Memory and Latency Efficient On-Device Continual Learning: Trends & Tricks

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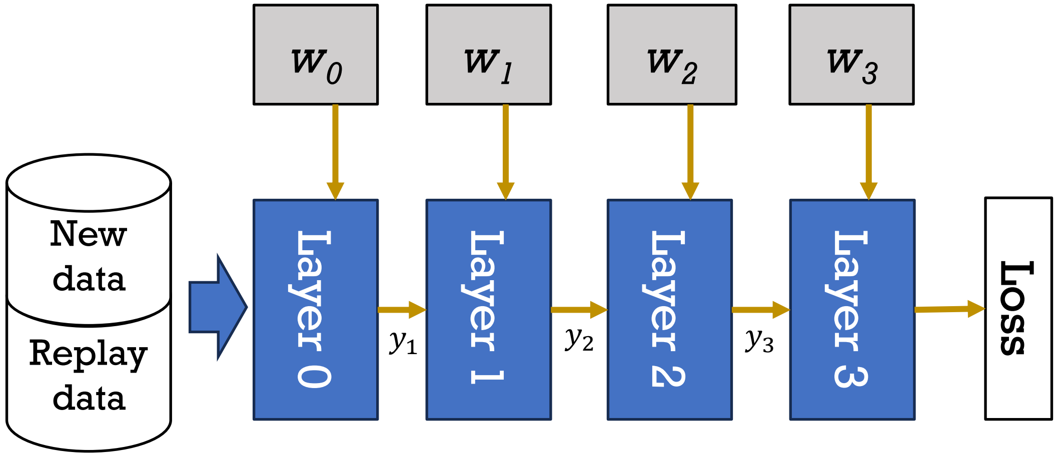
Recap: ODL costs

Forward, a.k.a. inference



inference		
	Working Mem*	$\max\ (sz(y_i) + sz(y_{i+1}) + sz(w_i))$
	Parameters	$\sum sz(w_i)$

$sz(\cdot)$ returns the number of elements

* assume layer-wise execution, sample-by-sample

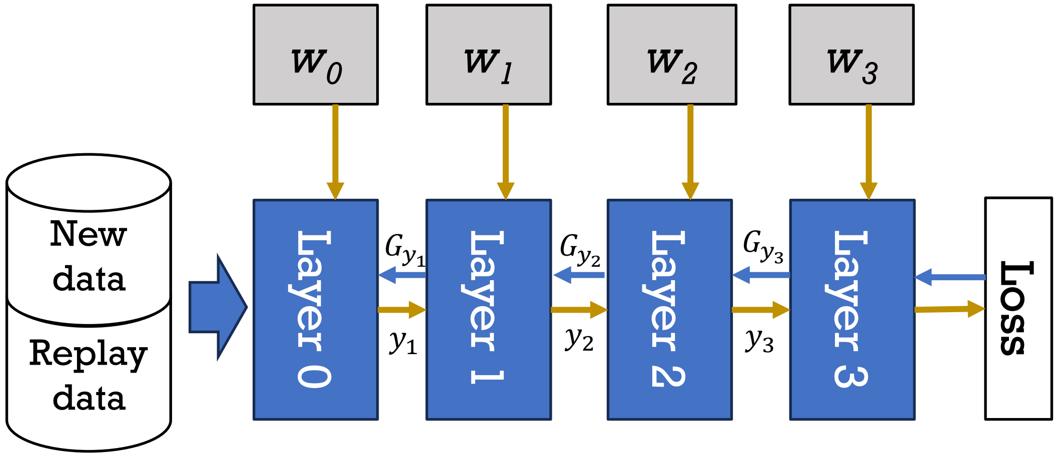
(batch)
Forward (FW)

