
# Lecture 07:
# Efficient DNN Training, Parameter efficient Finetuning, Federated Learning

# Some Notes: Project Proposal

- Due on Mar 19th (1 page)
- You should begin forming teams of 2-3 students and start brainstorming project ideas now.
- You should propose something feasible to do.
- Please discuss with me during office hours.

# Some Notes: Midterm

- April 2nd.
- Will cover materials up to lecture 8.
- Will release the detailed coverage.
- In-class exam.

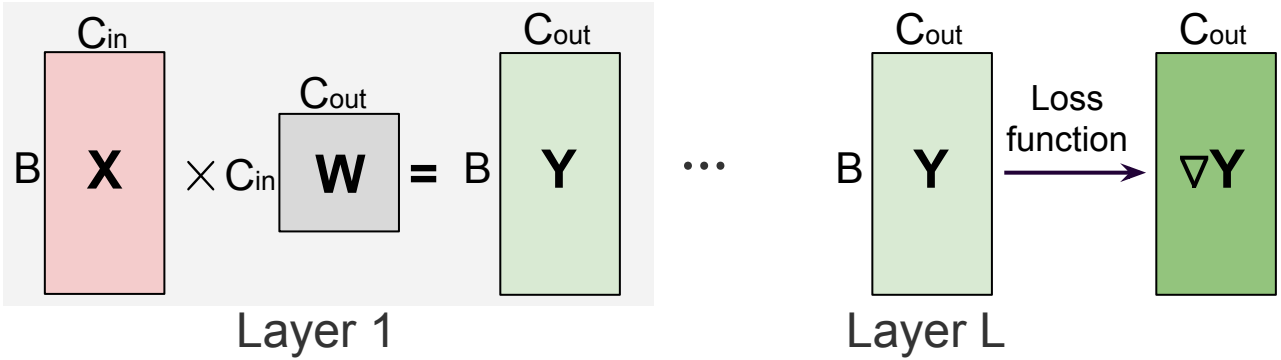
# Recap

- Distillation
- Low-rank factorization
- Neural Network Search (NAS)

# Topics

- Efficient training of DNNs
  - Efficient computing
  - Efficient storage
- Parameter efficient finetuning
- Federated Learning

# Forward Pass for Linear Layer



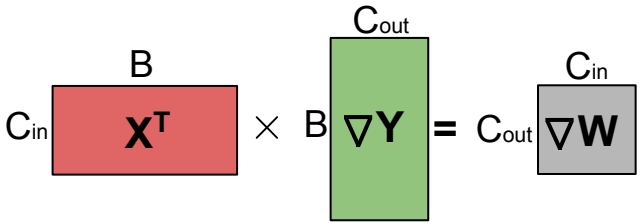

B: batch size $C_{in}$: input channels $C_{out}$: output channels

**X**: input maps **W**: weight filters **Y**: output maps

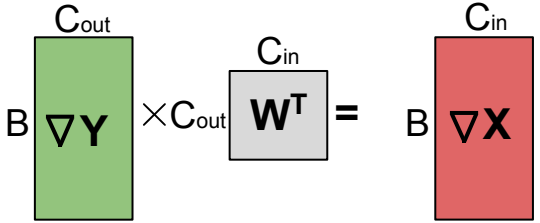
- The fully-connected layer during the forward propagation can be converted into matrix multiplications

# Backward Pass for Linear Layer

**Weight Gradient Computation**




**Data Gradient Computation**




**X**: input maps **W**: weight filters **Y**: output maps

**∇X**: input gradient **∇W**: weight gradient **∇Y**: output gradient

- DNN backward propagation involves two matrix multiplications

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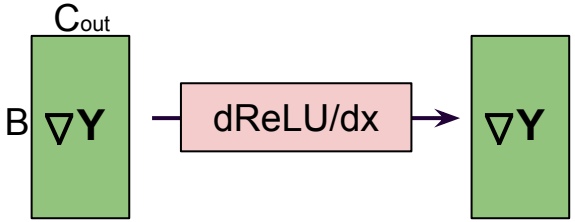
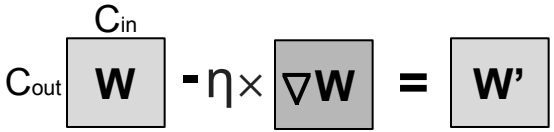
# Backward Pass for Linear Layer

**Data Gradient Computations**




**Weight Gradient Updates**

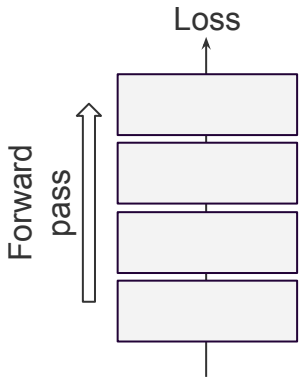



**X**: input maps **W**: weight filters **Y**: output maps

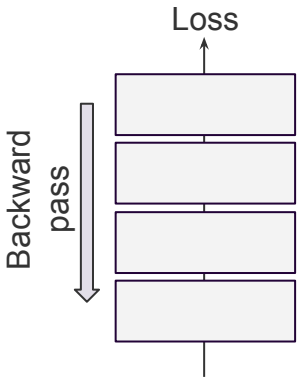
**∇X**: input gradient **∇W**: weight gradient **∇Y**: output gradient

- DNN backward propagation involves two matrix multiplications

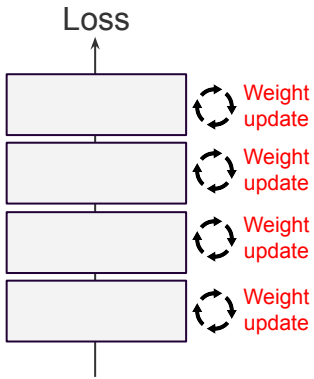
# Training Process




```
def forward(self, x):
    ...
return
```




```
loss.backward()
```




```
optimizer.step()
```

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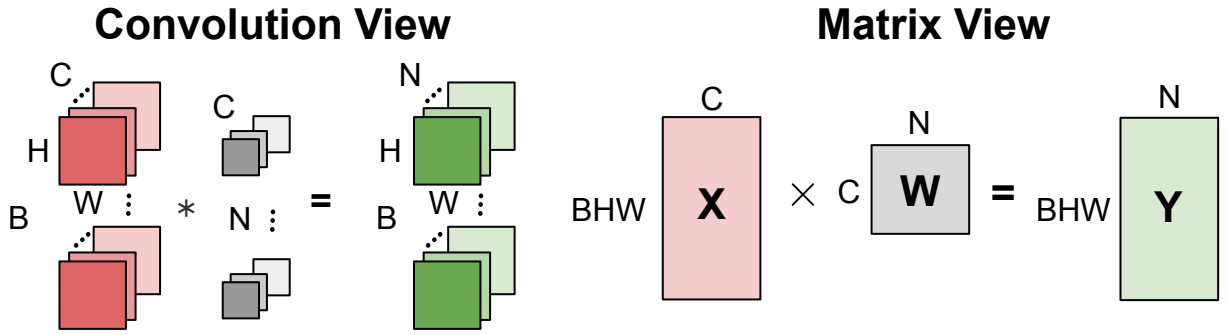
# Forward Pass for Convolutional Layer

Forward Pass

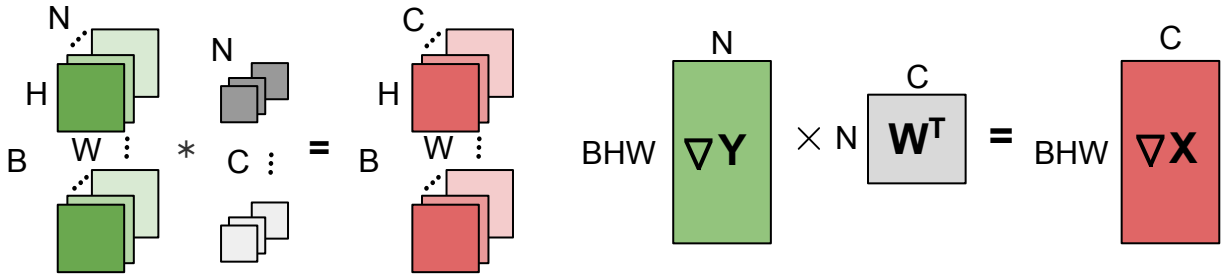
Compute output **Y**




- Assume a weight kernel size of 1✖1.

