香港中文大學
The Chinese University of Hong Kong

CMSC5743

L06: Binary/Ternary Network

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(Latest update: November 2, 2020)

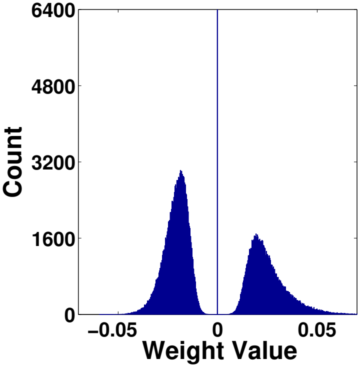
Fall 2020

These slides contain/adapt materials developed by

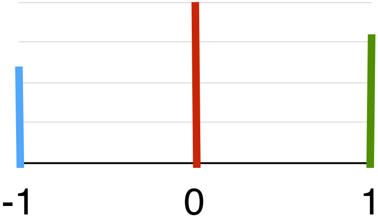
- Ritchie Zhao et al. (2017). “Accelerating binarized convolutional neural networks with software-programmable FPGAs”. In: *Proc. FPGA*, pp. 15–24
- Mohammad Rastegari et al. (2016). “XNOR-NET: Imagenet classification using binary convolutional neural networks”. In: *Proc. ECCV*, pp. 525–542

Motivation

Binary / Ternary Net: Motivation

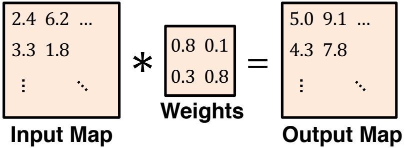


=>



Binarized Neural Networks (BNN)

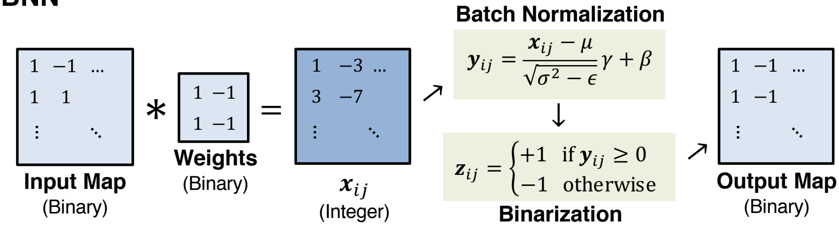
CNN



Key Differences

1. Inputs are binarized (–1 or +1)
2. Weights are binarized (–1 or +1)
3. Results are binarized after **batch normalization**

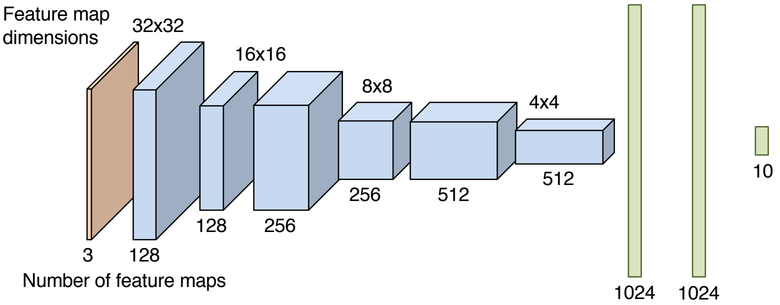
BNN



$$y_{ij} = \frac{x_{ij} - \mu}{\sqrt{\sigma^2 - \epsilon}}\gamma + \beta$$

$$z_{ij} = \begin{cases} +1 & \text{if } y_{ij} \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

BNN CIFAR-10 Architecture [2]



- 6 conv layers, 3 dense layers, 3 max pooling layers
- All conv filters are 3x3
- First conv layer takes in floating-point input
- **13.4 Mbits total model size** (after hardware optimizations)

[2] M. Courbariaux et al. **Binarized Neural Networks: Training Deep Neural Networks with Weights and Activations Constrained to +1 or -1**. *arXiv:1602.02830*, Feb 2016.