<u>Convolution Layer ***i***</u>

$$y_{i+1} = w_i \cdot y_i$$

Recap: ODL costs

Backward the input gradients



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Convolution Layer i

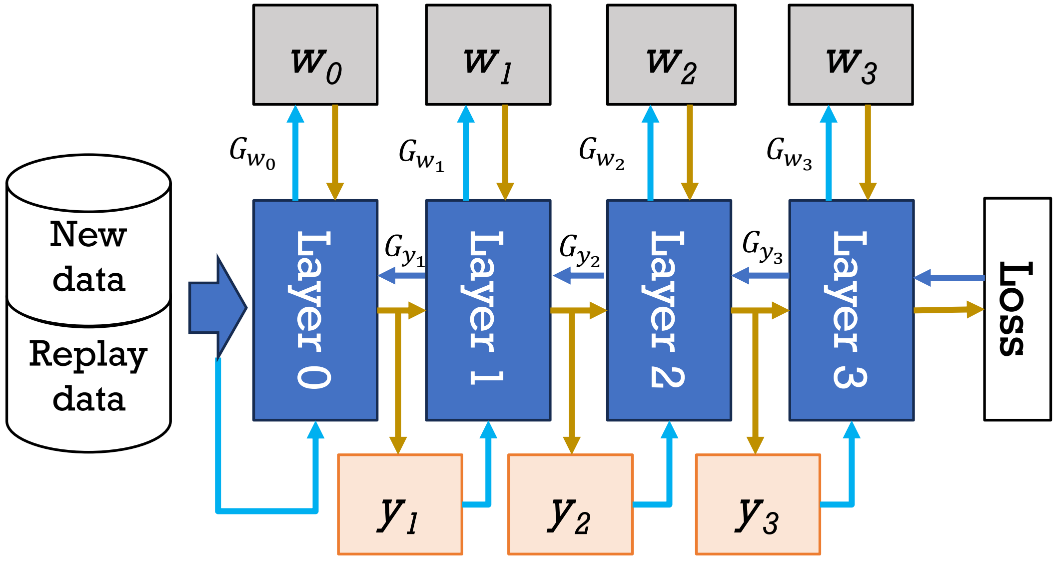
(batch) **Forward** (FW) → $y_{i+1} = w_i \cdot y_i$

Backward input gradient (BW_{ig}) ← $G_{y_i} = w_i \cdot G_{y_{i+1}}$

Note:
$G_x = \frac{\partial L}{\partial x}$

Recap: ODL costs

Backward the weight gradients



<u>Convolution Layer *i*</u>

(batch) **Forward** (FW)

$$y_{i+1} = w_i \cdot y_i$$

+ storing y_i

Backward input gradient (BW_{ig})

$$G_{y_i} = w_i \cdot G_{y_{i+1}}$$

Backward weight gradient (BW_{wg})

$$G_{w_i} = y_i \cdot G_{y_{i+1}}$$

then, update
$w_i \leftarrow w_i + \eta\, G_{w_i}$

Note:
$G_x = \frac{\partial L}{\partial x}$

inference	**Working Mem***	$\max\ (sz(y_i) + sz(y_{i+1}) + sz(w_i))$
	Parameters	$\sum sz(w_i)$
+ training	**Weight Gradients**	$\sum sz(G_{w_i})\ (== \sum sz(w_i))$
	Activation Storage for BW	$\sum sz(y_i) \cdot N_{data_b}$
	Data/Replay Mem Buffer	$N_{batch} \cdot N_{data_b} \cdot sz(data)$

$sz(\cdot)$ returns the number of elements
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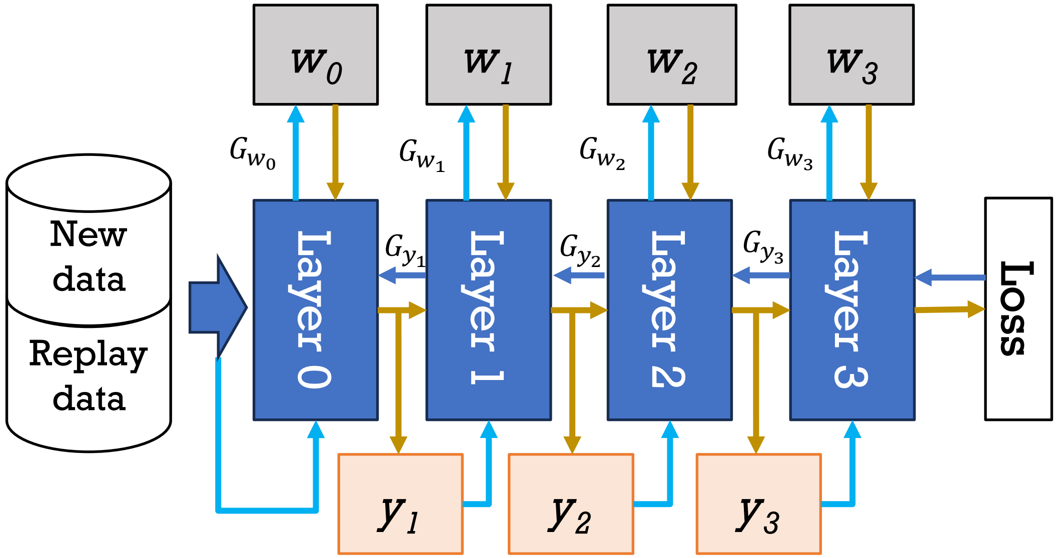
Recap: ODL costs



$$T = \underbrace{E}_{\#\text{epochs}} \cdot \overbrace{N_{batch}}^{\#\text{batches}} \cdot \underbrace{N_{data_b}}_{\#\text{data per batch}} \cdot \overbrace{(T_{FW} + T_{BW_{wg}} + T_{BW_{wg}})}^{\text{execution time per sample}}$$

Online (Streaming) Learning:
$N_{data_b} = 1$ and $E = 1$

inference	**Working Mem***	$\max\ (sz(y_i) + sz(y_{i+1}) + sz(w_i))$
inference	**Parameters**	$\sum sz(w_i)$
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<u>Convolution Layer ***i***</u>