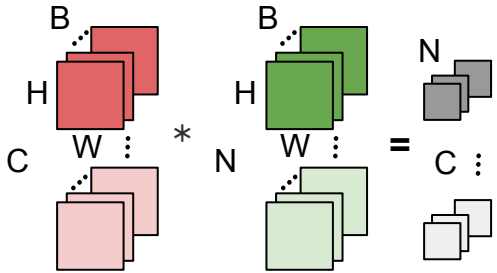
# Backward Pass for Convolutional Layer

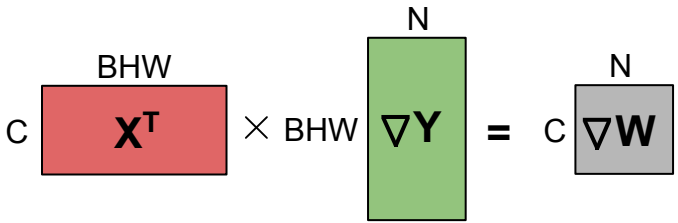
Backward Pass
Compute Activation gradients $\nabla X$



# Backward Pass for Convolutional Layer

Backward Pass
Compute weight gradients $\nabla \mathbf{W}$

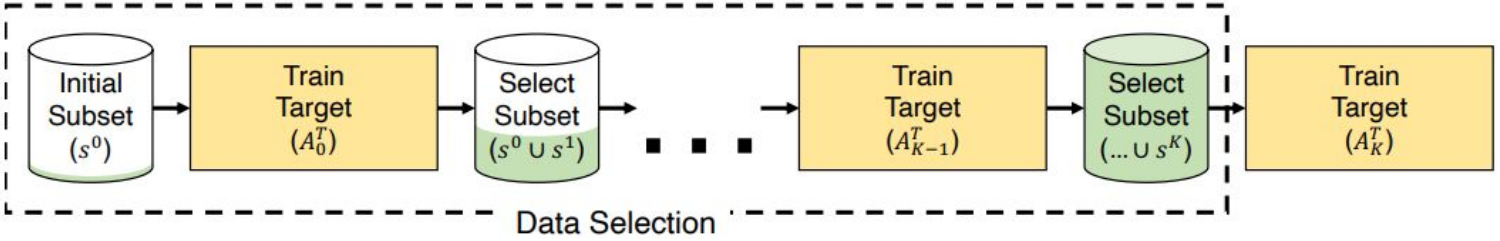


# Efficient Computing during Training

- To reduce the training cost of DNN, we can proceed from the following dimensions:
  - Training data sampling
  - Parameter sampling
  - Pruning during training
  - Quantization during training

# Training Data Sampling for Efficiency




- Assume a total b samples are targeted to be picked. We consider a batch setting with K rounds where we select b/K points in every round.
- Training the target model with b/K samples, then evaluate the rest of the sample over the model. Find the batch with the least confidence score. Append it to the training dataset.

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Cody Coleman, Stephen Mussmann, Baharan Mirzasoleiman, Peter Bailis, Percy Liang, Jure Leskovec, and Matei Zaharia. Select via proxy: Efficient data selection for training deep networks, 2019.

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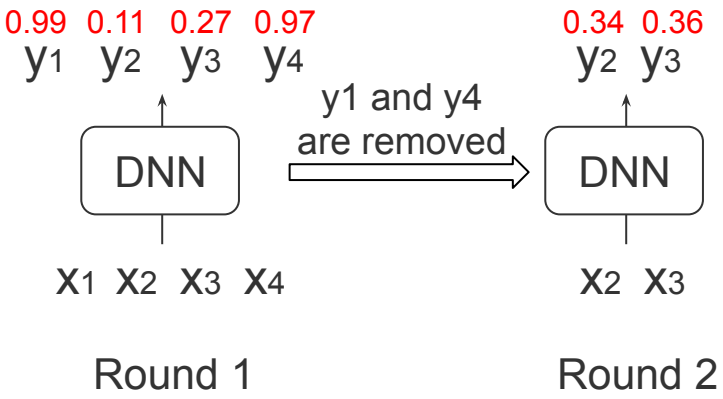


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# Efficient Computing during Training

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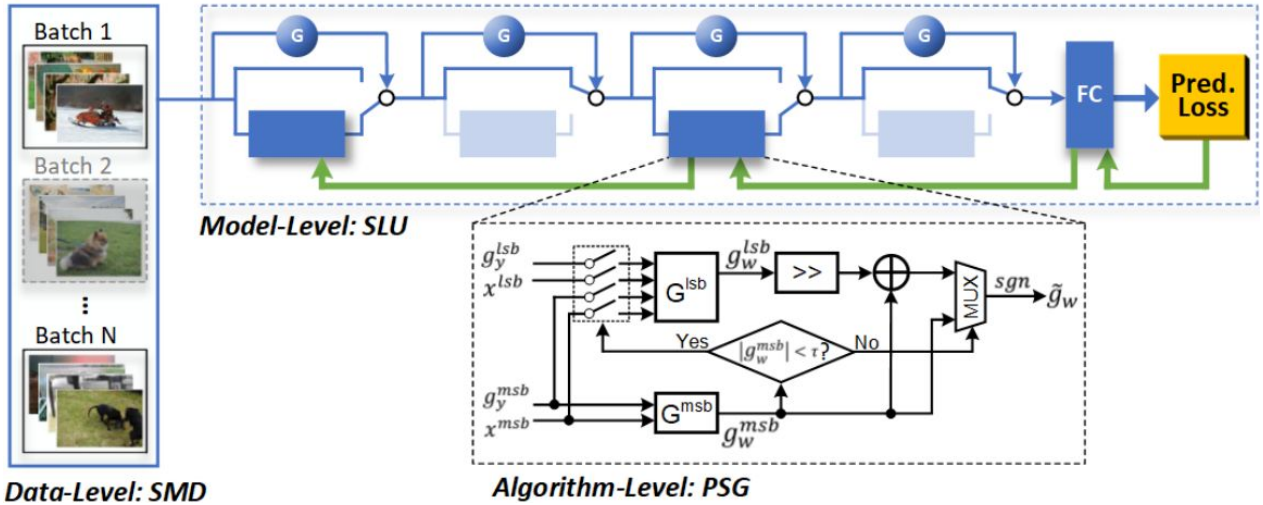
# E2-Train

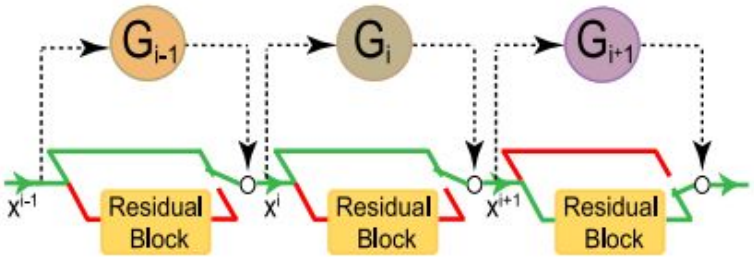



- A stochastic mini-batch dropping strategy is proposed.
- Stochastic minibatch dropping simply skips every mini-batch with a default probability of 0.5.
- For some easy dataset, this will generate negligible impact on performance.



Wang, Yue, et al. "E2-train: Training state-of-the-art cnns with over 80% energy savings." *Advances in Neural Information Processing Systems* 32 (2019).

# Dynamically Layer Skipping




- $G_i(x_i) \in \{0, 1\}$ is the gating function for layer i.
- It determines whether to skip to current residual block or not.
- During the training, G and residual blocks are trained together.
- Loss = acc_loss + computation_loss
- We will skip different layers adaptively based on inputs.


Wang, Xin, et al. "Skipnet: Learning dynamic routing in convolutional networks." *Proceedings of the European conference on computer vision (ECCV)*. 2018.

Wang, Yue, et al. "E2-train: Training state-of-the-art cnns with over 80% energy savings." *Advances in Neural Information Processing Systems* 32 (2019).

# Efficient Computing during Training

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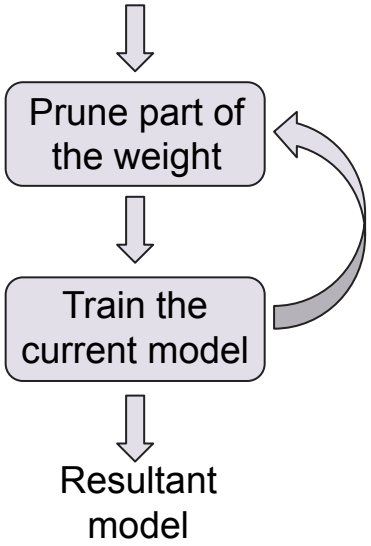
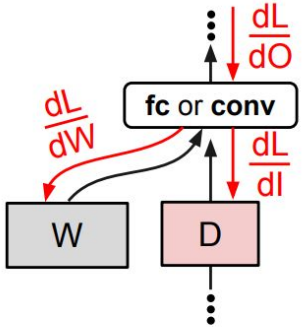
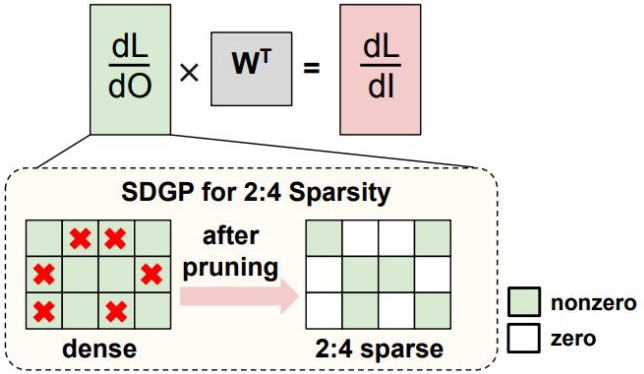
# Pruning during Training




- We can remove the unnecessary weight during the DNN training process.



McDanel, Bradley, Helia Dinh, and John Magallanes. "Accelerating dnn training with structured data gradient pruning." *2022 26th International Conference on Pattern Recognition (ICPR)*. IEEE, 2022.

