Towards Lower Bit Multiplication for Convolutional Neural Network Training

NICSEFC

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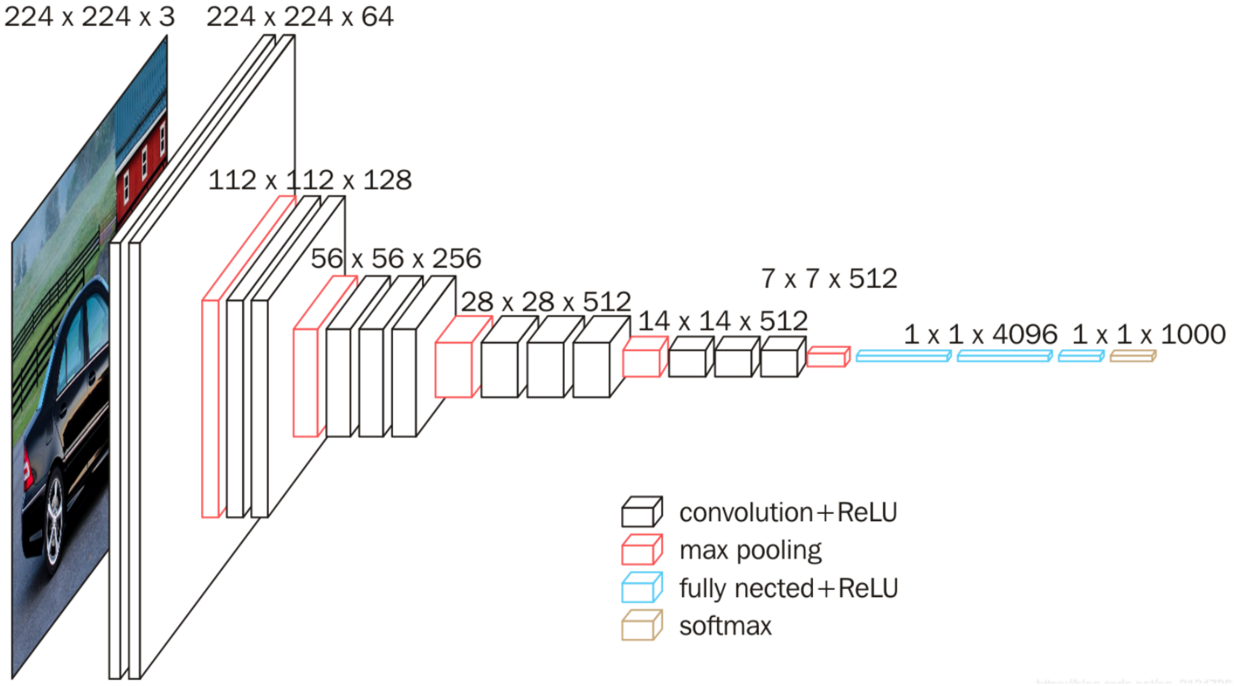
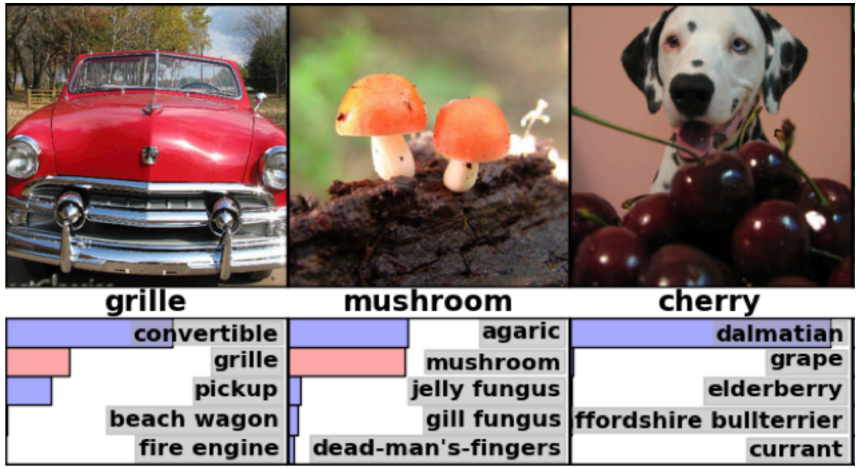
Introduction

- Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in many computer vision tasks[1][2].





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- Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in many computer vision tasks[1][2].
- The training process could consume up to hundreds of ExaFLOPs of computations and tens of GBytes of memory storage.

Op Name	Op Type	Res18	Res20
Conv (F)	Mul&Add	2.72E+10	4.05E+07
Conv (B)	Mul&Add	5.44E+10	8.11E+07
BN (F)	Mul&Add	3.01E+07	1.88E+05
BN (B)	Mul&Add	3.01E+07	1.88E+05
EW-Add (F)	Add	1.49E+07	7.37E+04
EW-Add (B)	Add	1.20E+07	7.37E+04
Params Update (B)	Add	1.12E+07	2.68E+05

Introduction

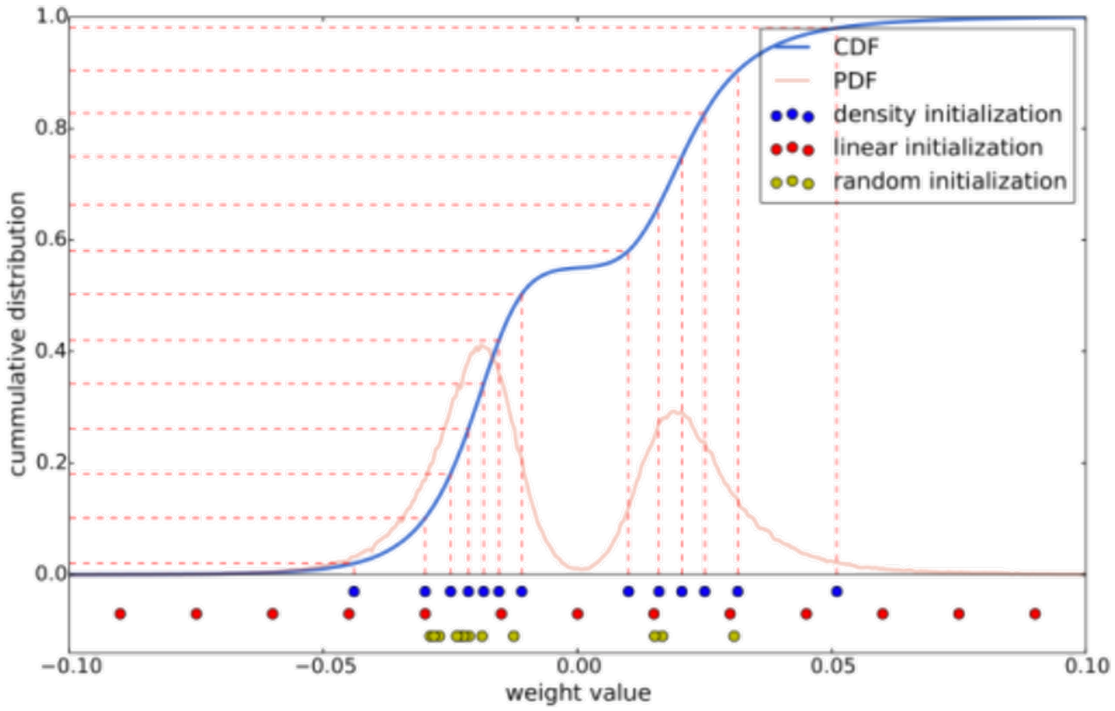
- Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in many computer vision tasks[1][2].
- The training process could consume up to hundreds of ExaFLOPs of computations and tens of GBytes of memory storage.
- Quantization in training has potential in significantly reducing both the memory and computational complexity.

Related Work

- Post-Training Quantization
- Quantize-Aware Training
- Low-Bit Training

Related Work: Post-Training Quantization

- Deep Compression[3] 8-bit -<1%
  - Larger weights plays more imoportant role than smaller weights.
  - Finetuning shared Quantized weights brings improvement.



Random： Initialization randomly chooses k observations from the data set and uses these as the initial centroids.

Density-based initialization： Linearly spaces the CDF of the weights in the y-axis, then finds the horizontal intersection with the CDF, and finally finds the vertical intersection on the x-axis.

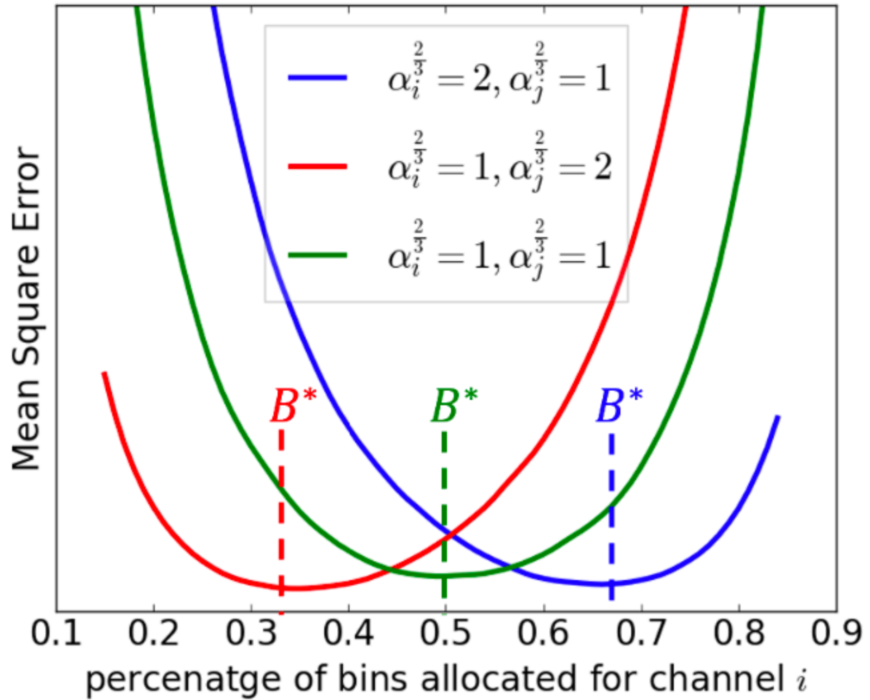
Linear initialization： Linearly spaces the centroids between the [min, max] of the original weights.