Advantages of BNN

1. Floating point ops replaced with binary logic ops

b_1	b_2	$b_1 \times b_2$
$+1$	$+1$	$+1$
$+1$	-1	-1
-1	$+1$	-1
-1	-1	$+1$

b_1	b_2	b_1 XOR b_2
0	0	0
0	1	1
1	0	1
1	1	0

- Encode {+1,–1} as {0,1} → multiplies become XORs
- Conv/dense layers do dot products → XOR and popcount
- Operations can map to LUT fabric as opposed to DSPs

2. Binarized weights may reduce total model size

- Fewer bits per weight may be offset by having more weights

BNN vs CNN Parameter Efficiency

Architecture	Depth	Param Bits (Float)	Param Bits (Fixed-Point)	Error Rate (%)
ResNet [3] (CIFAR-10)	164	51.9M	13.0M*	11.26
BNN [2]	9	-	13.4M	11.40

* Assuming each float param can be quantized to 8-bit fixed-point

- **Comparison:**
  - Conservative assumption: ResNet can use 8-bit weights
  - BNN is based on VGG (less advanced architecture)
  - BNN seems to hold promise!

[2] M. Courbariaux et al. **Binarized Neural Networks: Training Deep Neural Networks with Weights and Activations Constrained to +1 or -1**. *arXiv:1602.02830*, Feb 2016.

[3] K. He, X. Zhang, S. Ren, and J. Sun. **Identity Mappings in Deep Residual Networks.** *ECCV 2016.*

Overview

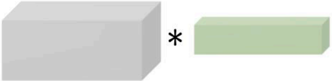
Minimize the Quantization Error

Reduce the Gradient Error

Overview

Minimize the Quantization Error

Reduce the Gradient Error

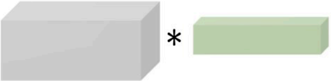
	Operations	Memory	Computation
$\mathbb{R}$ * $\mathbb{R}$	+ − ×	1x	1x

Binary Weight Networks

XNOR-Networks

[1]

[1] Mohammad Rastegari et al. (2016). “XNOR-NET: Imagenet classification using binary convolutional neural networks”. In: *Proc. ECCV*, pp. 525–542.

	Operations	Memory	Computation
$\mathbb{R} \quad * \quad \mathbb{R}$	+ − ×	1x	1x
$\mathbb{R} \quad * \quad \mathbb{B}$	+ −	~32x	~2x
$\mathbb{B} \quad * \quad \mathbb{B}$	XNOR Bit-count	~32x	~58x

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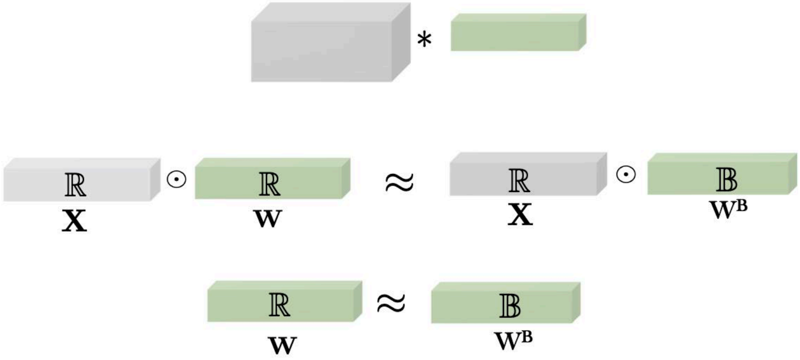

$$\mathbf{W}^{\mathbf{B}} = \mathrm{sign}(\mathbf{W})$$

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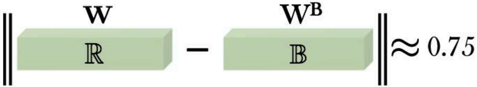
Quantization Error

$$W^B = \mathrm{sign}(W)$$



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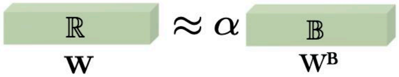
Optimal Scaling Factor



$$\alpha^*, \mathbf{W}^{\mathbf{B}^*} = \arg\min_{\mathbf{W}^{\mathbf{B}},\alpha} \{||\mathbf{W} - \alpha\mathbf{W}^{\mathbf{B}}||^{\mathbf{2}}\}$$

$$\boxed{\begin{aligned} \mathbf{W}^{\mathbf{B}^*} &= \operatorname{sign}(\mathbf{W}) \\ \alpha^* &= \frac{1}{n}\|\mathbf{W}\|_{\ell 1} \end{aligned}}$$