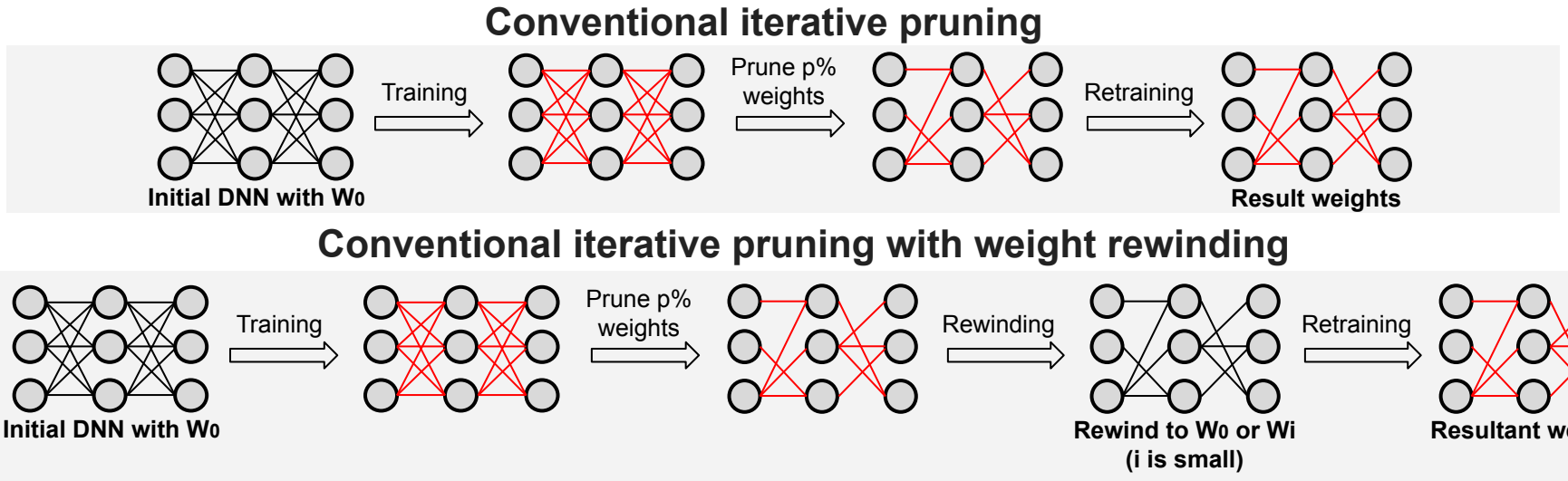
# How to Find the Winning Tickets?

- **Iterative Magnitude Pruning (IMP):**
  - Initialized DNN with random weights $w_0$.
  - While the sparsity level has not reached:
    - Train the DNN with k epochs until convergence
    - prune p% of the nonzero weights.
    - Reinitialize the remaining weights using the values in $w_0$, finetune the remaining weights for k epochs (**Rewind**).
  - Return the weights.
- Later work has shown that rewind to $w_i$ (i is small) works better for larger networks.



Frankle, Jonathan, et al. "Stabilizing the lottery ticket hypothesis." *arXiv preprint arXiv:1903.01611* (2019).

# Weight Rewinding




- The pruned architecture itself, rather than a set of inherited “important” weights, is more crucial to the accuracy in the final model, which suggests that in some cases pruning can be useful as an architecture search paradigm.

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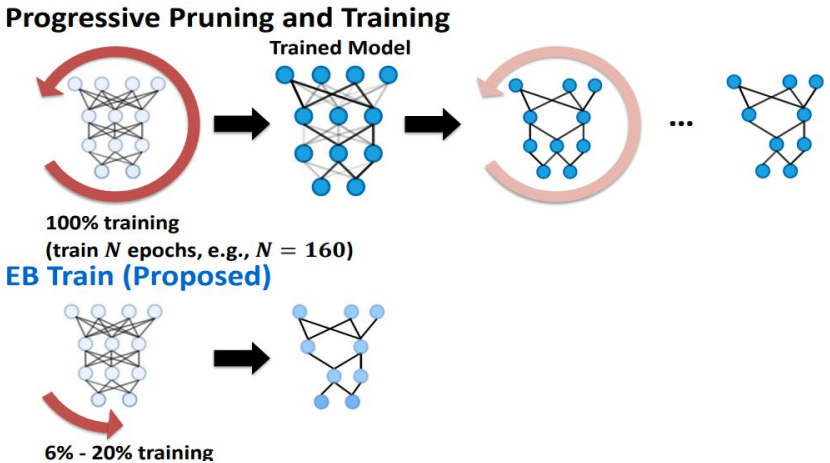
Liu, Zhuang, et al. "Rethinking the value of network pruning." *arXiv preprint arXiv:1810.05270* (2018).

# Early-bird Ticket




- LTH shows that there exist winning tickets (small but critical subnetworks) for dense, randomly initialized networks, that can be trained alone to achieve a comparable accuracy to the latter in a similar number of iterations.
- The winning tickets can be drawn very early in training and with aggressively low-cost training algorithms.
- Early-bird tickets can be founded via low-cost training schemes (e.g., early stopping and low-precision training) at large learning rates

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You, Haoran, et al. "Drawing early-bird tickets: Towards more efficient training of deep networks." *arXiv preprint arXiv:1909.11957* (2019).

# Early-bird Ticket

**Algorithm 1:** The Algorithm for Searching EB Tickets

Initialize the weights $\boldsymbol{W}$, scaling factor $r$, pruning ratio $p$, and the FIFO queue $Q$ with length $l$;
**while** $t$ (epoch) $< t_{max}$ **do**
  Update $\boldsymbol{W}$ and $r$ using SGD training;
  Perform structured pruning based on $r_t$ towards the target ratio $p$;
  Calculate the **mask distance** between the current and last subnetworks and add to $Q$.
  $t = t + 1$
  **if Max**$(Q) < \epsilon$ **then**
    $t^* = t$
    **Return** $f(x; m_{t^*} \odot \boldsymbol{W})$ (EB ticket);
  **end if**
**end while**

The mask pattern is stable

- To search for the lottery ticket, we can early stop the DNN training.



You, Haoran, et al. "Drawing early-bird tickets: Towards more efficient training of deep networks." *arXiv preprint arXiv:1909.11957* (2019).

# Efficient Computing during Training

- To reduce the training cost of DNN, we can proceed from the following dimensions:
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  - Quantization during training

# DoReFaNet

Compute $g_{a_L} = \frac{\partial C}{\partial a_L}$ knowing $a_L$ and $a^*$.
**for** $k = L$ **to** 1 **do**
  Back-propagate $g_{a_k}$ through activation function $h$
  $g^b_{a_k} \leftarrow f^G_\gamma(g_{a_k})$
  $g_{a_{k-1}} \leftarrow \texttt{backward\_input}(g^b_{a_k}, W^b_k)$
  $g_{W^b_k} \leftarrow \texttt{backward\_weight}(g^b_{a_k}, a^b_{k-1})$
  Back-propagate gradients through pooling layer if there is one
**end for**
{2. Accumulating the parameters gradients:}
**for** $k = 1$ **to** $L$ **do**
  $g_{W_k} = g_{W^b_k} \frac{\partial W^b_k}{\partial W_k}$
  $W^{t+1}_k \leftarrow Update(W_k, g_{W_k}, \eta)$
**end for**

- Linear quantize the weights and activations
- Apply stochastic quantization for the gradients.



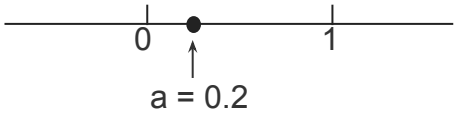
Zhou, Shuchang, et al. "Dorefa-net: Training low bitwidth convolutional neural networks with low bitwidth gradients." *arXiv preprint arXiv:1606.06160* (2016).

# DoReFaNet

- Usually gradients requires far more bitwidth than weight and activation.
- Usually gradient requires **stochastic quantization**.

| W | A | G | Training Complexity | Inference Complexity | Storage Relative Size | AlexNet Accuracy |
|---|---|---|---|---|---|---|
| 1 | 1 | 6 | 7 | 1 | 1 | 0.395 |
| 1 | 1 | 8 | 9 | 1 | 1 | 0.395 |
| 1 | 1 | 32 | - | 1 | 1 | 0.279 (BNN) |
| 1 | 1 | 32 | - | 1 | 1 | 0.442 (XNOR-Net) |
| 1 | 1 | 32 | - | 1 | 1 | 0.401 |
| 1 | 1 | 32 | - | 1 | 1 | 0.436 (initialized) |
| 1 | 2 | 6 | 8 | 2 | 1 | 0.461 |
| 1 | 2 | 8 | 10 | 2 | 1 | 0.463 |
| 1 | 2 | 32 | - | 2 | 1 | 0.477 |
| 1 | 2 | 32 | - | 2 | 1 | 0.498 (initialized) |
| 1 | 3 | 6 | 9 | 3 | 1 | 0.471 |
| 1 | 3 | 32 | - | 3 | 1 | 0.484 |
| 1 | 4 | 6 | - | 4 | 1 | 0.482 |
| 1 | 4 | 32 | - | 4 | 1 | 0.503 |
| 1 | 4 | 32 | - | 4 | 1 | 0.530 (initialized) |
| 8 | 8 | 8 | - | - | 8 | 0.530 |
| 32 | 32 | 32 | - | - | 32 | 0.559 |

# Deterministic and Stochastic Quantization



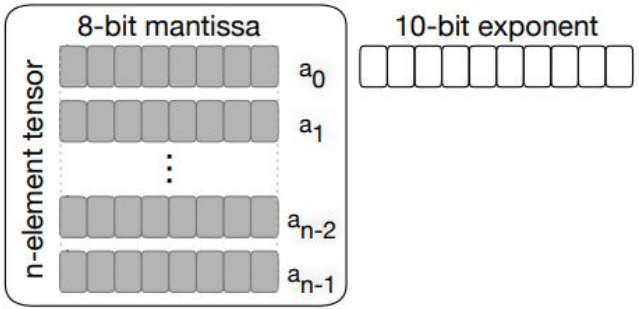

- To quantize a, conventional linear quantization will make q(a) = 0. However, this will cause a bias.
- With stochastic quantization:

$$q(a) = \begin{cases} 1 & \text{for } p = 0.2 \\ 0 & \text{for } p = 0.8 \end{cases}$$

- Stochastic quantization is extremely useful when applying quantization to accelerate DNN training.

# Training DNNs with Hybrid BFP


(a) FP repr. with an exponent per tensor element.




(b) BFP repr. with an exponent per tensor.