Related Work: Post-Training Quantization

- POST[4] 4-bit -2.7%
  - Analyze of clip value.

$$E[(X-Q(X))^2] \approx 2 \cdot b^2 \cdot e^{-\frac{\alpha}{b}} + \frac{2 \cdot \alpha^3}{3} \cdot \sum_{i=0}^{2^M-1} f(q_i) = 2 \cdot b^2 \cdot e^{-\frac{\alpha}{b}} + \frac{\alpha^2}{3 \cdot 2^{2M}}$$

  - Bit-allocation per-channel.
  - Bias correction



Related Work

- Post-Training Quantization[3][4]
  - Achieve good accuracy with 4-bit when inference after float training.
  - But the optimization is complex.
  - Prove the quantized model could have the same representation ability.
- Quantize-Aware Training
- Low-Bit Training

Related Work: Quantize-Aware Training

- DoReFa-Net[6] 8-bit -2.9%
  - The first one to quantize gradient and error in training.
  - Nolinear weights quantization.

$$\textbf{Forward: } r_o = f_\omega^k(r_i) = 2\,\mathrm{quantize}_\mathrm{k}\left(\frac{\tanh(r_i)}{2\max(|\tanh(r_i)|)} + \frac{1}{2}\right) - 1.$$

$$\textbf{Backward: } \frac{\partial c}{\partial r_i} = \frac{\partial r_o}{\partial r_i}\frac{\partial c}{\partial r_o} \quad 4$$

  - Scaled by max when quantizing gradient.

$$\tilde{f}_\gamma^k(\mathrm{d}r) = 2\max_0(|\mathrm{d}r|)\left[\mathrm{quantize}_k\left(\frac{\mathrm{d}r}{2\max_0(|\mathrm{d}r|)} + \frac{1}{2}\right) - \frac{1}{2}\right].$$

Related Work: Quantize-Aware Training

- PACT[5] 4-bit -1%
  - Training the clip value of activation as a parameter.
  - Not really quantized in training.

$$y = PACT(x) = 0.5(|x| - |x - \alpha| + \alpha) = \begin{cases} 0, & x \in (-\infty, 0) \\ x, & x \in [0, \alpha) \\ \alpha, & x \in [\alpha, +\infty) \end{cases}$$

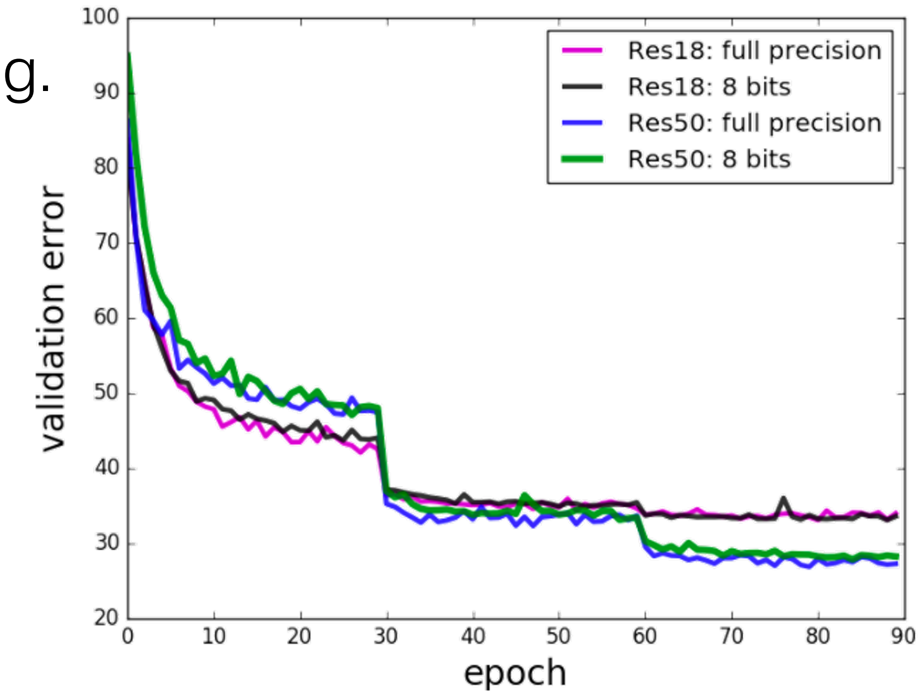
$$\frac{\partial y_q}{\partial \alpha} = \frac{\partial y_q}{\partial y}\frac{\partial y}{\partial \alpha} = \begin{cases} 0, & x \in (-\infty, \alpha) \\ 1, & x \in [\alpha, +\infty) \end{cases}$$

Related Work

- Post-Training Quantization
- Quantize-Aware Training[5][6]
  - Find the best quantized parameter during training.
  - Usually for ultra low-bit networks.
  - Not really care about the training cost.
- Low-Bit Training

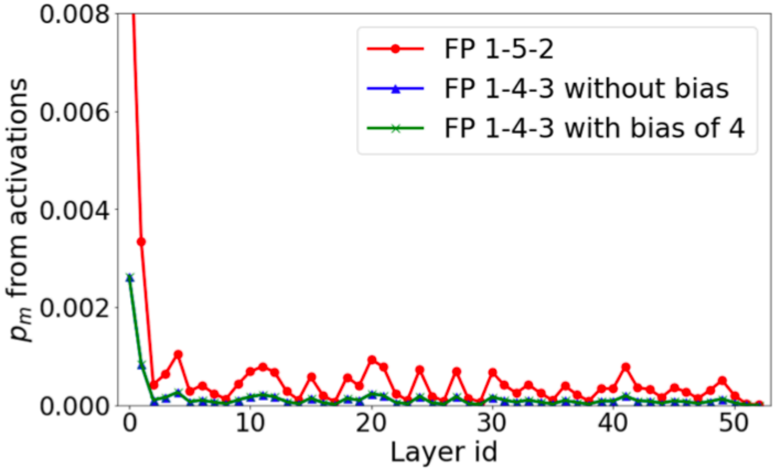
Related Work: Low-Bit Training

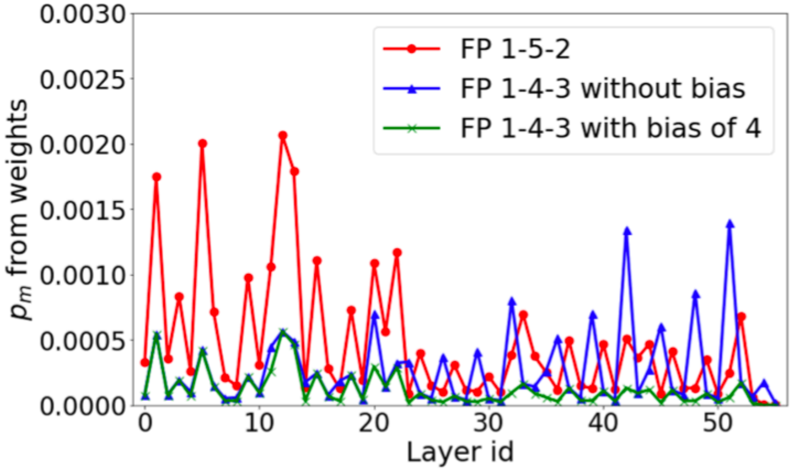
- RangeBN[8] 8(16)-bit <-2%
  - Using range to estimate variance in BN.
  - Double-precision for (W,E) Conv.
  - GEMMLOWP quantization with bias in training.
  - Can not really simplify the computation.

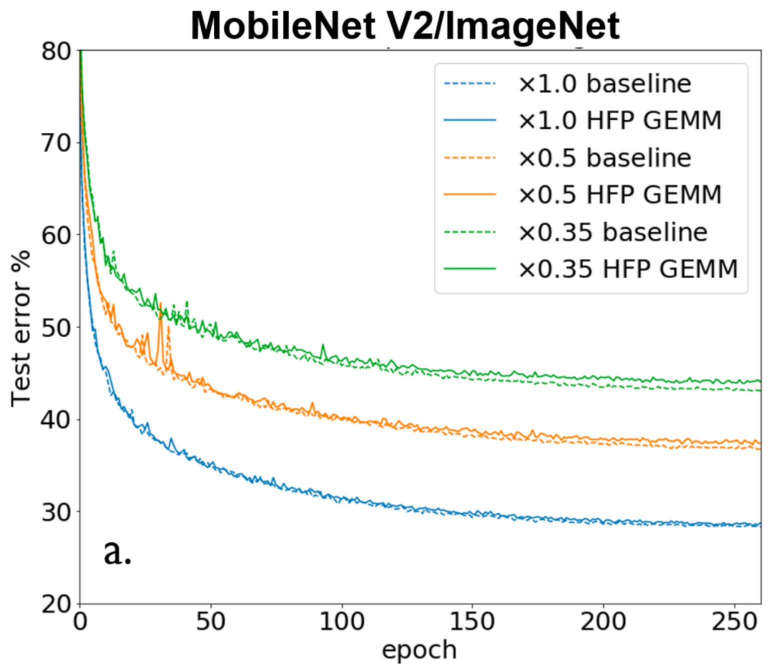


Related Work: Low-Bit Training

- HFP8[9] 8-bit <-1%
  - 1-5-2 in inference and 1-4-3 in back propagation.
  - Exponent bias of error.
  - FP16 for depth-wise convolution.