(batch) **Forward** (FW)	$y_{i+1} = w_i \cdot y_i$	+ storing y_i
Backward input gradient (BW_{ig})	$G_{y_i} = w_i \cdot G_{y_{i+1}}$	
Backward weight gradient (BW_{wg})	$G_{w_i} = y_i \cdot G_{y_{i+1}}$	then, update $w_i \leftarrow w_i + \eta\, G_{w_i}$

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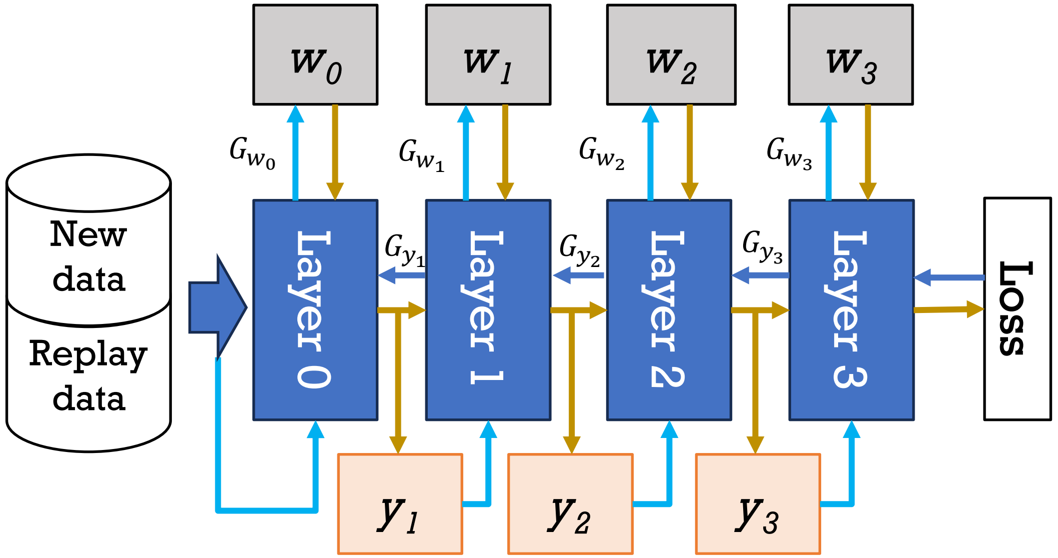
Recap: ODL costs



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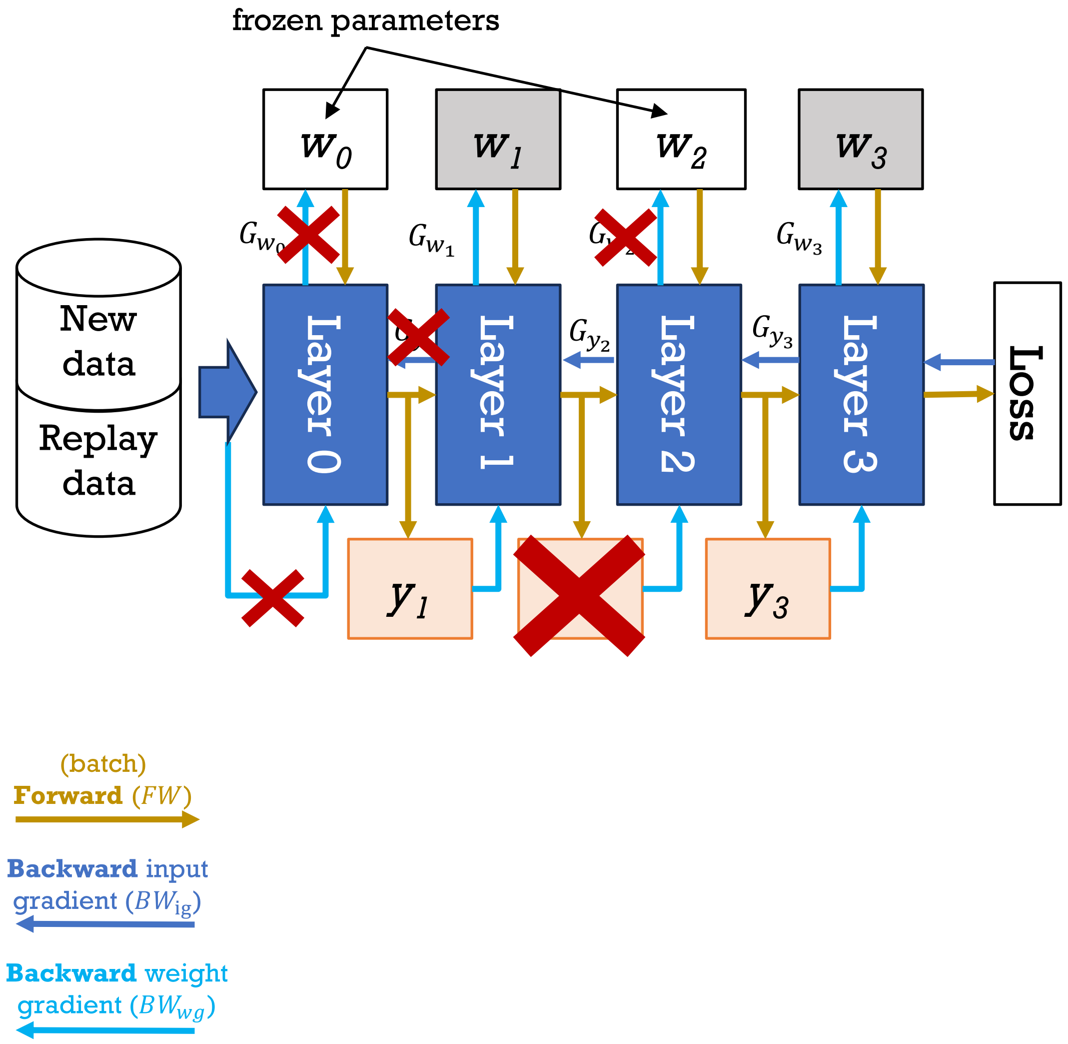
Problem: High latency and (activation) memory costs