1

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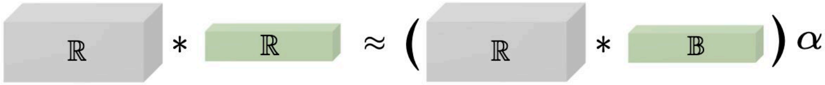
How to train a CNN with binary filters?



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Training Binary Weight Networks

Naive Solution:

1. Train a network with real value parameters
2. Binarize the weight filters

[1]

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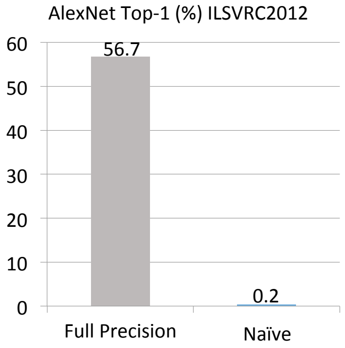

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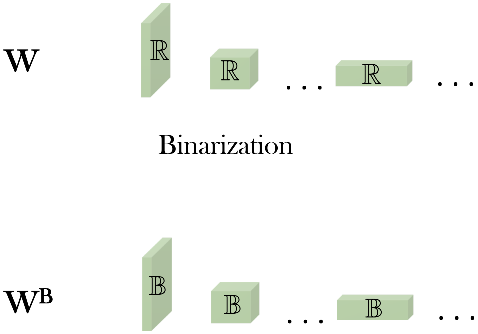

Binarization

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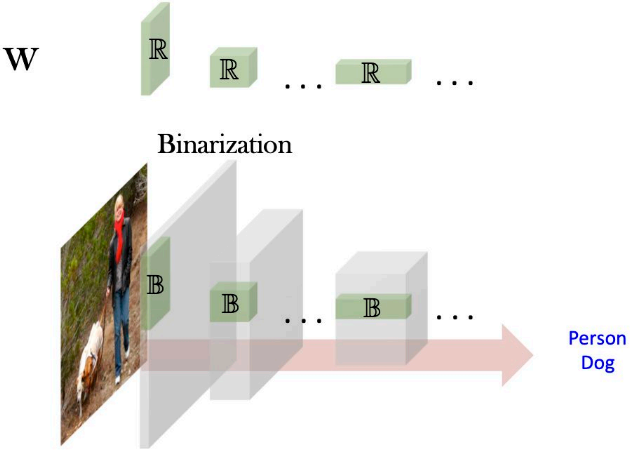