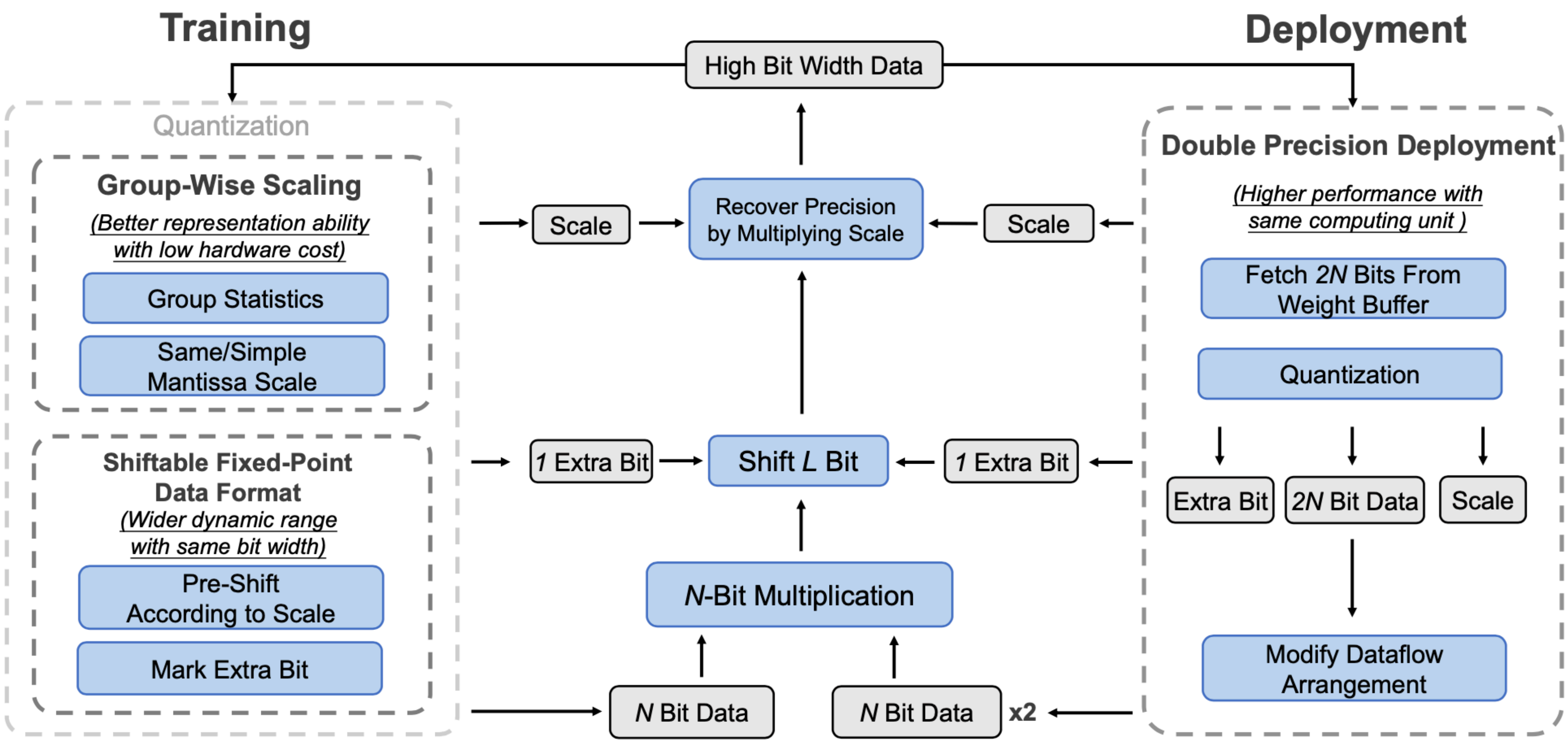
Related Work

- Post-Training Quantization
- Quantize-Aware Training
- Low-Bit Training[7][8][9]
    - Some earlier studies have significant accuracy drop.
    - 8-bit fixed-point is realized without well consideration of hardware costs.
    - Training with hyper 8-bit floating could achieve the same accuracy.

Our Methods

- Basic Quantization Method
- Shiftable Fixed-Point Data Format
- Constrained Group-Wise Scaling
- Double-Precision Deployment

Our Methods



Training
Deployment
High Bit Width Data
Quantization
Group-Wise Scaling
(Better representation ability with low hardware cost)
Group Statistics
Same/Simple Mantissa Scale
Shiftable Fixed-Point Data Format
(Wider dynamic range with same bit width)
Pre-Shift According to Scale
Mark Extra Bit
Scale
Recover Precision by Multiplying Scale
Scale
1 Extra Bit
Shift L Bit
1 Extra Bit
N-Bit Multiplication
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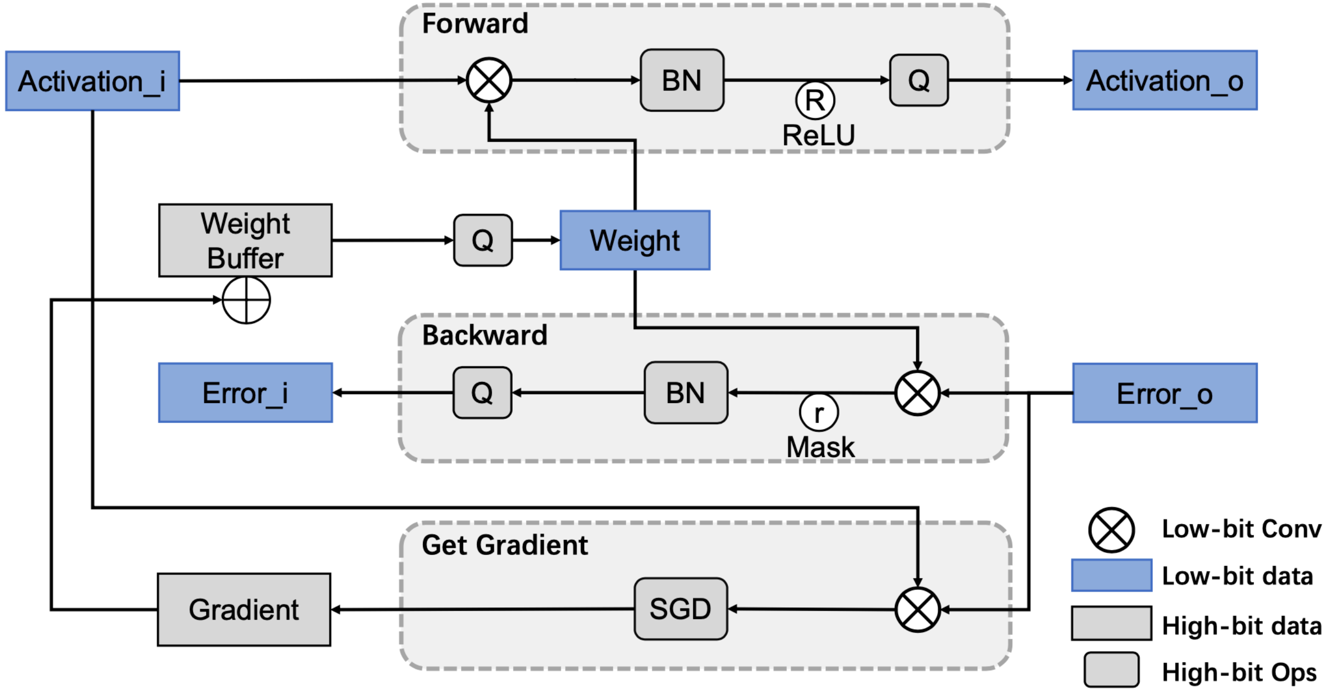
N Bit Data
x2
Double Precision Deployment
(Higher performance with same computing unit)
Fetch 2N Bits From Weight Buffer
Quantization
Extra Bit
2N Bit Data
Scale
Modify Dataflow Arrangement

Our Methods: Basic Quantization Method

- The multiplications in convolution account for the main computational cost of the CNN training process.
- Our goal is to use low-bit fixed-point multiplication to calculate all three types of convolution: (W,A) (W,E) and (A,E).