Efficient Trainable Models

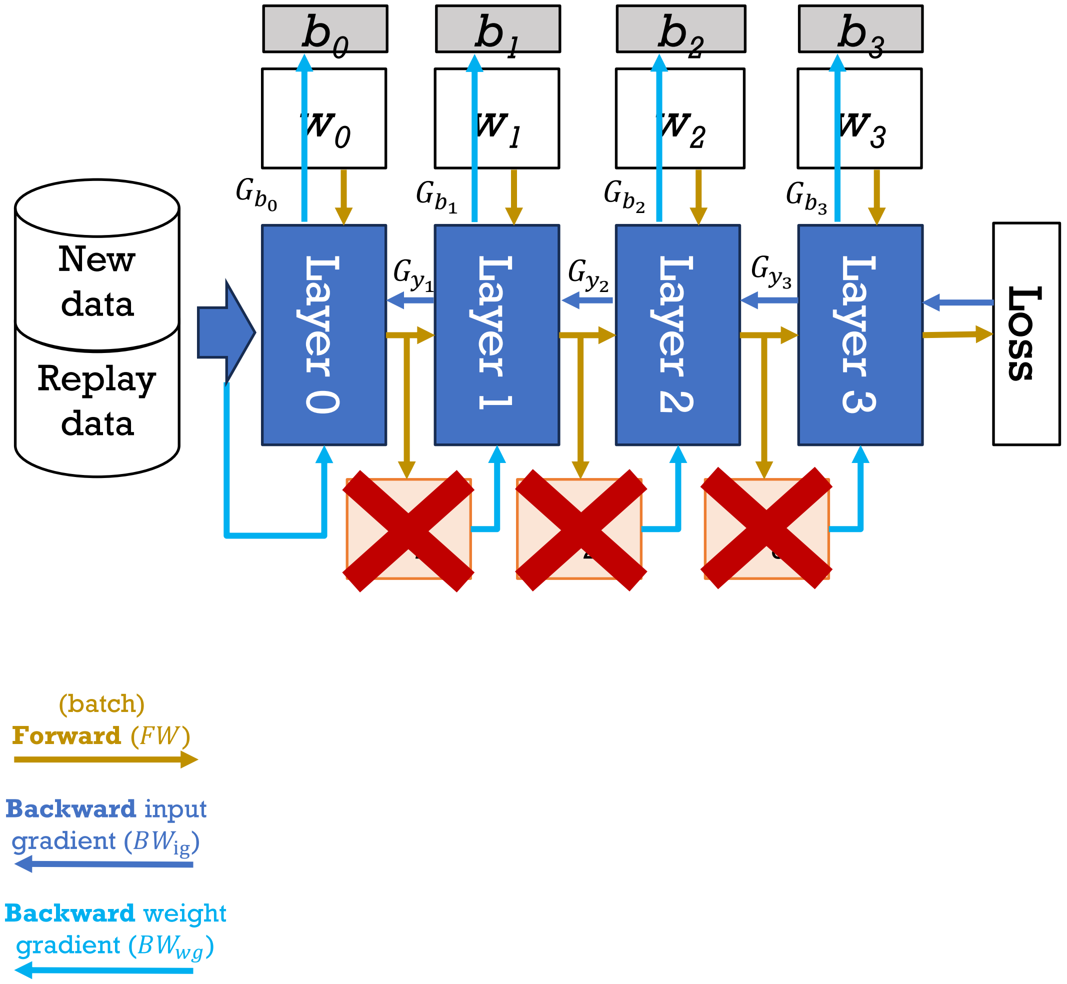


<u>Update only few layers</u> (w_1, w_3)

- ✓ Lower backward time ($T_{BW_{ig}}$, $T_{BW_{wg}}$) vs. full-backprop
- ✓ Lower gradient & activations vs. full-backprop
- × Lower accuracy than full-backprop

- Retraining only the last layer on MCUs, e.g. *TinyOL* [Ren2021]
- First layers have larger activation sizes (and more generic features): keep them frozen!

