracy over naive int8 training, and shows no inferior performance than fp32 results.

Summary So Far

- Gradient is not safe to share. Staying local is important.
- CNN's training memory bottleneck is the activation.
- Efficient transfer learning with bias-only and lite-residual.
- Full-update is too expensive and using sparse back-propagation for on-device training.
- Why training a quantized model is difficult and how to improve by QAS.



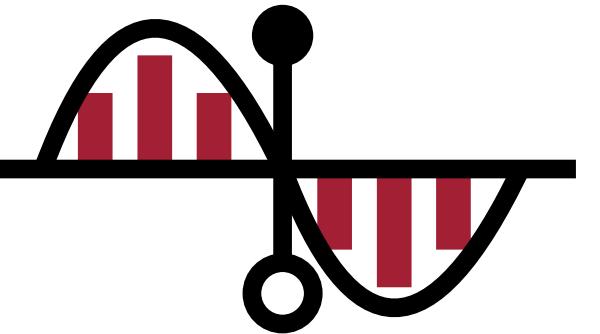
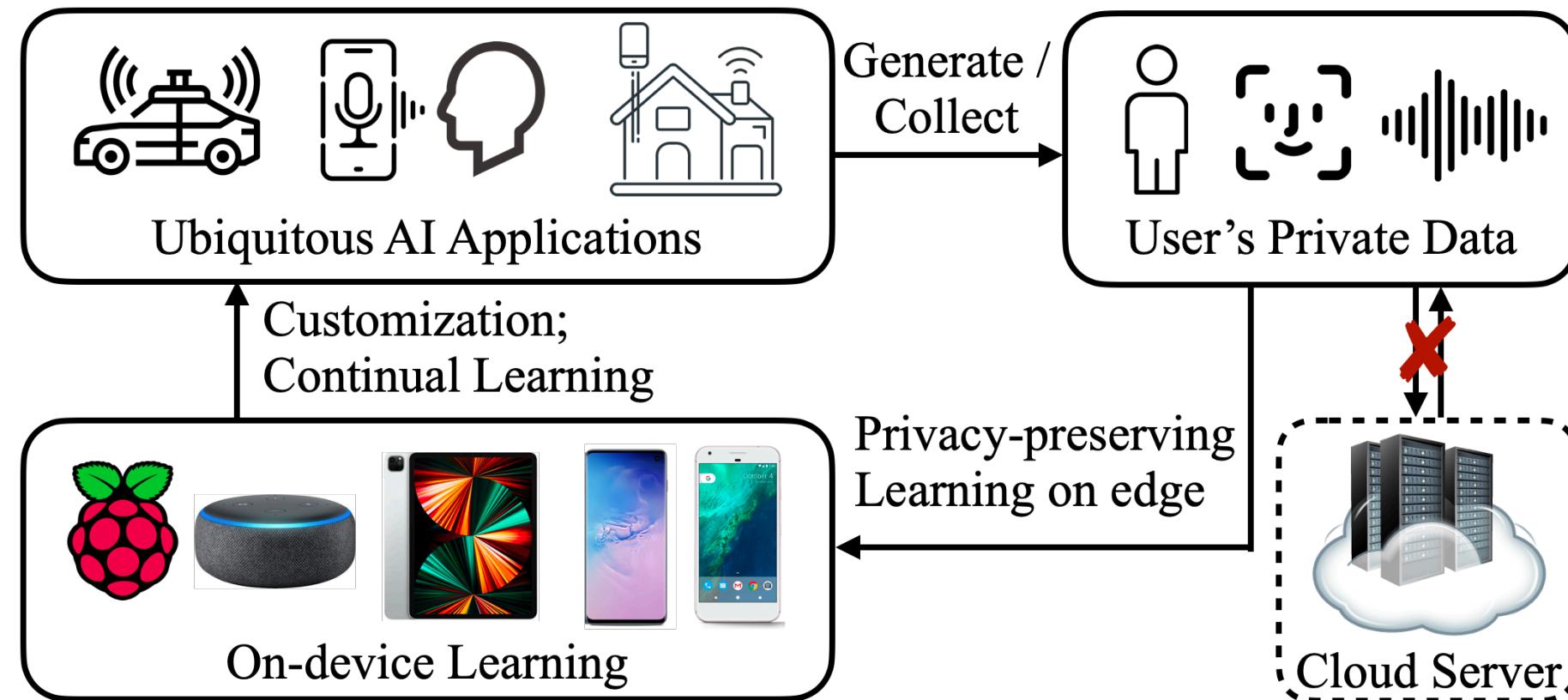
How can we translate the algorithmic improvement
into actual savings?

Algorithm System Co-Design.

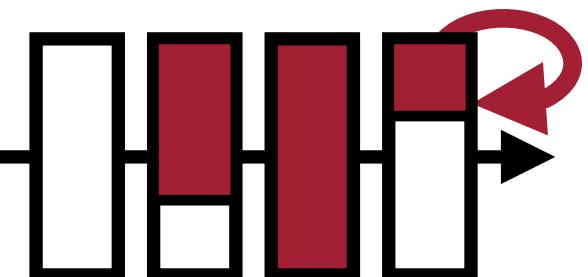
Summary of Today's Lecture

Today we will discuss:

1. Deep leakage from gradients, gradient is not safe to share
2. Memory bottleneck of on-device training
3. Tiny transfer learning (TinyTL)
4. Sparse back-propagation (SparseBP)
5. Quantized training with quantization aware scaling (QAS)
6. PockEngine: system support for sparse back-propagation



Quantized Training



Sparse Training



PockEngine

References

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- Do better imagenet models transfer better? [Kornblith. 2019]
- TinyTL: Reduce Activations, Not Trainable Parameters for Efficient On-Device Learning [Cai et al. NeurIPS 2020]
- K for the Price of 1: Parameter-efficient Multi-task and Transfer Learning [Mudrarkarta et al., ICLR 2019]
- Do We Have Brain to Spare? [Drachman et al. 2004]
- Peter Huttenlocher (1931–2013) [Walsh. 2013]
- MCUNet: Tiny Deep Learning on IoT Devices [Lin et al 2020]
- On-Device Training Under 256KB Memory [Lin et al. 2022]