Our Methods: Basic Quantization Method

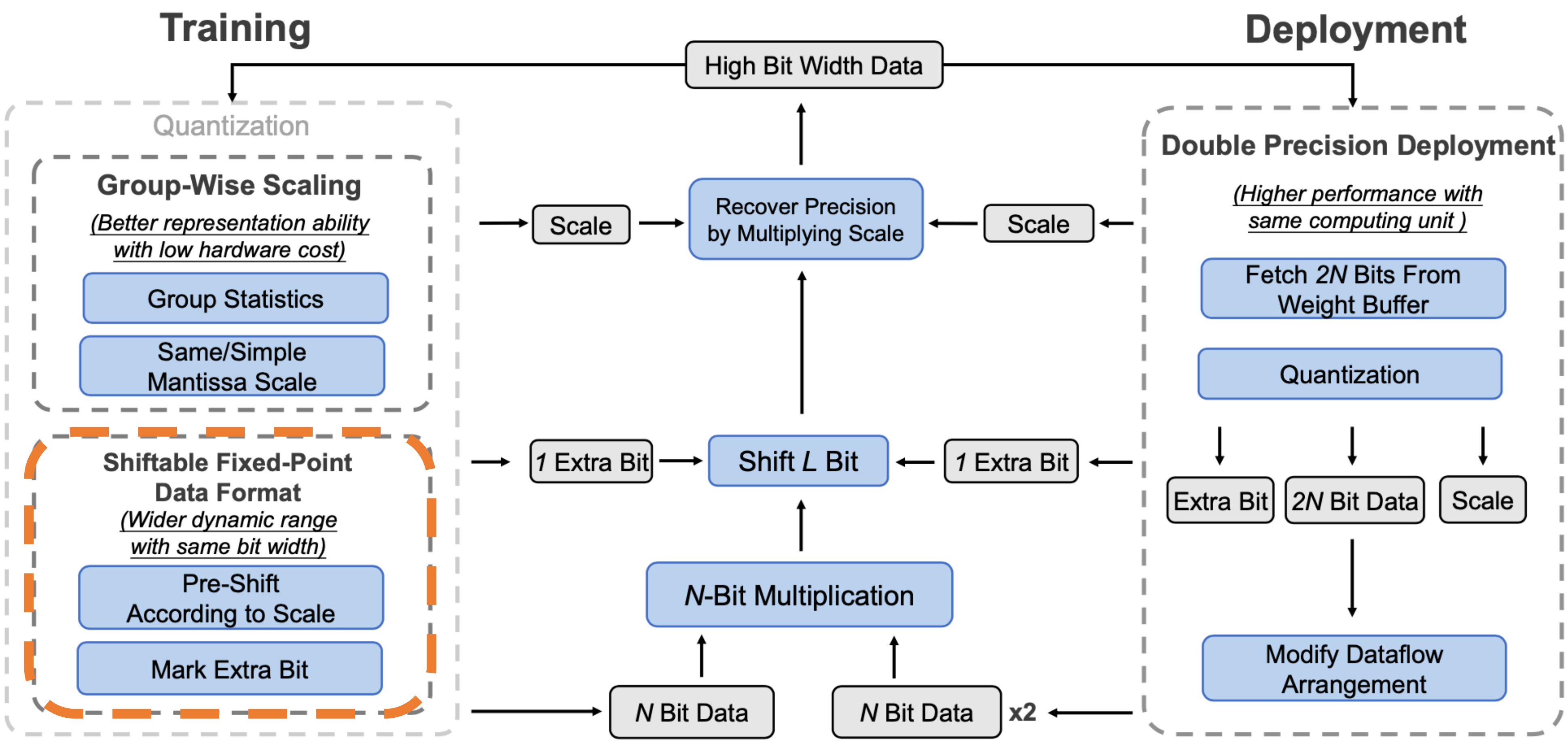
- The unbiased but scaled quantization method is used.

$$Fix = quantize(float) = Round(Clip(\frac{float}{scale}, 2^N))$$

- The stochastic rounding is used instead of rounding to the nearest[10].

$$Round(x) = \begin{cases} \lceil x \rceil & \text{w.p. } x - \lfloor x \rfloor \\ \lfloor x \rfloor & \text{w.p. } \lceil x \rceil - x \end{cases}$$

Our Methods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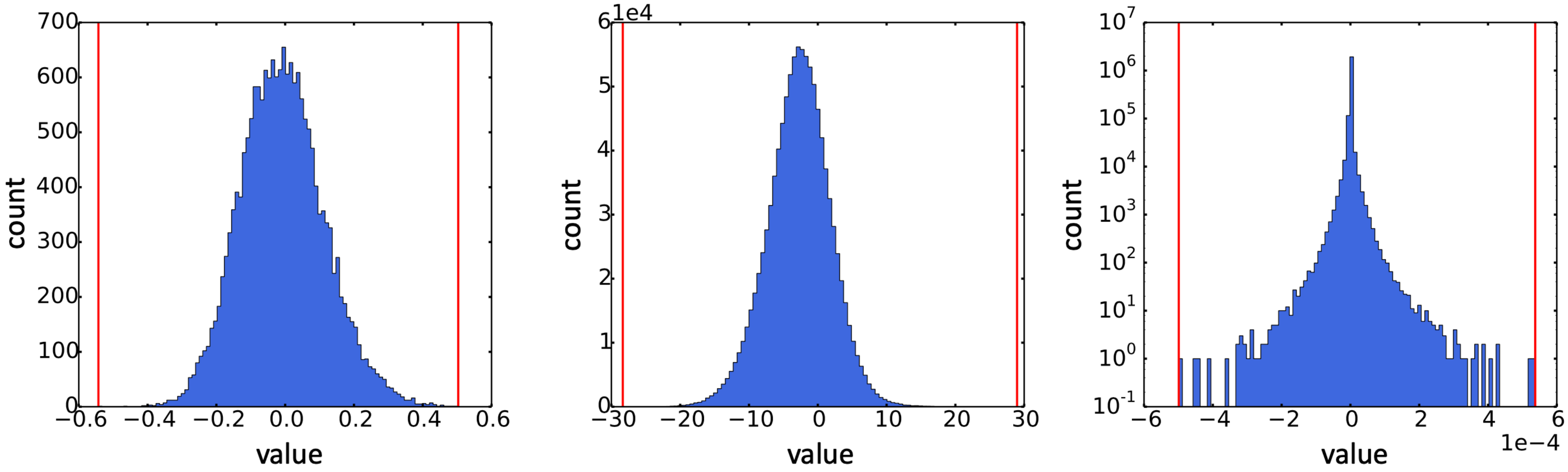
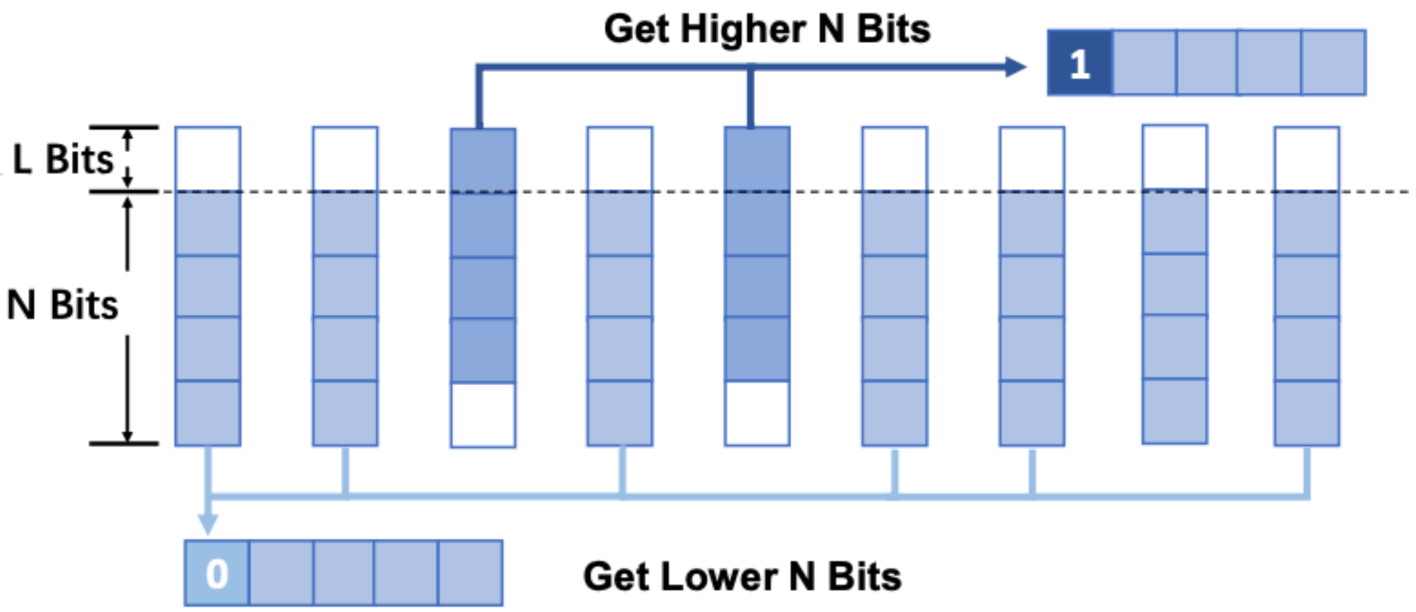
Our Methods: Shiftable Fixed-Point Data Format

- One of the challenges in quantization is to balance the overflow error and the rounding error.



Our Methods: Shiftable Fixed-Point Data Format

- Get lower N bits of values less than $max \times 2^{-L}$ in quantization, so that more significant bits can be remained.
- Need one extra bit to mark which value is shifted, but no need to involve in multiplication.