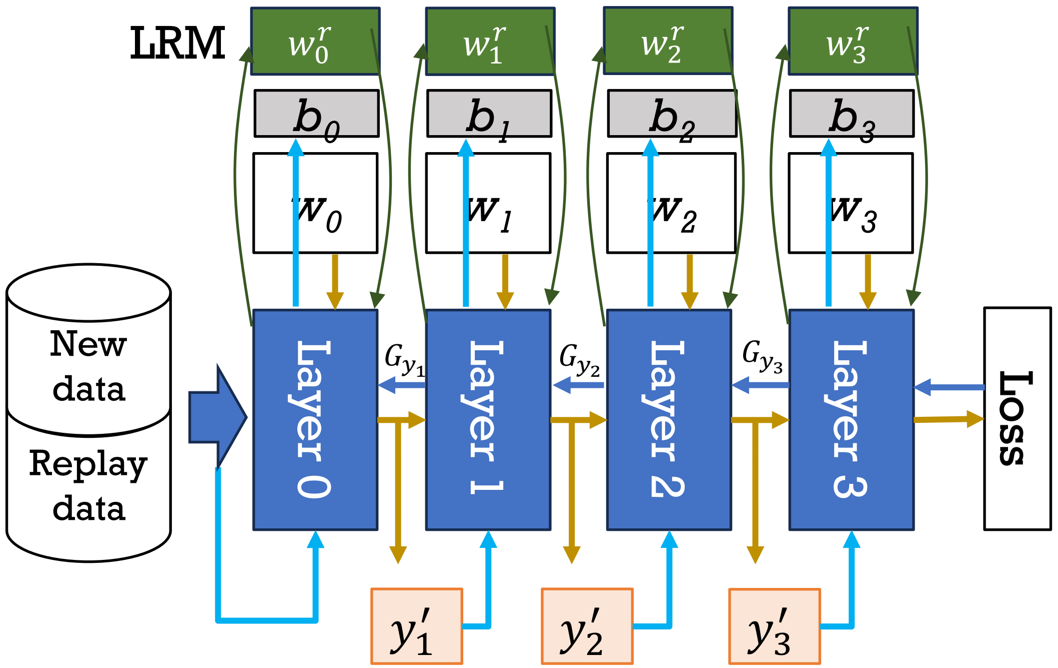
TinyTL: Tiny Transfer Learning [Cai2020]



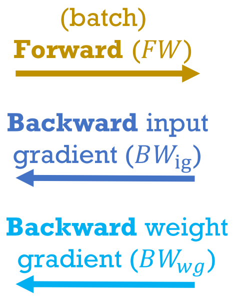
<u>Retraining only the biases</u>

$y_{i+1} = w_i \cdot y_i + b_i \rightarrow \boxed{G_{b_i} = G_{y_{i+1}}}$ does *not* depend from y_i

TinyTL: Tiny Transfer Learning [Cai2020]



smaller than y_1, y_2, y_3



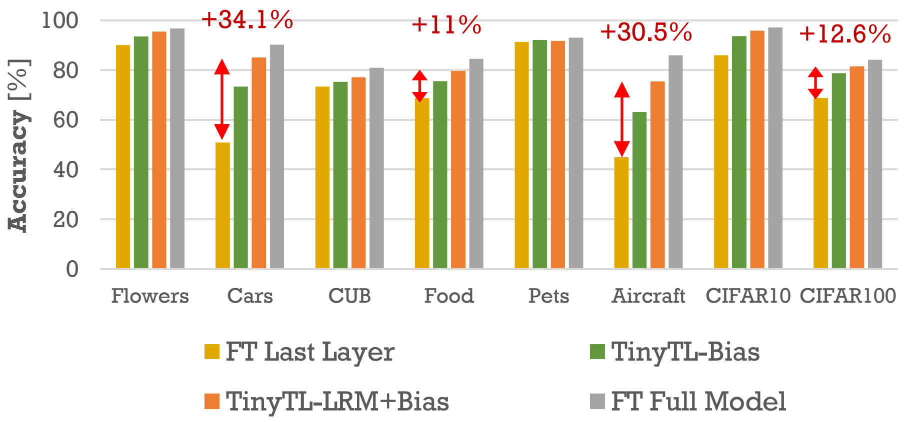
Retraining only the biases

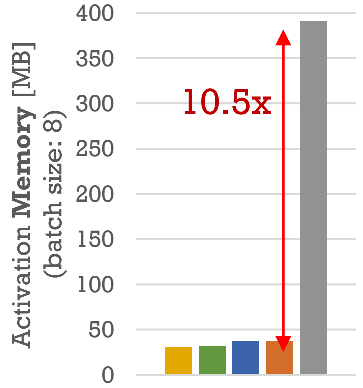
$$y_{i+1} = w_i \cdot y_i + b_i \rightarrow \boxed{G_{b_i} = G_{y_{i+1}}}$$

does *not* depend from y_i

Lite Residual Modules (LRM)