- Block floating point format achieves a better hardware efficiency and comparable representation capability than FP.

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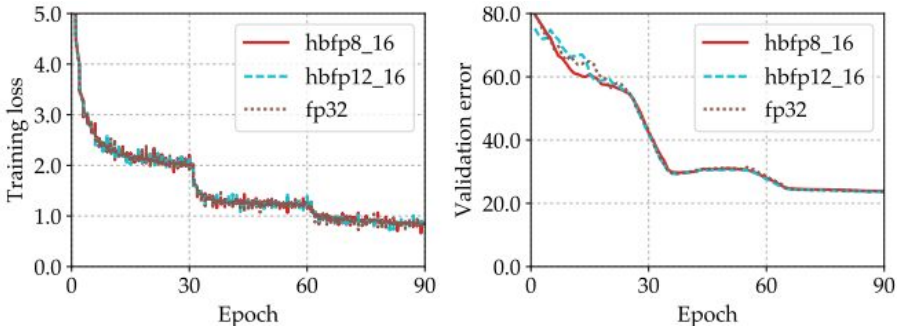
Drumond, Mario, et al. "Training dnns with hybrid block floating point." *Advances in Neural Information Processing Systems* 31 (2018).

# Training DNNs with Hybrid BFP

- Use BFP in all dot-product-based operations present in DNNs (i.e., convolutions, matrix multiplications, and outer products), and floating-point representations for all other operations (i.e., activations, regularizations, etc).
- To minimize data loss in long-lasting training state, the weights are stored with wider mantissas.




- ResNet-50 trained on ImageNet for 90 epochs.
- 8 bit mantissa, 16 bits weight seems to achieve comparable performance as FP32. A mantissa bitwidth of 12 achieves an even better performance.
- A tile size of 24

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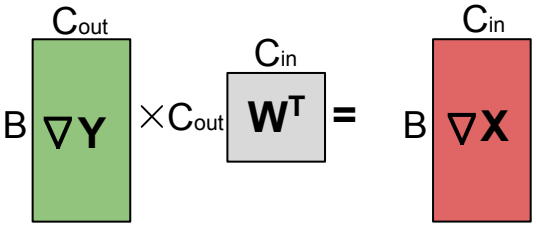
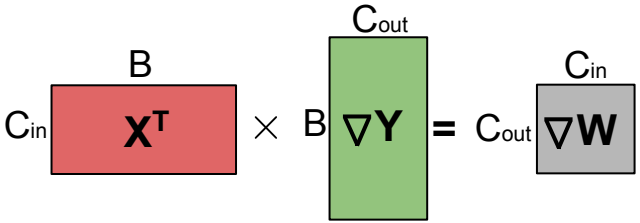
Drumond, Mario, et al. "Training dnns with hybrid block floating point." *Advances in Neural Information Processing Systems* 31 (2018).

# Two Copies of Weights

**Input data gradient Computation**




**Weight Gradient Computation**




**Weight Gradient Updates**


- Gradient and forward propagation are performed using BFP.
- Weights are updated using FP.
- Two copies of weights are used.

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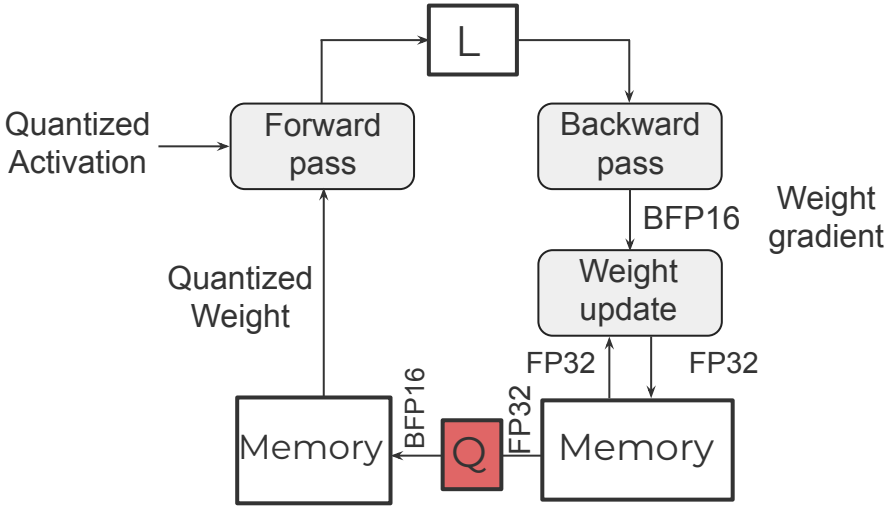
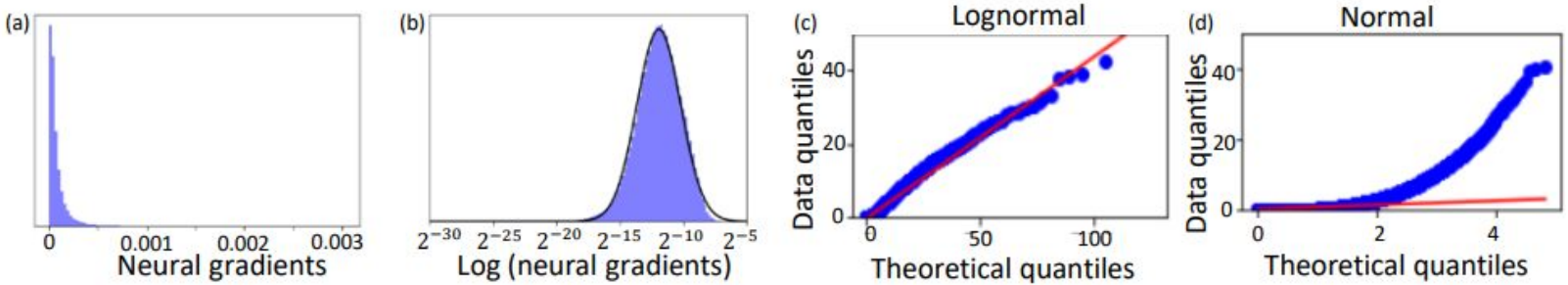
# Two Copies of Weights




- Two pieces of copies are needed to be kept in the memory.
- The weight updates are usually performed with higher precision (e.g., FP16).

# Neural Gradients are Near-Lognormal: Improved Quantized and Sparse Training




- The distribution of neural gradients is approximately lognormal.
- We can use lognormal regression to determine the optimal quantization setting (e.g., bitwidth, quantization interval).

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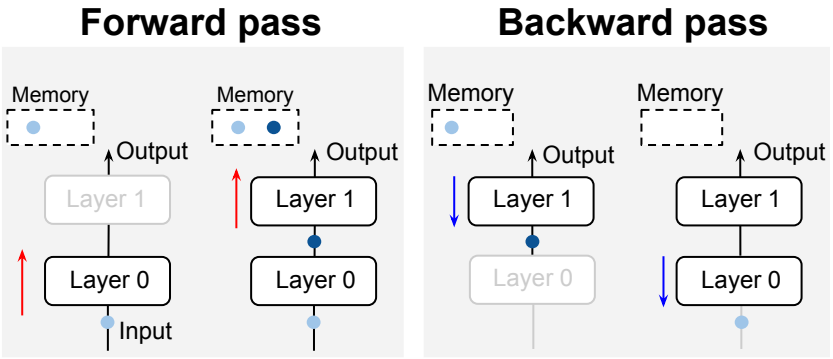
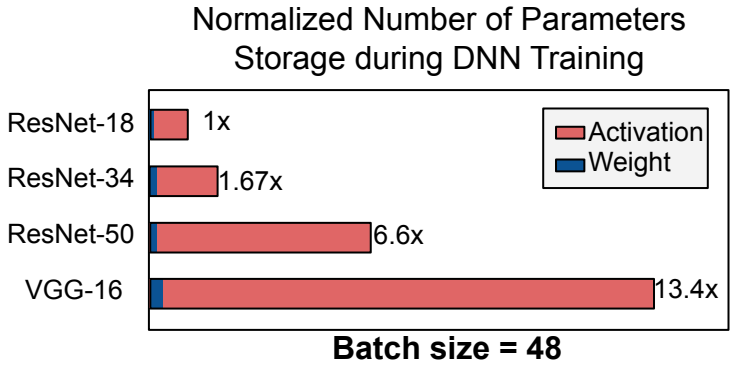
Chmiel, Brian, et al. "Neural gradients are near-lognormal: improved quantized and sparse training." *arXiv preprint arXiv:2006.08173* (2020).

# Topics

- Efficient training of DNNs
  - Efficient computing
  - Efficient storage
- Parameter efficient finetuning
- Federated Learning

# Memory Consumption During Training




- The memory footprint grows proportional with the layer depth. The activation in the early DNN layers need to be stored for a long time.
- Activations consume most of the memory space, approximately 13 times larger than the weights on average.