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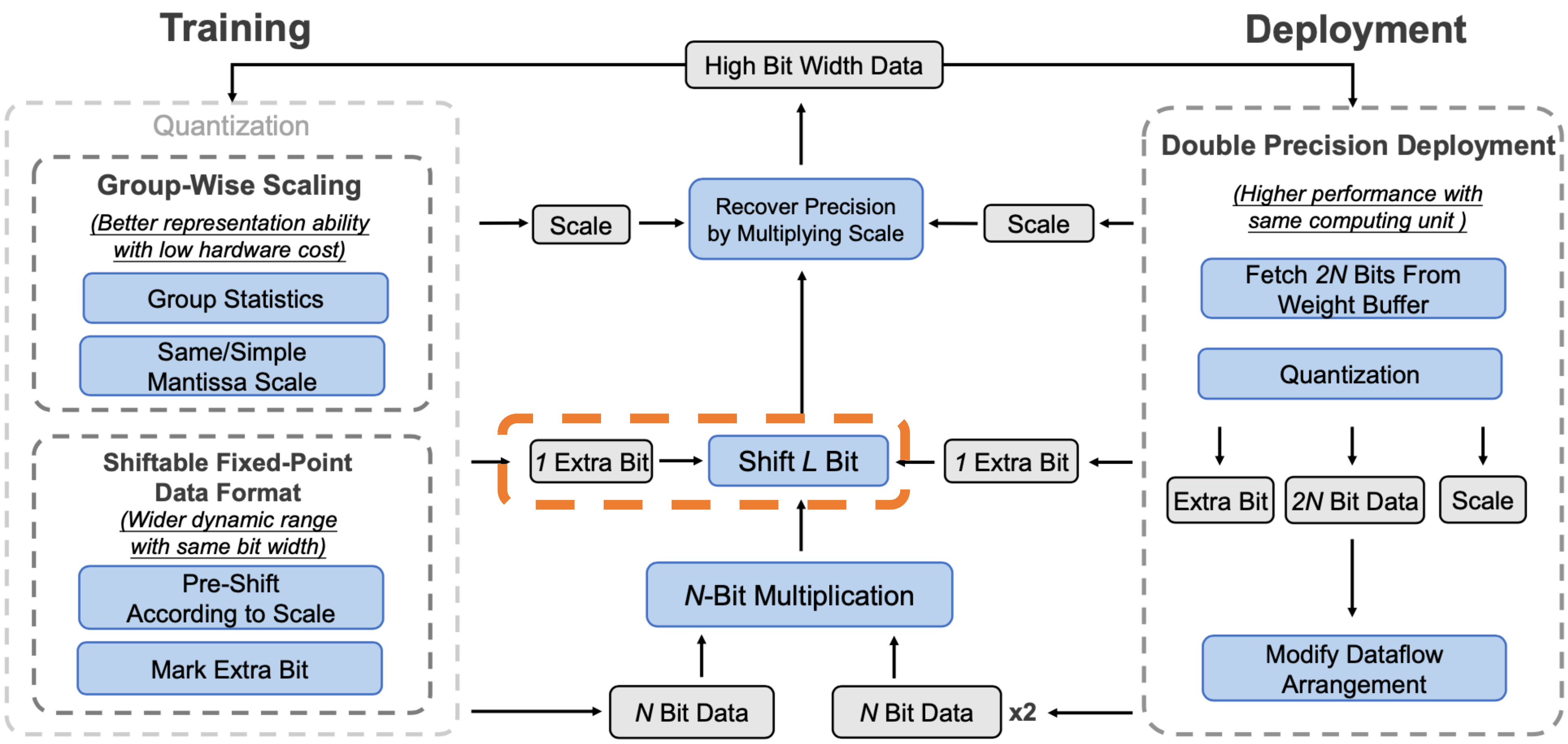

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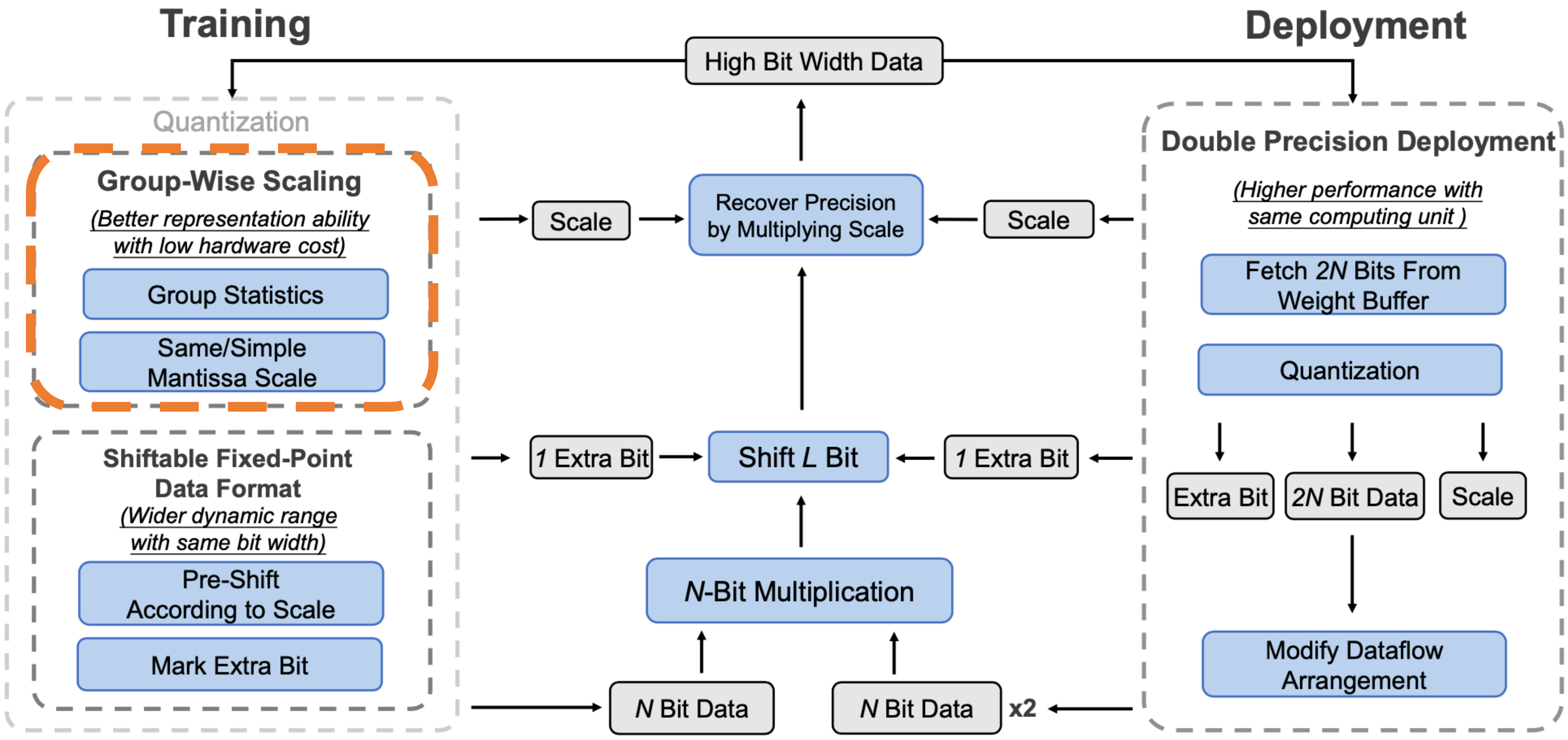

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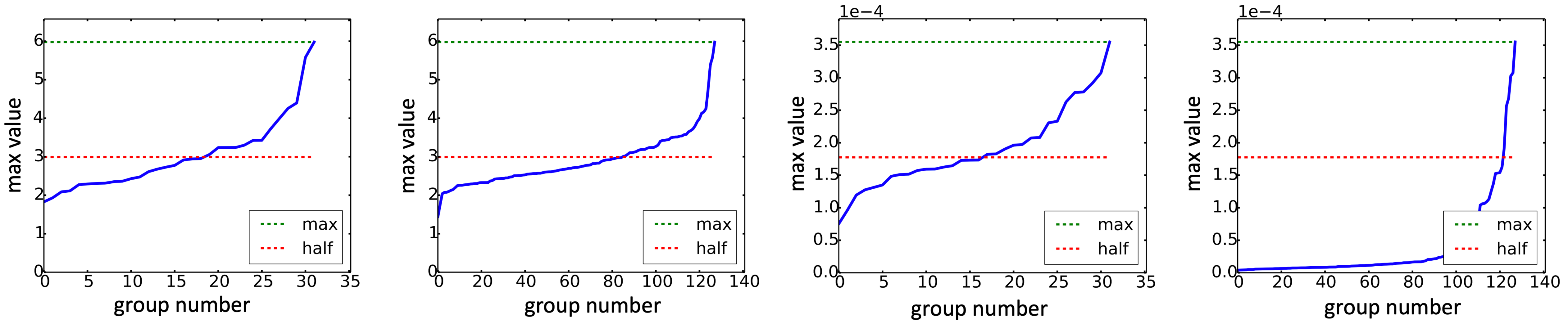
Our Methods: Constrained Group-Wise Scaling

- W, A, E to be quantized are 4-D tensors in training process.
- Data ranges are quite various in different groups.