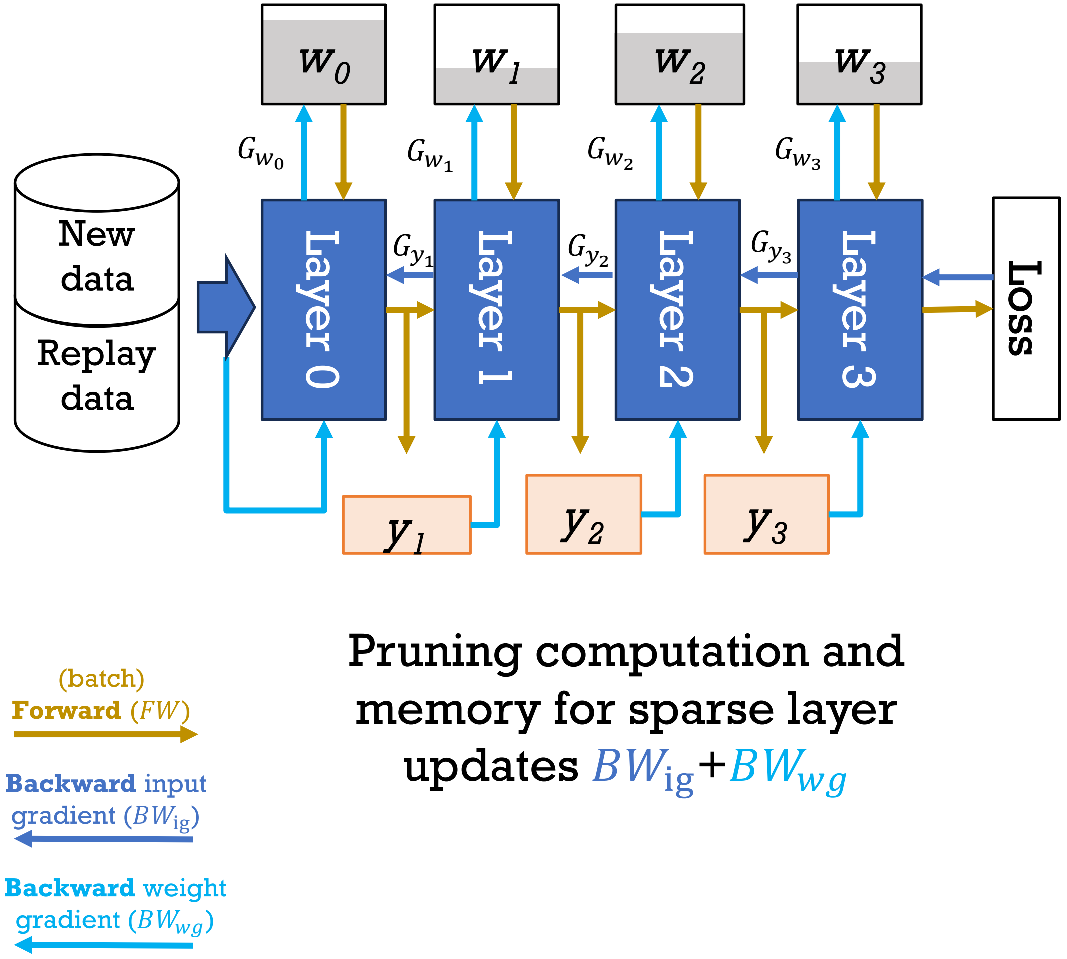
$$y_{i+1} = w_i \cdot y_i + b_i + \boxed{f_{w_i^r}(y'_i = pool(y_i))}$$