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Binary Weight Network

Train for binary weights:

```
1. Randomly initialize $\mathbf{W}$
2. For $iter = 1$ to $N$
3.     Load a random input image $\mathbf{X}$
4.     $\mathbf{W^B} = \text{sign}(\mathbf{W})$
5.     $\alpha = \frac{\|W\|_{\ell 1}}{n}$
6.     Forward pass with $\alpha, \mathbf{W^B}$
7.     Compute loss function $\mathbf{C}$
8.     $\frac{\partial \mathbf{C}}{\partial \mathbf{W}} =$ Backward pass with $\alpha, \mathbf{W^B}$
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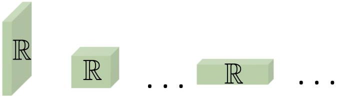

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$\mathbf{W}$

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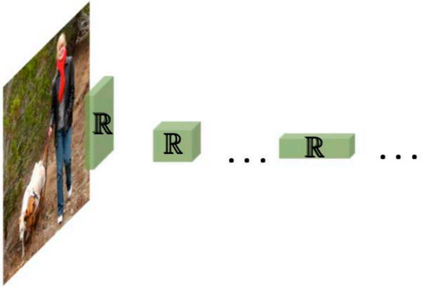

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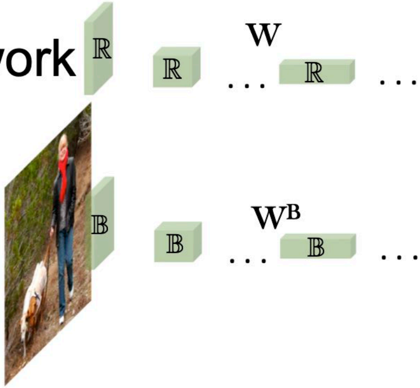

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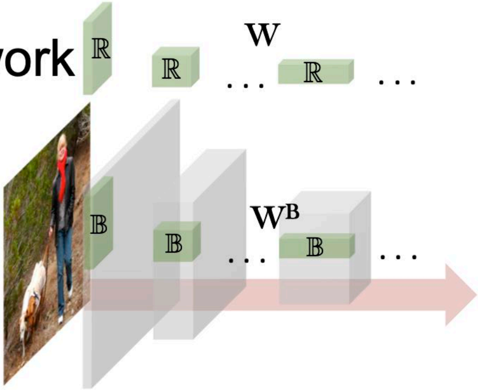

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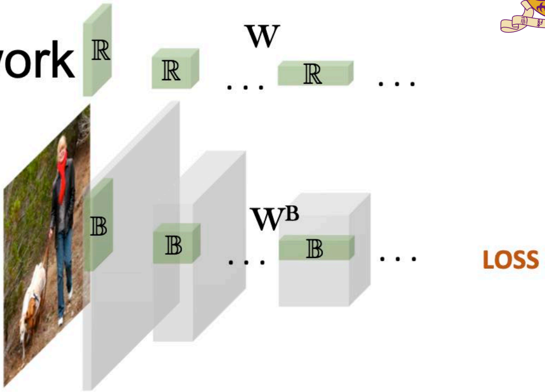

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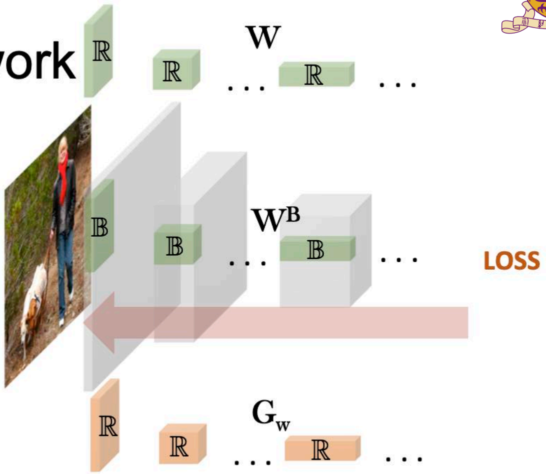

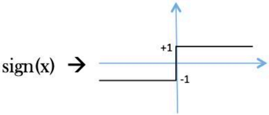

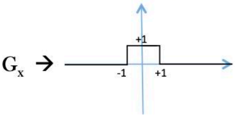

[Hinton et al. 2012] [1]