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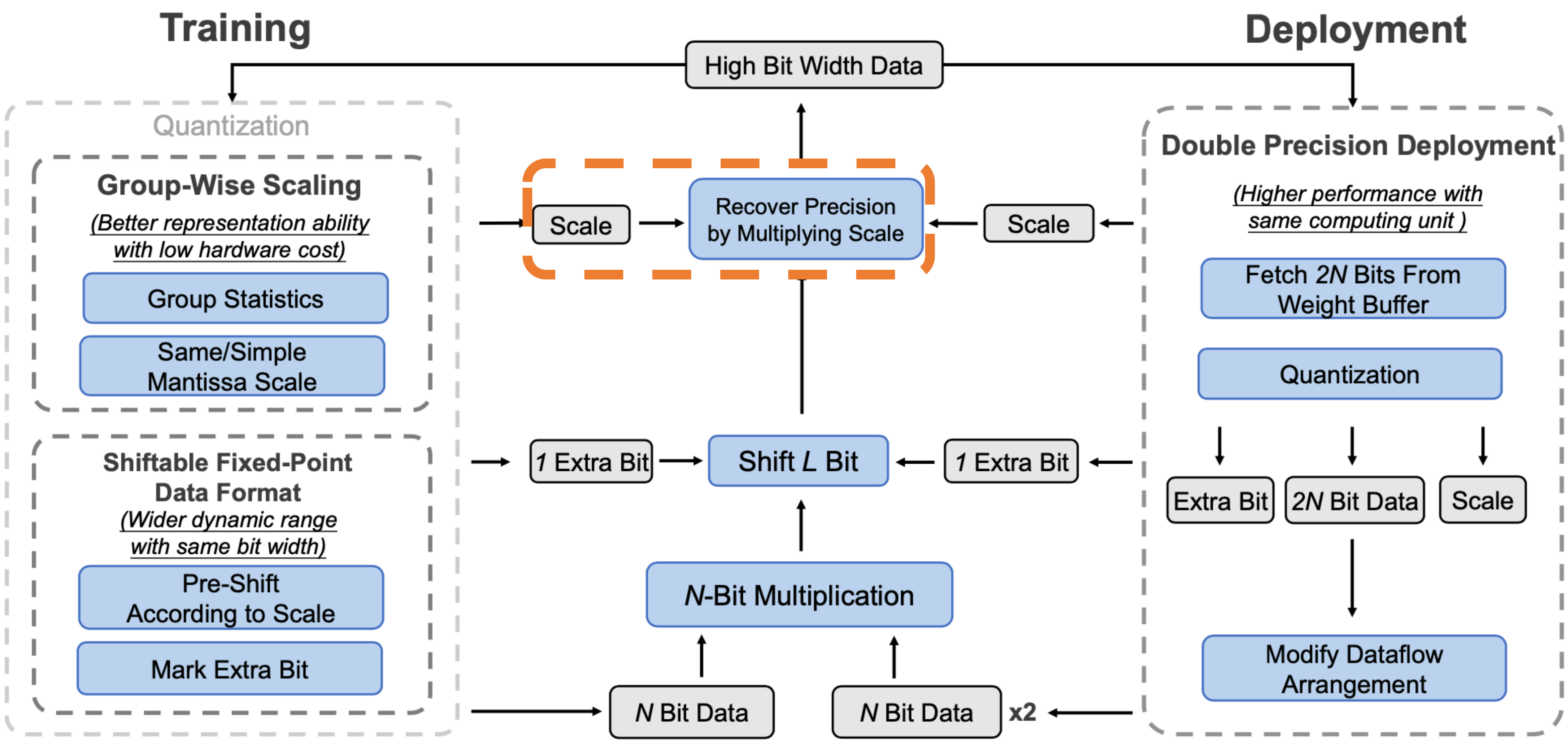

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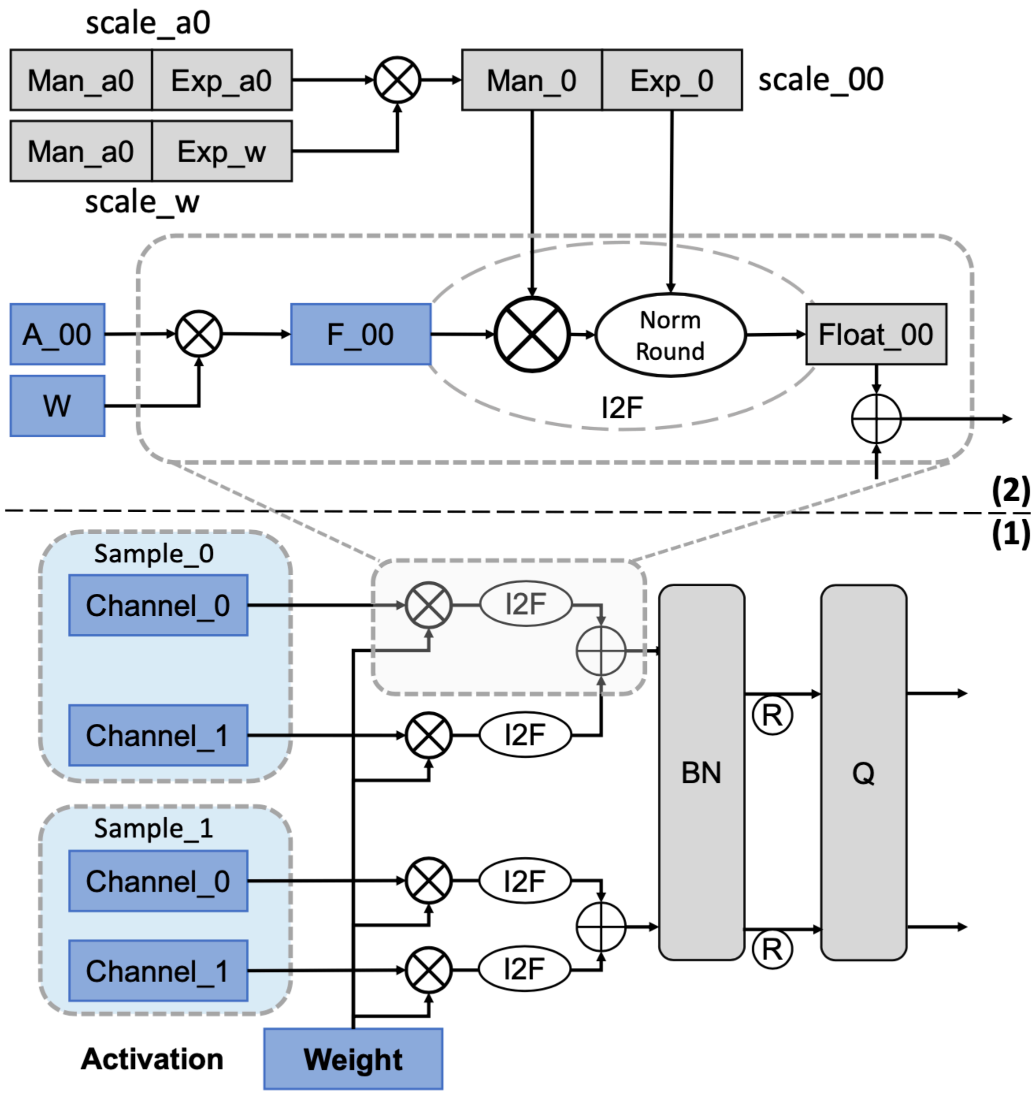
Our Methods: Constrained Group-Wise Scaling

- Simple group-wise floating-point scaling are not hardware friendly.
- Numbers to be added with different scale have to be convert to floating-point.

$$float_i = scale_i \times Fix_i$$

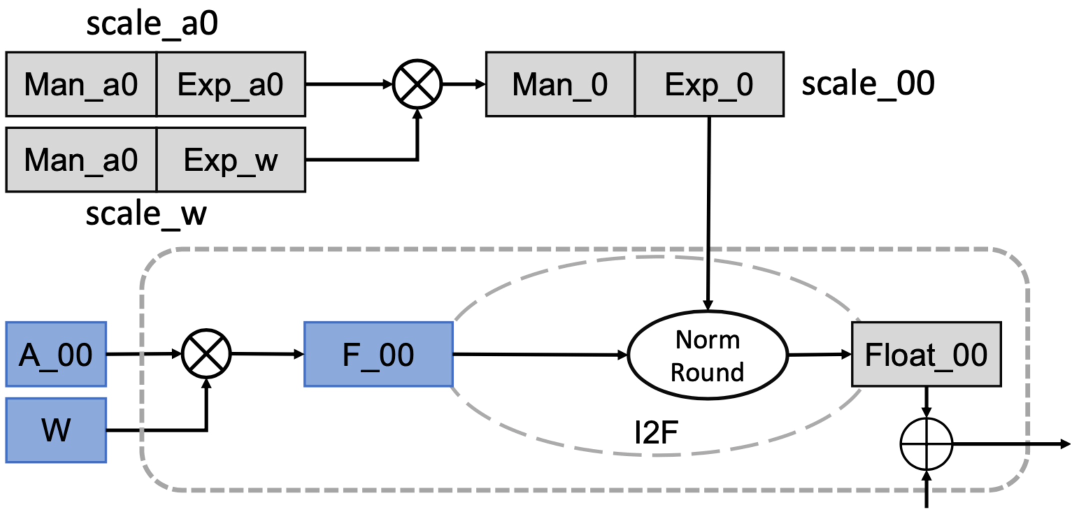
$$float_{00} + float_{01} = (Fix_{00} \times Man_0) \times 2^{Exp_0} + (Fix_{01} \times Man_1) \times 2^{Exp_1}$$