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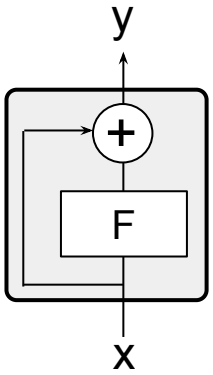
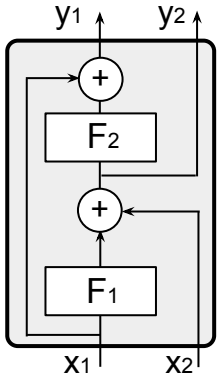
# Memory Efficiency During Training

**Residual Architecture**




**Reversible Architecture**




**Forward pass:**

$y_2 = F_1(x_1) + x_2$

$y_1 = F_2(y_2) + x_1$

**Backward Pass:**

$x_1 = y_1 - F_2(y_2)$

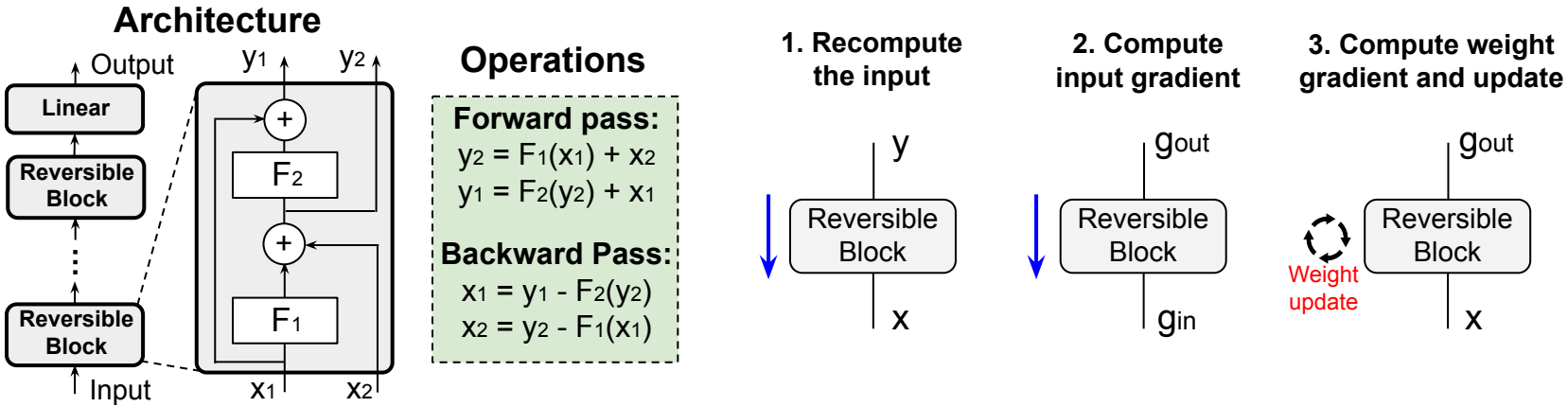
$x_2 = y_2 - F_1(x_1)$

- A reversible residual network (RevNet) is a variant of the canonical residual neural network (ResNet).



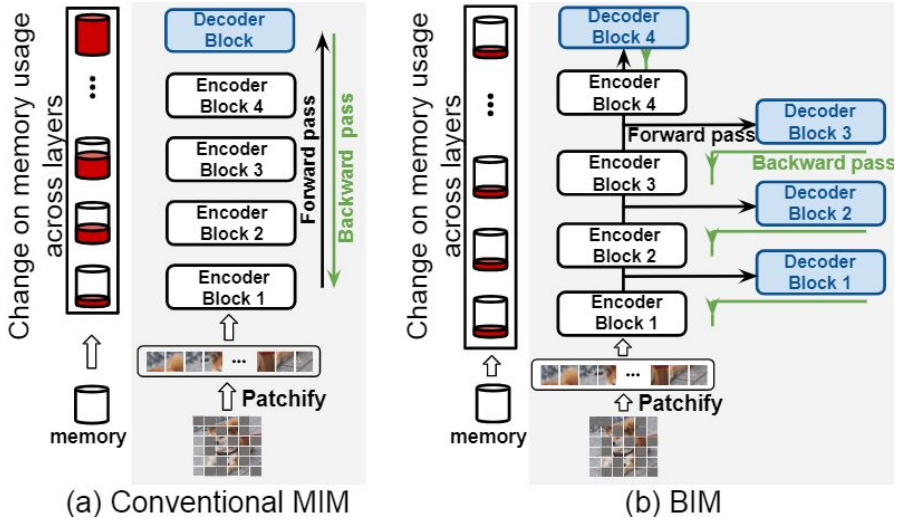
Gomez, Aidan N., et al. "The reversible residual network: Backpropagation without storing activations." *Advances in neural information processing systems* 30 (2017).

# Memory Efficiency During Training




- The backward pass computations can be performed without storing the input activations.
- Given the output y, the input activations are first recomputed. Afterwards, the input and weight gradients are computed with standard backward pass operations.

# BIM: Block-Wise Local Learning with Masked Image Modeling

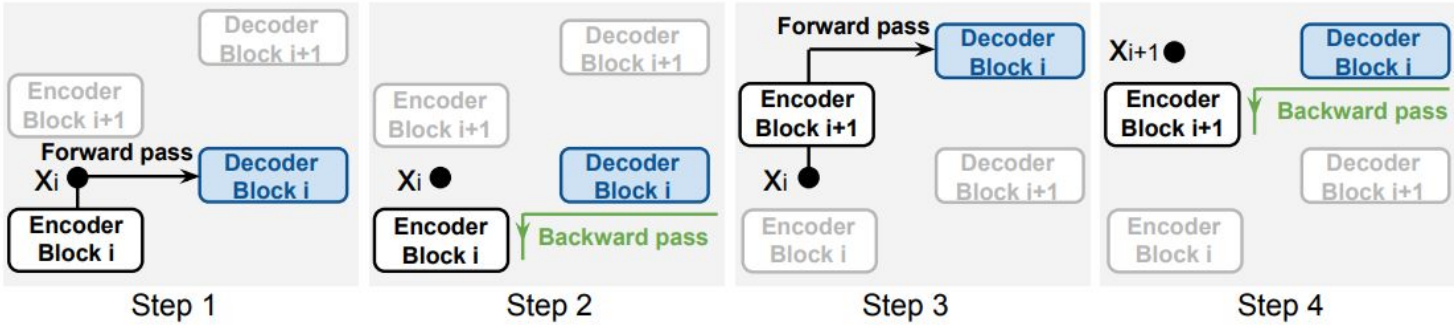



- Local exist is introduced during the training process.
- The intermediate results can be discarded once the training process for the current layer is complete.



Luo, Yixuan, Mengye Ren, and Sai Qian Zhang. "BIM: Block-Wise Self-Supervised Learning with Masked Image Modeling." *arXiv preprint arXiv:2311.17218* (2023).

# BIM: Block-Wise Local Learning with Masked Image Modeling




- Once the parameter updates in encoder block i and decoder block i are finished, all intermediate features stored in the buffer, except for xi , can be cleared from memory, preserving them for future use.

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Luo, Yixuan, Mengye Ren, and Sai Qian Zhang. "BIM: Block-Wise Self-Supervised Learning with Masked Image Modeling." *arXiv preprint arXiv:2311.17218* (2023).

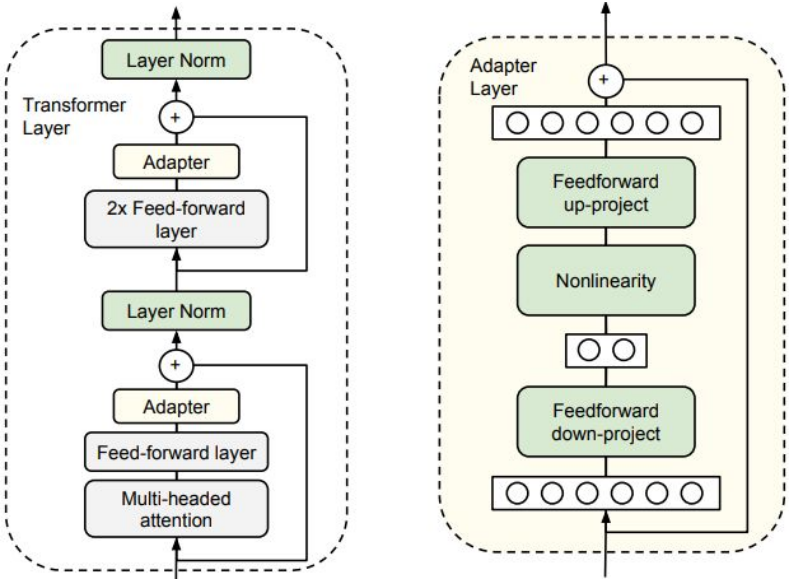
# Topics

- Efficient training of DNNs
  - Efficient computing
  - Efficient storage
- Parameter efficient finetuning
- Federated Learning

# Parameter-efficient Finetuning (PEFT)

- Large models (LMs), often consisting of billions of parameters, require vast amounts of computational resources for execution.
- The expansive scale and computational demands pose considerable challenges when customizing them for particular downstream tasks.
- To better adapt the LMs over the downstream tasks, we can finetune a small portion of the LM parameters. This will make LMs achieve great performance over the downstream tasks while minimizing the training cost.
- Some of the popular PEFT Algorithms:
  - LoRA
  - Adapter
  - BitFit

# Parameter-Efficient Transfer Learning for NLP




- We add the adapter module twice to each Transformer layer.
- The adapter consists of a bottleneck which contains few parameters relative to the attention and feedforward layers in the original model. The adapter also contains a skip-connection.
- The learnable parameters contributes to around 0.5 − 8% of the parameters of the original model.



Houlsby, Neil, et al. "Parameter-efficient transfer learning for NLP." *International conference on machine learning*. PMLR, 2019.