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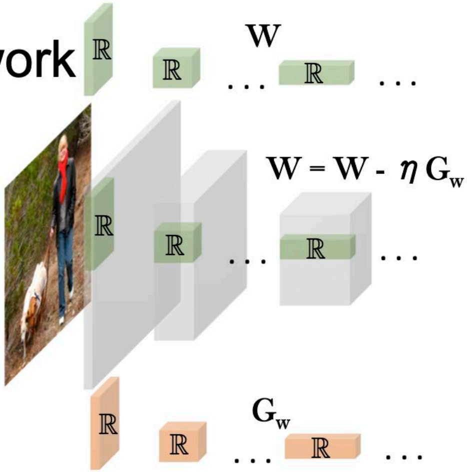

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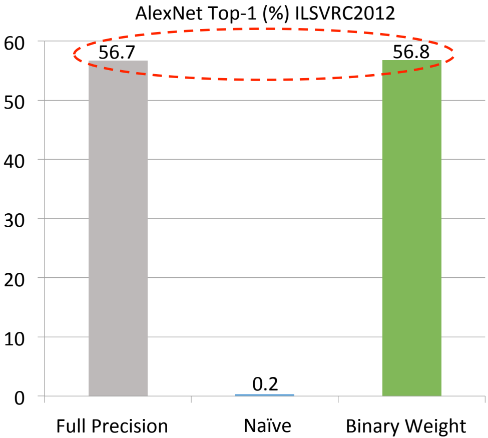

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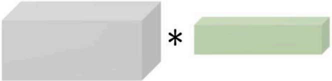	Operations	Memory	Computation
$\mathbb{R} * \mathbb{R}$	+ − ×	1x	1x
$\mathbb{R} * \mathbb{B}$	$\boxed{+ \; -}$	$\boxed{\sim 32x}$	$\boxed{\sim 2x}$
$\boxed{\mathbb{B} * \mathbb{B}}$ XNOR-Networks	XNOR Bit-count	~32x	~58x

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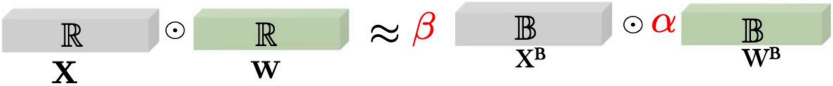
Binary Input and Binary Weight (XNOR-Net)



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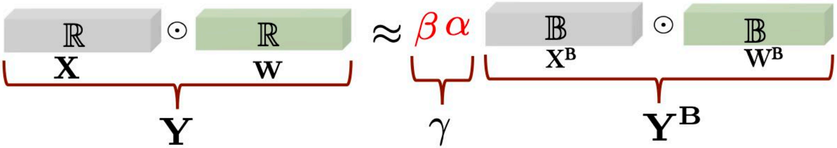

$$\mathbf{Y} \approx \gamma\ \mathbf{Y^B}$$

$$\mathbf{Y^B}^*, \gamma^* = \arg\min_{\mathbf{Y^B},\gamma} \|\mathbf{Y} - \gamma \mathbf{Y^B}\|^2$$

$$\boxed{\mathbf{Y^B}^* = \text{sign}(\mathbf{Y}) \quad \gamma^* = \frac{1}{n}\|\mathbf{Y}\|_{\ell 1}}$$

$$\boxed{\mathbf{X^B}^* = \text{sign}(\mathbf{X}) \quad \mathbf{W^B}^* = \text{sign}(\mathbf{W})} \qquad \boxed{\alpha^* = \frac{1}{n}\|\mathbf{W}\|_{\ell 1} \qquad \beta^* = \frac{1}{n}\|\mathbf{X}\|_{\ell 1}}$$