LRM+B achieves the best memory accuracy trade-off

(Structured) Sparse Updates



Pruning computation and memory for sparse layer updates BW_{ig}+BW_{wg}

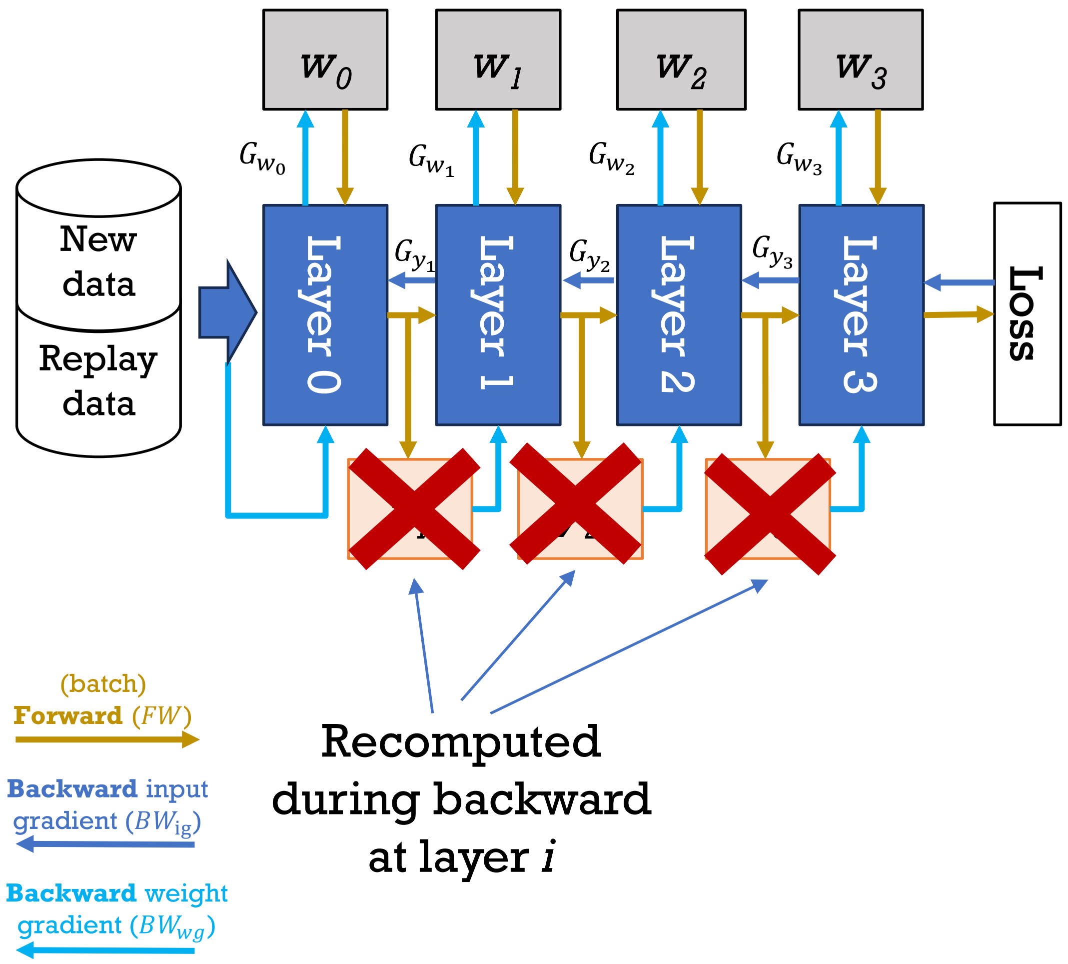
Pruning weight gradient computation BW_{wg} (and BW_{ig}) of less important weight or sub-tensors [Lin2022][Kwon2023]

- High transfer learning capacity (less overfitting vs. full-retraining) but **4.5-7x** memory saving [Lin2022]

Which weights to update?

- Evolutionary search (offline) with a per-layer contribution as the cost function [Lin2022]
- Multi-objective cost w/ Fisher information (online) [Kwon2023]