# BitFit

$$\mathbf{Q}^{m,\ell}(\mathbf{x}) = \mathbf{W}_q^{m,\ell}\mathbf{x} + \mathbf{b}_q^{m,\ell}$$
$$\mathbf{K}^{m,\ell}(\mathbf{x}) = \mathbf{W}_k^{m,\ell}\mathbf{x} + \mathbf{b}_k^{m,\ell}$$
$$\mathbf{V}^{m,\ell}(\mathbf{x}) = \mathbf{W}_v^{m,\ell}\mathbf{x} + \mathbf{b}_v^{m,\ell}$$

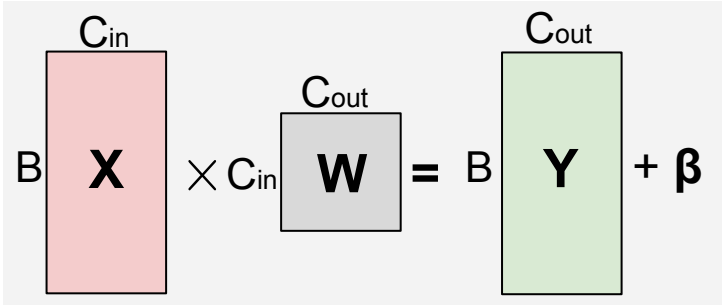
$$\mathbf{h}_2^\ell = \text{Dropout}\left(\mathbf{W}_{m_1}^\ell \cdot \mathbf{h}_1^\ell + \mathbf{b}_{m_1}^\ell\right)$$
$$\mathbf{h}_3^\ell = \mathbf{g}_{LN_1}^\ell \odot \frac{(\mathbf{h}_2^\ell + \mathbf{x}) - \mu}{\sigma} + \mathbf{b}_{LN_1}^\ell$$
$$\mathbf{h}_4^\ell = \text{GELU}\left(\mathbf{W}_{m_2}^\ell \cdot \mathbf{h}_3^\ell + \mathbf{b}_{m_2}^\ell\right)$$
$$\mathbf{h}_5^\ell = \text{Dropout}\left(\mathbf{W}_{m_3}^\ell \cdot \mathbf{h}_4^\ell + \mathbf{b}_{m_3}^\ell\right)$$
$$\text{out}^\ell = \mathbf{g}_{LN_2}^\ell \odot \frac{(\mathbf{h}_5^\ell + \mathbf{h}_3^\ell) - \mu}{\sigma} + \mathbf{b}_{LN_2}^\ell$$

- BitFiT is a sparse-finetuning method where only the bias-terms of the model are being modified.
- Applying BitFit on pre-trained BERT models is competitive with (and sometimes better than) fine-tuning the entire model.
- Bias parameters make up 0.09% of the total number of parameters in BER.



Zaken, Elad Ben, Shauli Ravfogel, and Yoav Goldberg. "Bitfit: Simple parameter-efficient fine-tuning for transformer-based masked language-models." *arXiv preprint arXiv:2106.10199* (2021).

# Finetune Bias is Cheap



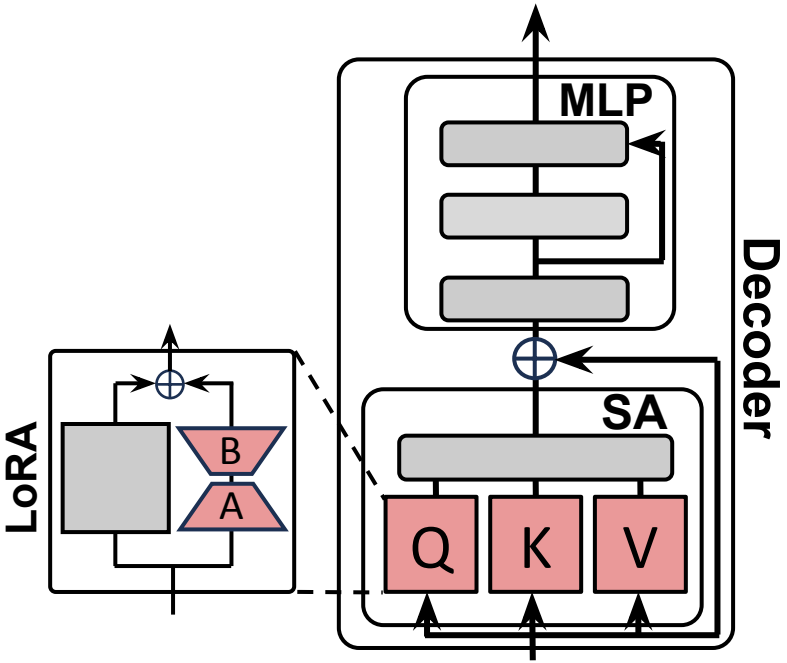

$$\frac{dL}{d\beta} = \sum_{y \in Y} \frac{dL}{dy}$$

- Updating the bias does not require buffering any intermediate results during the forward pass of DNN training.



Cai, Han, et al. "Tinytl: Reduce activations, not trainable parameters for efficient on-device learning." *arXiv preprint arXiv:2007.11622* (2020).

# Low-rank Adaptation (LoRA)




$$h = W_0 x + \Delta W x = W_0 x + BAx$$

- Only the weights within the red blocks are updated.
- Assume the weight matrix has a dimension of k×k, A and B have a size of k×r and r×k, where r << k (e.g., r=4).
- BA can be merged with the original weight $W_0$, leading to no additional computational and storage cost.



Hu, Edward J., et al. "Lora: Low-rank adaptation of large language models." *arXiv preprint arXiv:2106.09685* (2021).

# Low-rank Adaptation (LoRA)

| Model & Method | # Trainable Parameters | MNLI | SST-2 | MRPC | CoLA | QNLI | QQP | RTE | STS-B | Avg. |
|---|---|---|---|---|---|---|---|---|---|---|
| $\text{RoB}_{\text{base}}$ (FT)* | 125.0M | **87.6** | 94.8 | 90.2 | **63.6** | 92.8 | **91.9** | 78.7 | 91.2 | 86.4 |
| $\text{RoB}_{\text{base}}$ (BitFit)* | 0.1M | 84.7 | 93.7 | **92.7** | 62.0 | 91.8 | 84.0 | 81.5 | 90.8 | 85.2 |
| $\text{RoB}_{\text{base}}$ ($\text{Adpt}^{\text{D}}$)* | 0.3M | $87.1_{\pm.0}$ | $94.2_{\pm.1}$ | $88.5_{\pm1.1}$ | $60.8_{\pm.4}$ | $93.1_{\pm.1}$ | $90.2_{\pm.0}$ | $71.5_{\pm2.7}$ | $89.7_{\pm.3}$ | 84.4 |
| $\text{RoB}_{\text{base}}$ ($\text{Adpt}^{\text{D}}$)* | 0.9M | $87.3_{\pm.1}$ | $94.7_{\pm.3}$ | $88.4_{\pm.1}$ | $62.6_{\pm.9}$ | $93.0_{\pm.2}$ | $90.6_{\pm.0}$ | $75.9_{\pm2.2}$ | $90.3_{\pm.1}$ | 85.4 |
| $\text{RoB}_{\text{base}}$ (LoRA) | 0.3M | $87.5_{\pm.3}$ | $\mathbf{95.1}_{\pm.2}$ | $89.7_{\pm.7}$ | $63.4_{\pm1.2}$ | $\mathbf{93.3}_{\pm.3}$ | $90.8_{\pm.1}$ | $\mathbf{86.6}_{\pm.7}$ | $\mathbf{91.5}_{\pm.2}$ | **87.2** |
| $\text{RoB}_{\text{large}}$ (FT)* | 355.0M | 90.2 | **96.4** | **90.9** | 68.0 | 94.7 | **92.2** | 86.6 | 92.4 | 88.9 |
| $\text{RoB}_{\text{large}}$ (LoRA) | 0.8M | $\mathbf{90.6}_{\pm.2}$ | $96.2_{\pm.5}$ | $\mathbf{90.9}_{\pm1.2}$ | $\mathbf{68.2}_{\pm1.9}$ | $\mathbf{94.9}_{\pm.3}$ | $91.6_{\pm.1}$ | $\mathbf{87.4}_{\pm2.5}$ | $\mathbf{92.6}_{\pm.2}$ | **89.0** |
| $\text{RoB}_{\text{large}}$ ($\text{Adpt}^{\text{P}}$)† | 3.0M | $90.2_{\pm.3}$ | $96.1_{\pm.3}$ | $90.2_{\pm.7}$ | $\mathbf{68.3}_{\pm1.0}$ | $\mathbf{94.8}_{\pm.2}$ | $\mathbf{91.9}_{\pm.1}$ | $83.8_{\pm2.9}$ | $92.1_{\pm.7}$ | 88.4 |
| $\text{RoB}_{\text{large}}$ ($\text{Adpt}^{\text{P}}$)† | 0.8M | $\mathbf{90.5}_{\pm.3}$ | $\mathbf{96.6}_{\pm.2}$ | $89.7_{\pm1.2}$ | $67.8_{\pm2.5}$ | $\mathbf{94.8}_{\pm.3}$ | $91.7_{\pm.2}$ | $80.1_{\pm2.9}$ | $91.9_{\pm.4}$ | 87.9 |
| $\text{RoB}_{\text{large}}$ ($\text{Adpt}^{\text{H}}$)† | 6.0M | $89.9_{\pm.5}$ | $96.2_{\pm.3}$ | $88.7_{\pm2.9}$ | $66.5_{\pm4.4}$ | $94.7_{\pm.2}$ | $92.1_{\pm.1}$ | $83.4_{\pm1.1}$ | $91.0_{\pm1.7}$ | 87.8 |
| $\text{RoB}_{\text{large}}$ ($\text{Adpt}^{\text{H}}$)† | 0.8M | $90.3_{\pm.3}$ | $96.3_{\pm.5}$ | $87.7_{\pm1.7}$ | $66.3_{\pm2.0}$ | $94.7_{\pm.2}$ | $91.5_{\pm.1}$ | $72.9_{\pm2.9}$ | $91.5_{\pm.5}$ | 86.4 |
| $\text{RoB}_{\text{large}}$ (LoRA)† | 0.8M | $\mathbf{90.6}_{\pm.2}$ | $96.2_{\pm.5}$ | $\mathbf{90.2}_{\pm1.0}$ | $68.2_{\pm1.9}$ | $\mathbf{94.8}_{\pm.3}$ | $91.6_{\pm.2}$ | $\mathbf{85.2}_{\pm1.1}$ | $\mathbf{92.3}_{\pm.5}$ | **88.6** |
| $\text{DeB}_{\text{XXL}}$ (FT)* | 1500.0M | 91.8 | **97.2** | 92.0 | 72.0 | **96.0** | 92.7 | 93.9 | 92.9 | 91.1 |
| $\text{DeB}_{\text{XXL}}$ (LoRA) | 4.7M | $\mathbf{91.9}_{\pm.2}$ | $96.9_{\pm.2}$ | $\mathbf{92.6}_{\pm.6}$ | $\mathbf{72.4}_{\pm1.1}$ | $\mathbf{96.0}_{\pm.1}$ | $\mathbf{92.9}_{\pm.1}$ | $\mathbf{94.9}_{\pm.4}$ | $\mathbf{93.0}_{\pm.2}$ | **91.3** |

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- LoRA achieves better results than Adapter and BitFit.