Our Methods: Constrained Group-Wise Scaling

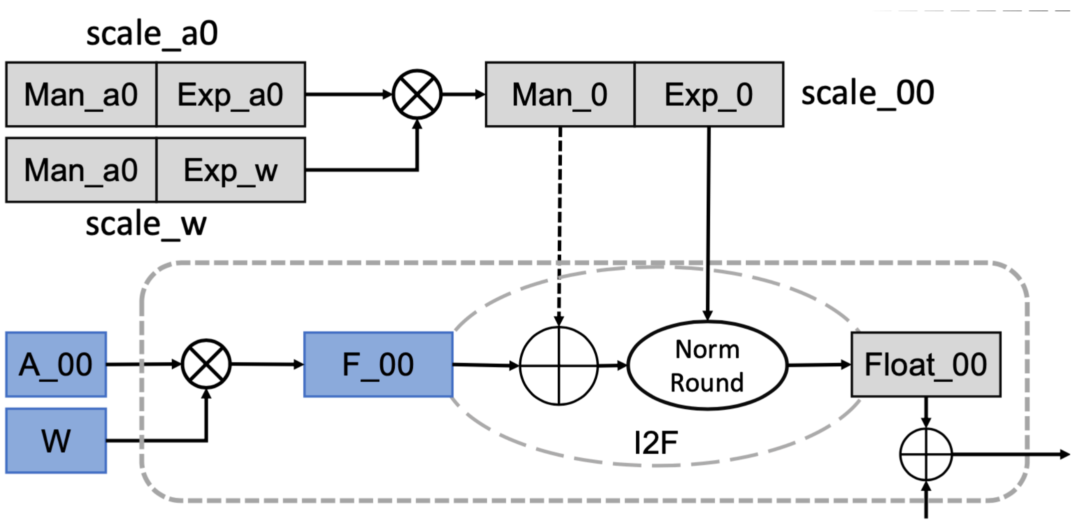
- The **same mantissa scale** means that we select scales of different groups from the list of $max, \frac{1}{2}max, \frac{1}{4}\mathrm{max}\cdots$
- They have the same mantissa that can be processed seprately.

$$float_{00} + float_{01} = Mantissa \times (Fix_{00} \times 2^{Exp_0} + Fix_{01} \times 2^{Exp_1})$$



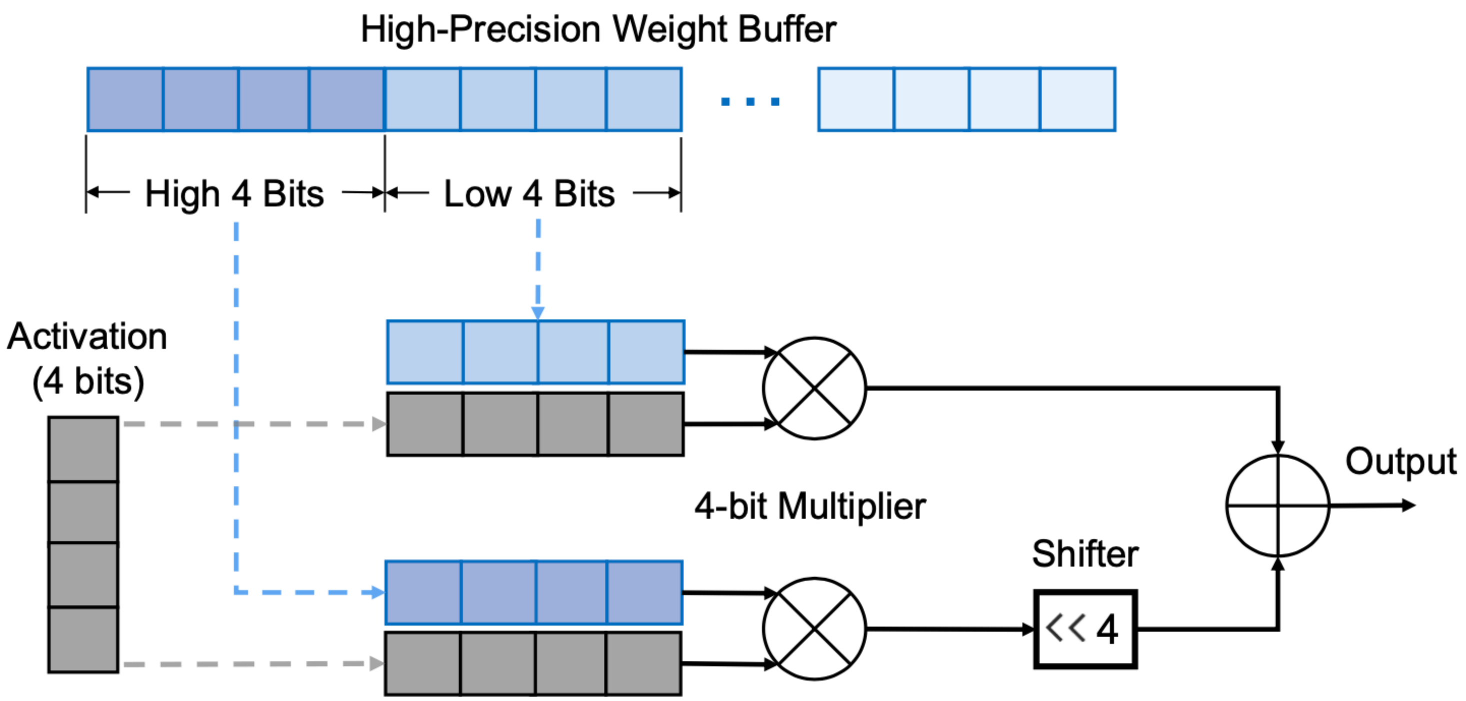
Our Methods: Constrained Group-Wise Scaling

- The **simple mantissa scale** is to use different scales with simple mantissa.
- Multiplication between Fix and Man would be simplified to an addition.



Our Methods: Double-Precision Deployment

- There is a high-bit copy of weights in the training process.
- We can boost the performance of the quantized model by quantize high-bit data to double low-bit data, without any extra training.



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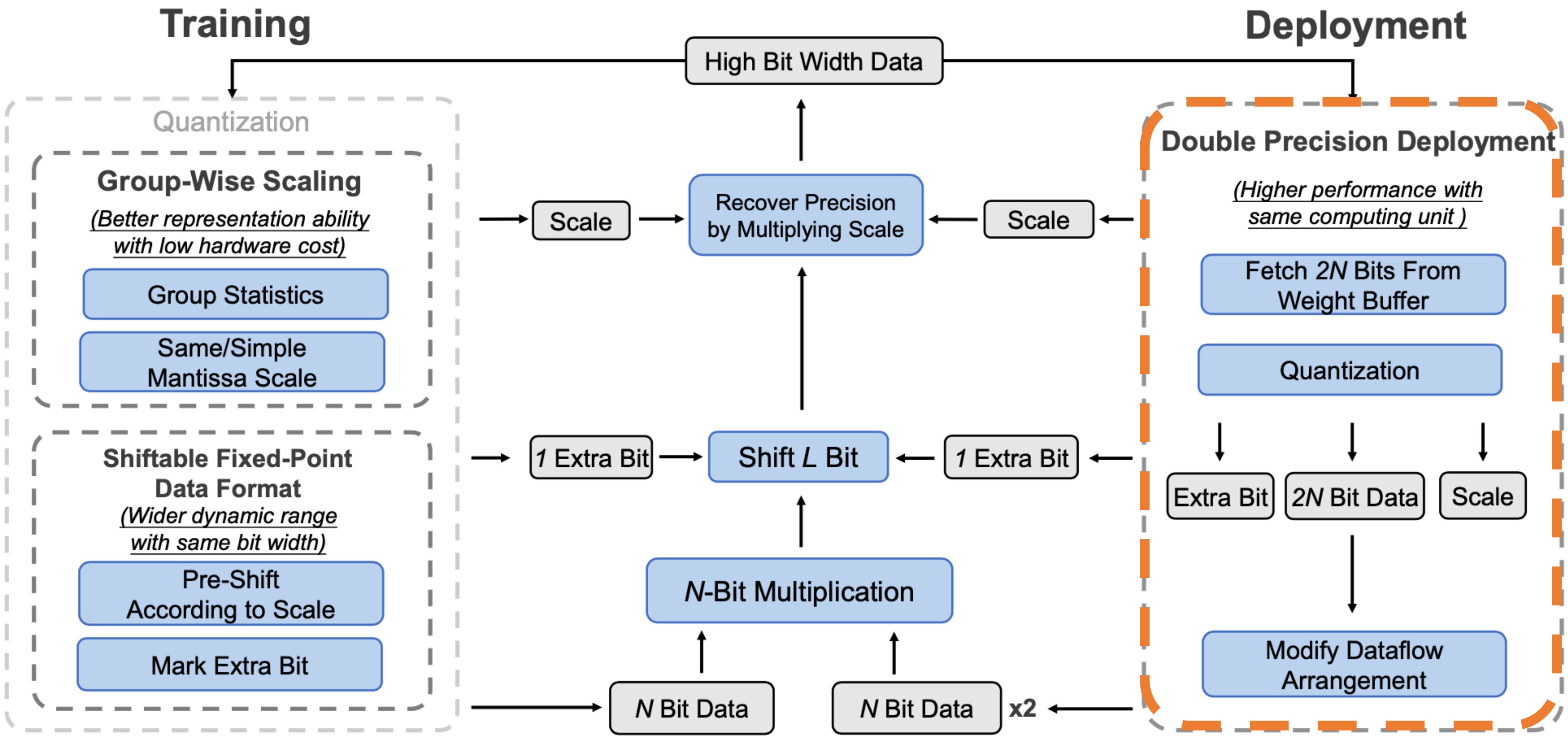