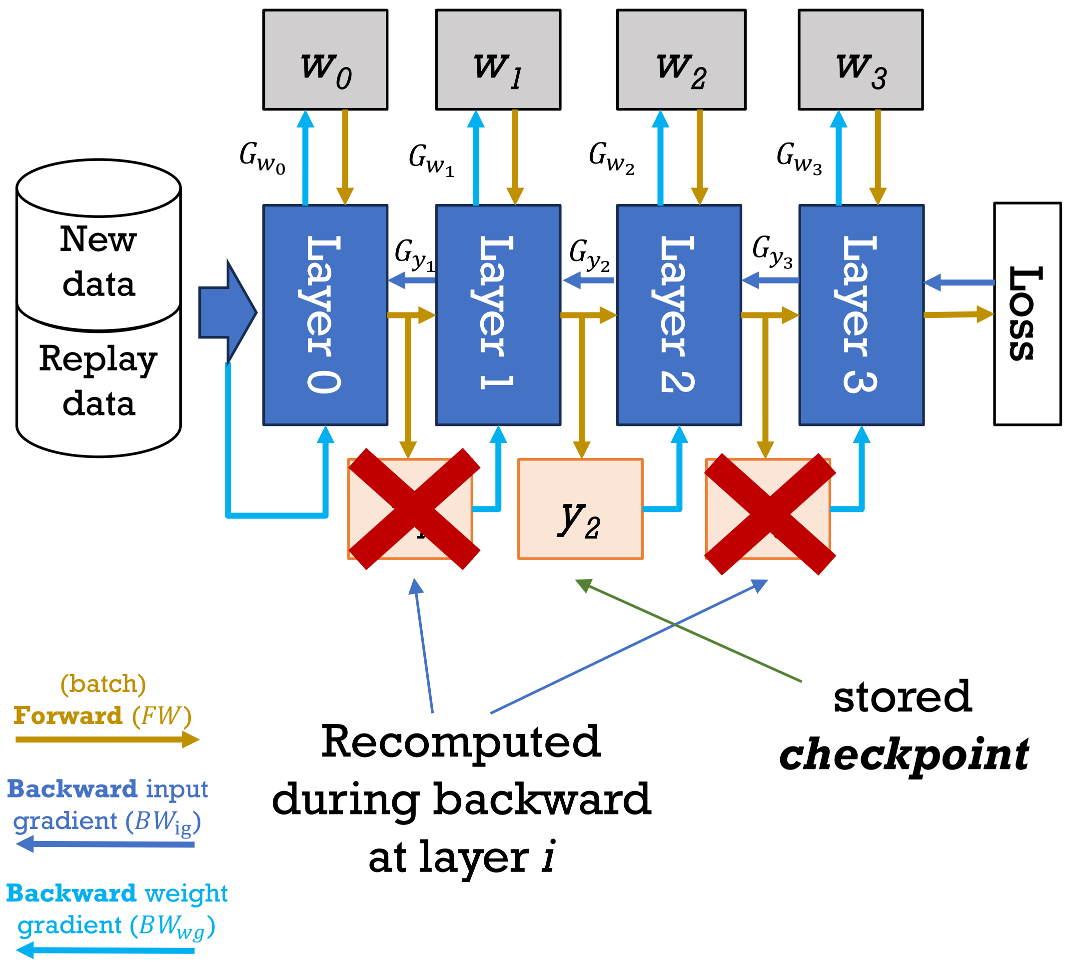
“Removing” the Memory Constraints



Update **all** parameters **without** storing the activations

- Activation tensors are recomputed layer-wise backward

"Removing" the Memory Constraints



Update **all** parameters **without** storing the activations

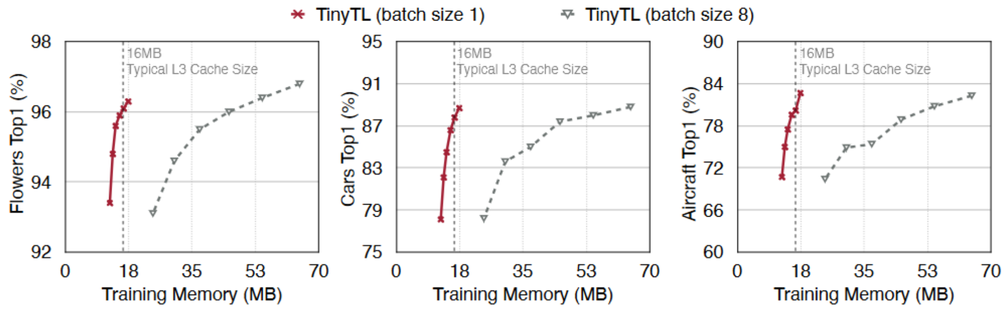
- Activation tensors are recomputed layer-wise backward

Only stores some **checkpoints** for faster training

- Convenient to recompute cheap-to-compute yet memory-intensive tensors, e.g., ReLU layers.
- *DaCapo* [Khan2023]
  - Exhaustive search to select checkpoints (w/ mem and latency constraints)
- *POET* [Patil2022]
  - Mixed Integer Linear Programming
  - Combined with paging: activations copied to off-chip memories
  - Trains ResNet-18 and BERT on tiny ARM Cortex M class devices

Other Relevant Tricks

- Batch Norm requires large batch sizes for accurate stats
  - **Group Norm** for small batch size [Cai2020]



Group Norm with batch size=1 same acc. vs. bs=8

- Lossless Low-precision training
  - Mixed-precision Training (FP32+FP16) [Narang2017]
  - INT8 [Lin2022] with Quantization-Aware Scaling: $G_W = G_W \cdot s_W^{-2}$

Scaling factor from quantization

- Replay Storage (& activation)
  - Low-bitwidth quantization (≤8-bit) [Ravaglia2021]
  - Product Quantization (PQ) compression [Hayes2020]

What is (or can be) next!

- HW-SW co-design for ODL for real-world continual learning benchmarks
  - Training algorithms under memory and latency constraints
  - Absence of or few labels available for continual learning
    - Few-shot & auxiliary tasks
  - Convergence time of the training algorithms (#epochs, #data)
    - Under-explored domain.

- Applications of On-Device Continual Learning
  - Detaching from “classic” benchmark datasets (Cifar10, Mnist,….)

- Novel MCU HW architectures
  - Always-on inference + <u>occasionally training</u>
  - New opportunities for heterogeneity

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Questions

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