# Topics

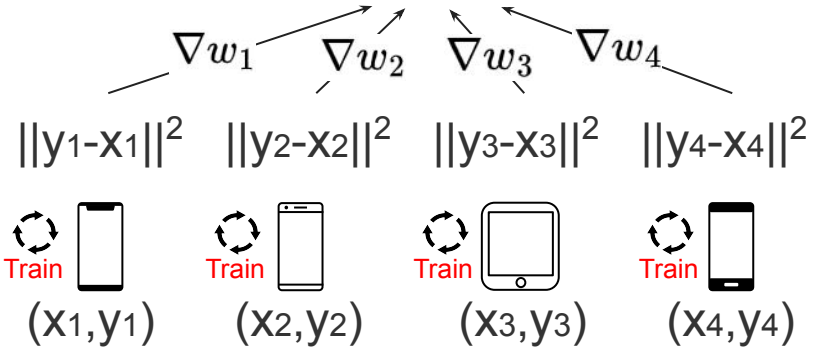
- Efficient training of DNNs
  - Efficient computing
  - Efficient storage
- Parameter efficient finetuning
- Federated Learning

# Federated Learning

- Training data: $(x_1,y_1)$, $(x_2,y_2)$, $(x_3,y_3)$, $(x_4,y_4)$

$$\sum_{i=1}^{4} ||y_i - F(x_i)||^2$$

$$\nabla w = \frac{\nabla w_1 + \nabla w_2 + \nabla w_3 + \nabla w_4}{4}$$




- Non-iid training data distribution
- Heterogeneity among the edge devices
- Communication error

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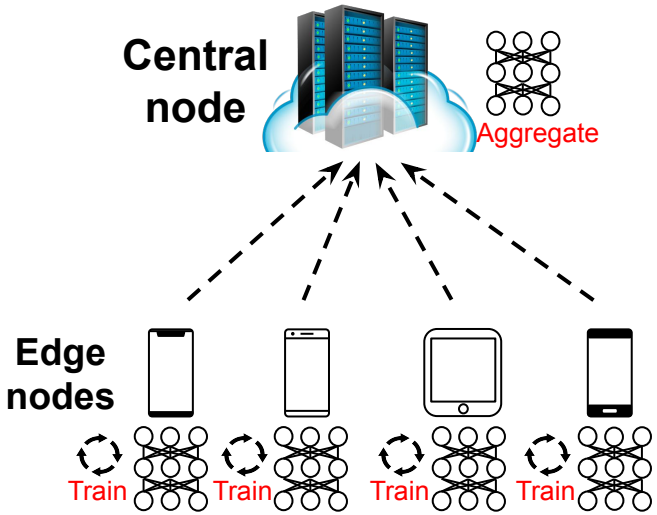
# Federated Learning

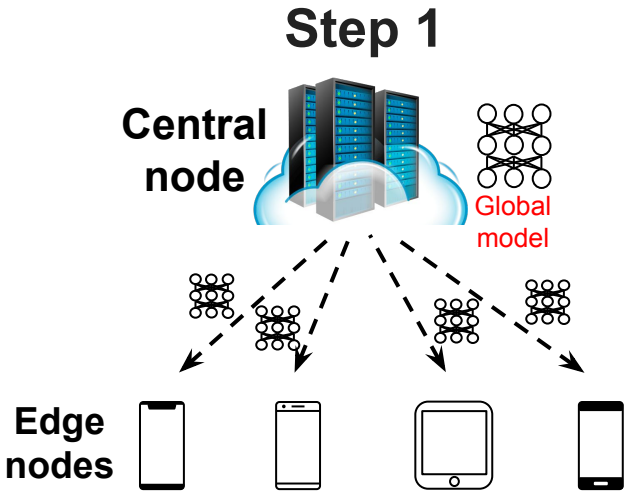



- Federated learning is a machine learning technique that allows the training of models across multiple decentralized nodes holding local data samples, **without exchanging their data**.
- This approach enhances privacy, user can train the powerful DNN model **without sharing the dataset**.



McMahan, Brendan, et al. "Communication-efficient learning of deep networks from decentralized data." *Artificial intelligence and statistics*. PMLR, 2017.

# FedAvg



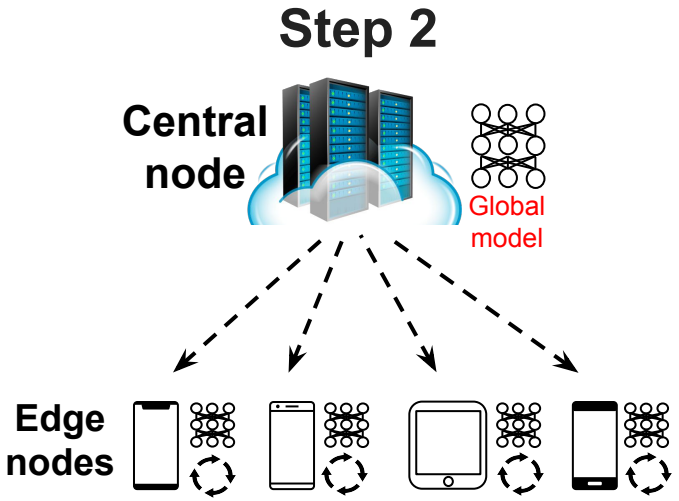

- A global model is initialized on the central node and sent to all participating nodes .

$$w_i = w_{global} \quad \text{For each i}$$



McMahan, Brendan, et al. "Communication-efficient learning of deep networks from decentralized data." *Artificial intelligence and statistics*. PMLR, 2017.

# FedAvg



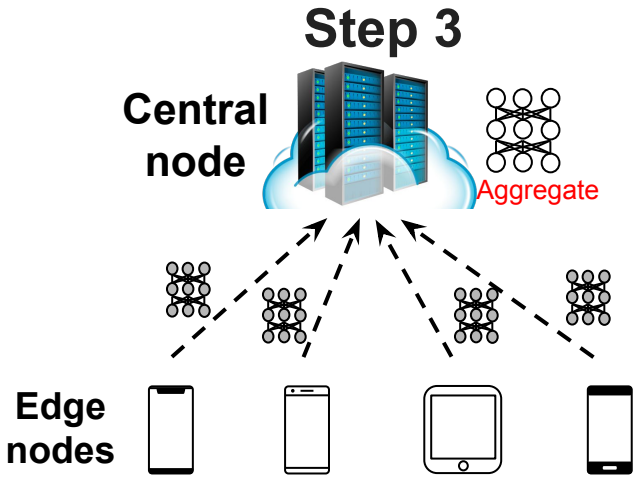

$$w_i' = \underset{w_i}{min} L(F(D_i), Y_i)$$

- Each node i trains the global model locally using its own data for a few epochs.
- The length of local training process may vary.



McMahan, Brendan, et al. "Communication-efficient learning of deep networks from decentralized data." *Artificial intelligence and statistics*. PMLR, 2017.

# FedAvg



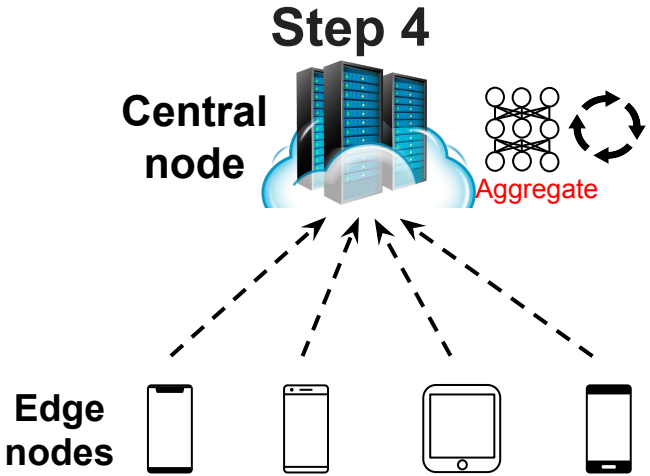

$$\Delta w_i = w - w_i$$

- Local updates are sent from each node to the central node.



McMahan, Brendan, et al. "Communication-efficient learning of deep networks from decentralized data." *Artificial intelligence and statistics*. PMLR, 2017.

# FedAvg




- The central node aggregates the local updates to update the global model.