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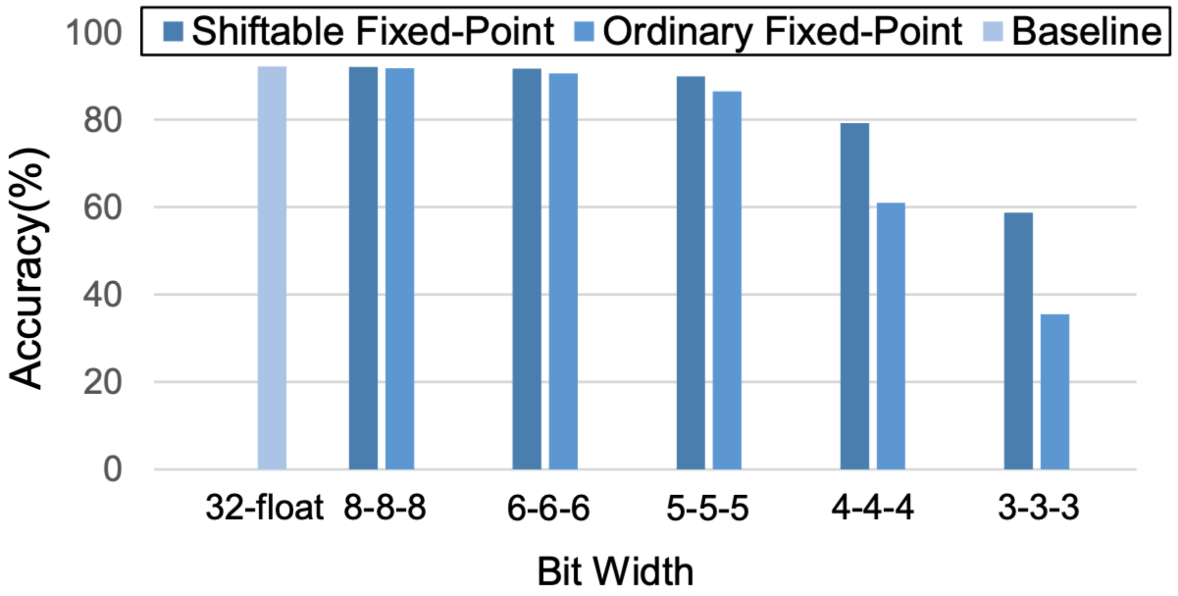
Some Experimental results

- Comparation on ImageNet[6][7][8][9]

Method	Bit-Width (W/A/E)	Model	Accuracy	Baseline
DoReFa (Zhou et al., 2016)	8 8 8	AlexNet	53.0%	55.9%
WAGE (Wu et al., 2018)	2 8 8	AlexNet	48.4%	56.0%
RangeBN (Banner et al., 2018a)	8 8 16	ResNet-18	66.4%	67.0%
HFP8 (Mellempudi et al., 2019)	8f 8f 8f	ResNet-18	69.0%	69.3%
Ours	8 8 8	ResNet-18	69.1%	69.7%
Ours	6 6 6	ResNet-18	67.4%	69.7%
Ours	4 4 4	ResNet-18	63.2%	69.7%
Ours-Double	6 6 6	ResNet-18	68.2%	69.7%
Ours-Double	4 4 4	ResNet-18	64.9%	69.7%

Some Experimental results

- Shiftable fixed-point data format
  - Best shifting bit for different variable are not the same.



Shifting Bit L (W/A/E)	Accuracy
1 1 1	88.38%
2 1 1	88.56%
1 2 1	87.68%
1 1 2	88.92%
1 1 3	89.53%
2 1 3	**90.63%**

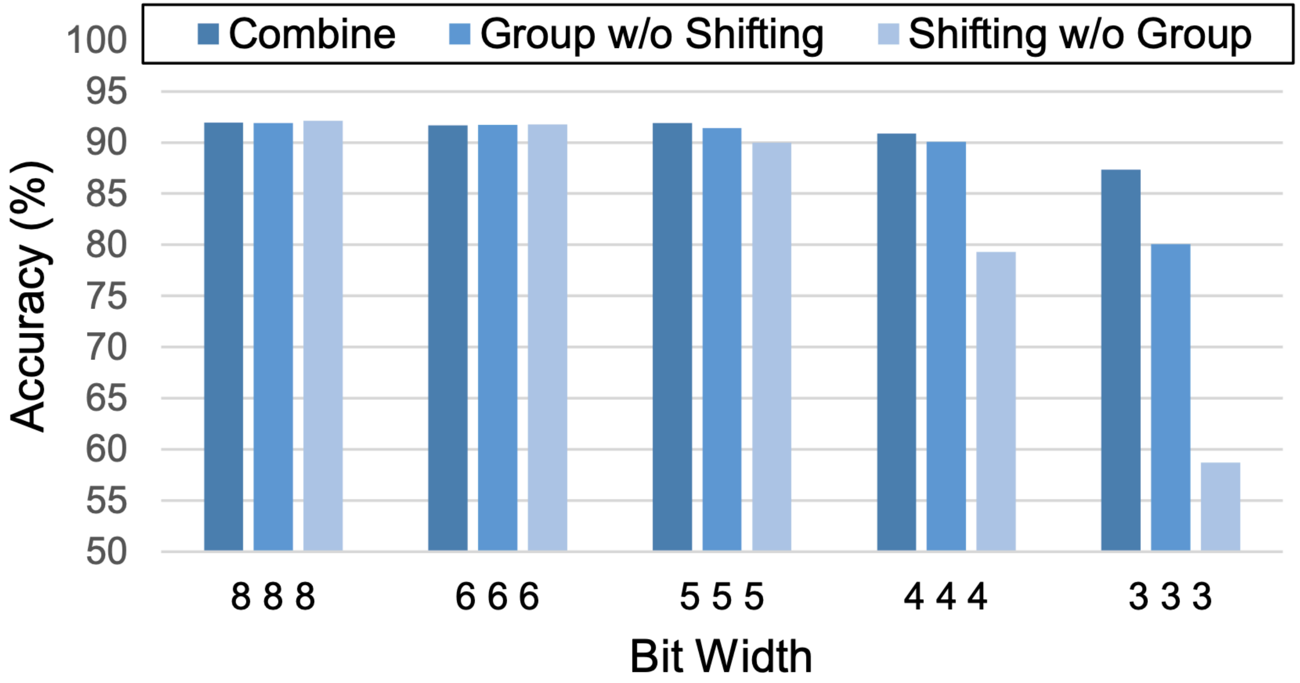
Some Experimental results

- Constrained group-wise scaling
  - Simple mantissa scale works better than the others in low-bit training.

Bit-Width	Float Scale	Group-wise Power Scale	Group-wise Same Mantissa Scale	Group-wise Simple Mantissa Scale
6 6 6	91.26%	**91.71**%	91.55%	91.67%
5 5 5	88.87%	91.40%	91.35%	**91.68**%
4 4 4	78.95%	90.08%	90.54%	**90.66**%
3 3 3	62.50%	80.06%	82.73%	**84.29**%

Some Experimental results

- Combination of shiftable fixed-point and group-wise scaling
  - The combination scheme is the best.



Some Experimental results

- Double-precision deployment
  - Boost performance without any extra training.
  - Finetuning with double precision can further improve the accuracy.

Bit-Width	Finetune	None	W	A	W+A
4 4 4	No	91.46	-	-	-
3 3 3	No	89.12	91.41	90.12	**91.74**
2 2 2	No	87.34	89.14	88.72	**90.75**
2 2 2	Yes	-	89.34	89.18	**91.1**

Discussion: Hardware Cost Estimation

- Comparation of circuit units(45nm, 0.9V)[11]
- Statistic of computation

Params	Energy(pJ)		Area(μm^2)	
	Mul	Add	Mul	Add
8-bit Fix	0.2	0.03	282	36
16-bit Float	1.1	0.40	1640	1360
32-bit Float	3.7	0.90	7700	4184

Op Name	Op Type	Res18	Res20
Conv (F)	Mul&Add	2.72E+10	4.05E+07
Conv (B)	Mul&Add	5.44E+10	8.11E+07
BN (F)	Mul&Add	3.01E+07	1.88E+05
BN (B)	Mul&Add	3.01E+07	1.88E+05
EW-Add (F)	Add	1.49E+07	7.37E+04
EW-Add (B)	Add	1.20E+07	7.37E+04
Params Update (B)	Add	1.12E+07	2.68E+05

- Our algorithm has the potential to save at least 75% energy cost of the computation cost when we train ResNet-18 with N = 8.

Next

- Do more experiments on ImageNet with more networks.
  - Different experiment parameters
  - VGG, AlexNet
  - MobileNet
- Try more detailed techniques.
  - different quantization parameters for different layers
  - Shifting bit
  - Group dimention
  - Double or not
- Hardware design.

Reference

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