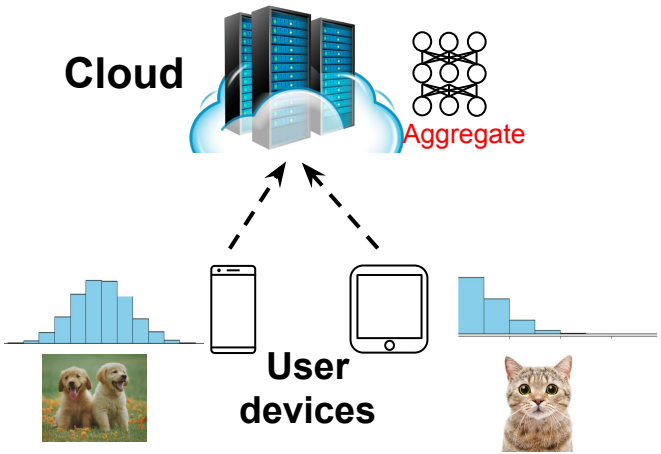
$$w + \frac{1}{N} \sum_i \Delta w_i$$



McMahan, Brendan, et al. "Communication-efficient learning of deep networks from decentralized data." *Artificial intelligence and statistics*. PMLR, 2017.

# Federated Learning Problems: Non-IID

- However, in FL, the data distributed across different devices or clients is not drawn from the same statistical distribution.
- Unlike the scenario distributed training, where the training data are randomly distributed. For FL, the data stored in each device is highly biased.
- This may lead to significant accuracy degradation for the global model.

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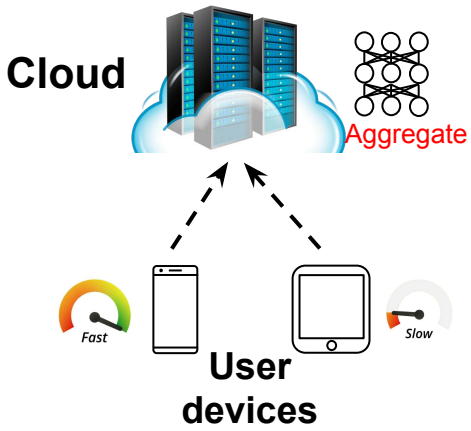
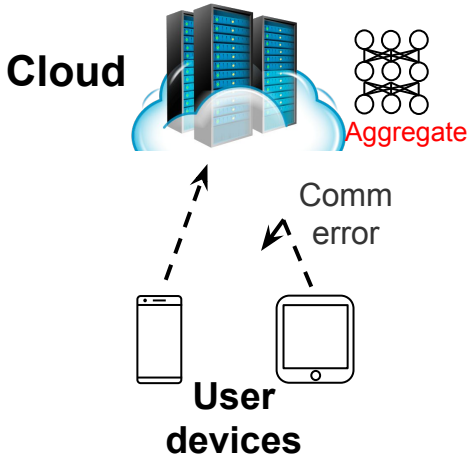
# Federated Learning Problems: Heterogeneity



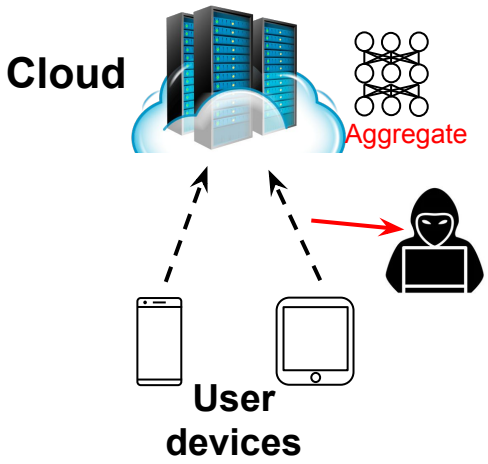

- Different edge device may have different processing speed.
- This will cause the total latency of each training round bottlenecked by the straggler, leading to a slow convergence of the training process.

# Federated Learning Problems: Communication



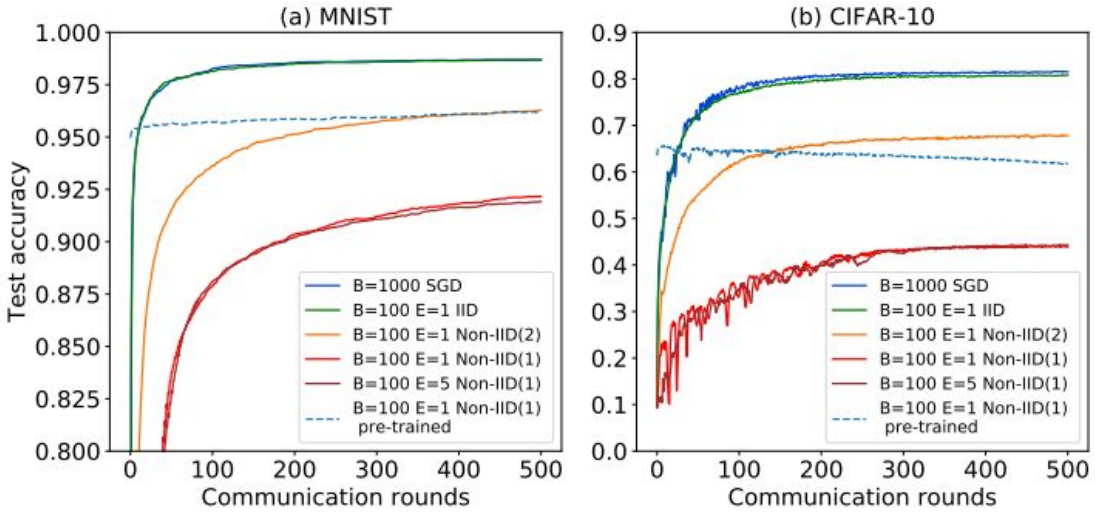

- The communication between edge devices and central cloud may incur transmission loss or error.
- This will impact the training latency and accuracy.

# Federated Learning Problems: Privacy




- The attacker can leverage the transmitted gradient to reconstruct the original input training data.
- This will lead to privacy leakage.

# Federated Learning with Non-iid Data



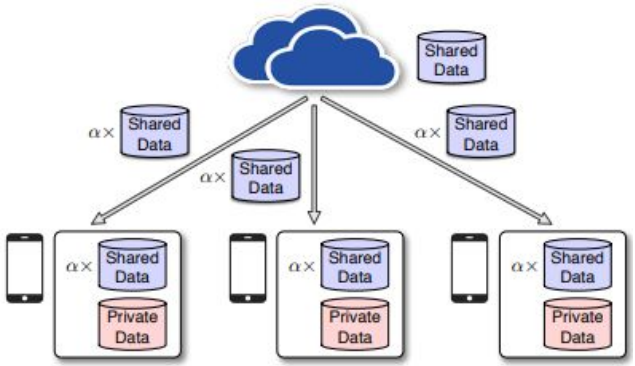

- The training sets are evenly partitioned into 10 clients.
- For IID setting, each client is randomly assigned a uniform distribution over 10 classes.
- For non-IID setting, the data is sorted by class and divided to create two extreme cases: (a) 1-class non-IID, where each client receives data partition from only a single class, and (b) 2-class non-IID, where the sorted data is divided into 20 partitions and each client is randomly assigned 2 partitions from 2 classes.



Zhao, Yue, et al. "Federated learning with non-iid data." *arXiv preprint arXiv:1806.00582* (2018).

# Federated Learning with Non-iid Data

- We propose a data-sharing strategy to improve FedAvg with non-IID data by creating a small subset of data which is globally shared between all the edge devices.
- Experiments show that test accuracy can be increased by ~30% on CIFAR-10 dataset with only 5% globally shared data.

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Zhao, Yue, et al. "Federated learning with non-iid data." *arXiv preprint arXiv:1806.00582* (2018).

# FedProx

**Algorithm 2** `FedProx` (Proposed Framework)

**Input:** $K, T, \mu, \gamma, w^0, N, p_k, k = 1, \cdots, N$
**for** $t = 0, \cdots, T-1$ **do**
  Server selects a subset $S_t$ of $K$ devices at random (each device $k$ is chosen with probability $p_k$)
  Server sends $w^t$ to all chosen devices
  Each chosen device $k \in S_t$ finds a $w_k^{t+1}$ which is a $\gamma_k^t$-inexact minimizer of: $w_k^{t+1} \approx \arg\min_w \; h_k(w;\; w^t) = F_k(w) + \frac{\mu}{2}\|w - w^t\|^2$
  Each device $k \in S_t$ sends $w_k^{t+1}$ back to the server
  Server aggregates the $w$'s as $w^{t+1} = \frac{1}{K}\sum_{k \in S_t} w_k^{t+1}$
**end for**

$$\min_w h_k(w;\; w^t) = F_k(w) + \frac{\mu}{2}\|w - w^t\|^2$$

- We add an extra term to minimize the $l_2$ distance between the initial weight $w_t$ and the learned weight w.
- This loss ensures that the learnt w is not too different from the original w.



Li, Tian, et al. "Federated optimization in heterogeneous networks." *Proceedings of Machine learning and systems* 2 (2020): 429-450.

# Presentation

- FBNet: Hardware-Aware Efficient ConvNet Design via Differentiable Neural Architecture Search (Monish)
- Neural gradients are near-lognormal: improved quantized and sparse training (Rahil)
- Lora: Low-rank adaptation of large language models (Minghui)
- COAT: Compressing Optimizer states and Activation for Memory-Efficient FP8 Training (Yash)
- Federated optimization in heterogeneous networks (Rujuta)

# Project Proposal

- Due on Mar 19th (1 page)
  - Project summary (1 paragraph)
  - Project plan (1 paragraph, gantt chart (optional))
  - Individual responsibilities (1 paragraph)
- You should begin forming teams of 2-3 students and start brainstorming project ideas now.
- Please discuss with me during office hours.
- You should propose something feasible to do.
  - Difficulty, Resource,…

# Some Example

- Study the pruning/quantization behavior for CNN/Diffusion model/Large Models.
- Distillation using Large Model.
- Low precision Parameter efficient finetuning.
- Federated learning with Large Model.
- Hardware simulation on Large Model.