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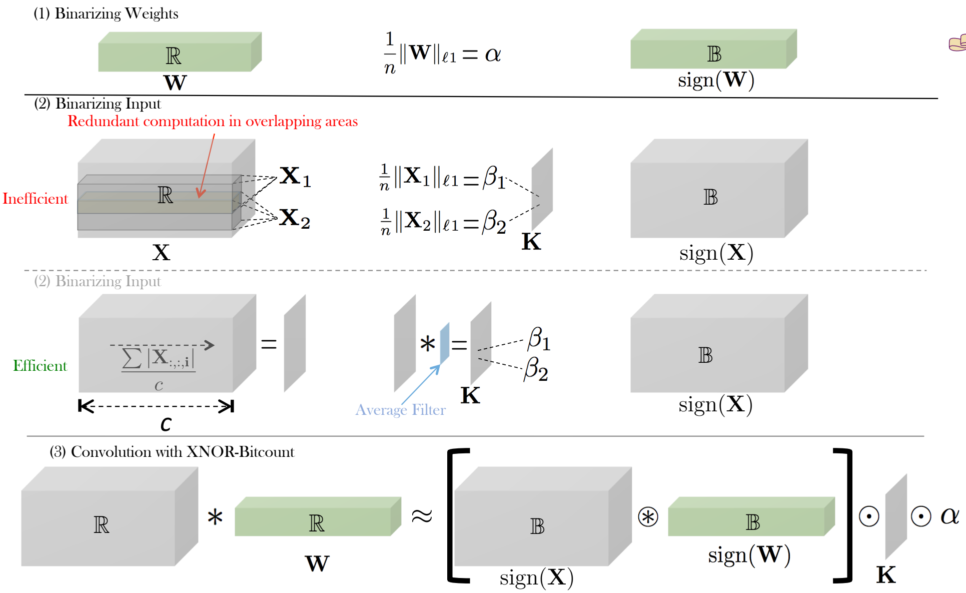
(1) Binarizing Weights
$\mathbb{R}$
$\mathbf{W}$
$\frac{1}{n}\|\mathbf{W}\|_{\ell 1} = \alpha$
$\mathbb{B}$
$\mathrm{sign}(\mathbf{W})$
(2) Binarizing Input
Redundant computation in overlapping areas
Inefficient
$\mathbb{R}$
$\mathbf{X}_1$
$\mathbf{X}_2$
$\mathbf{X}$
$\frac{1}{n}\|\mathbf{X}_1\|_{\ell 1} = \beta_1$
$\frac{1}{n}\|\mathbf{X}_2\|_{\ell 1} = \beta_2$
$\mathbf{K}$
$\mathbb{B}$
$\mathrm{sign}(\mathbf{X})$
(2) Binarizing Input
Efficient
$\frac{\sum |\mathbf{X}_{:,:,i}|}{c}$
$=$
c
$*$
$=$
β_1
β_2
Average Filter
$\mathbf{K}$
$\mathbb{B}$
$\mathrm{sign}(\mathbf{X})$
(3) Convolution with XNOR-Bitcount
$\mathbb{R}$
$*$
$\mathbb{R}$
$\mathbf{W}$
$\approx$
$\mathbb{B}$
$\mathrm{sign}(\mathbf{X})$
$\circledast$
$\mathbb{B}$
$\mathrm{sign}(\mathbf{W})$
$\odot$
$\mathbf{K}$
$\odot\ \alpha$

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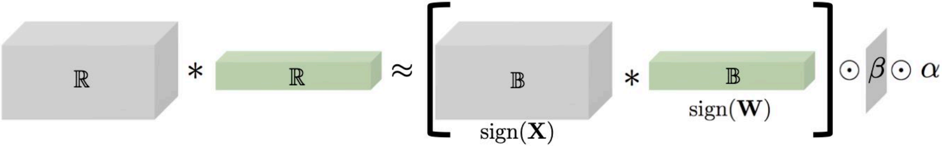
$\mathbb{R}$
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$\mathbb{B}$
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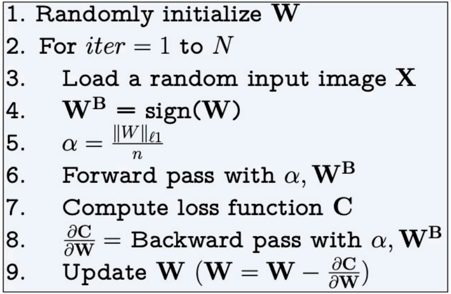
$\odot \beta \odot \alpha$



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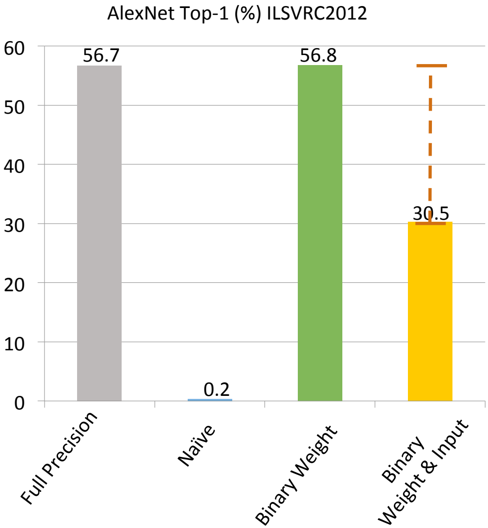
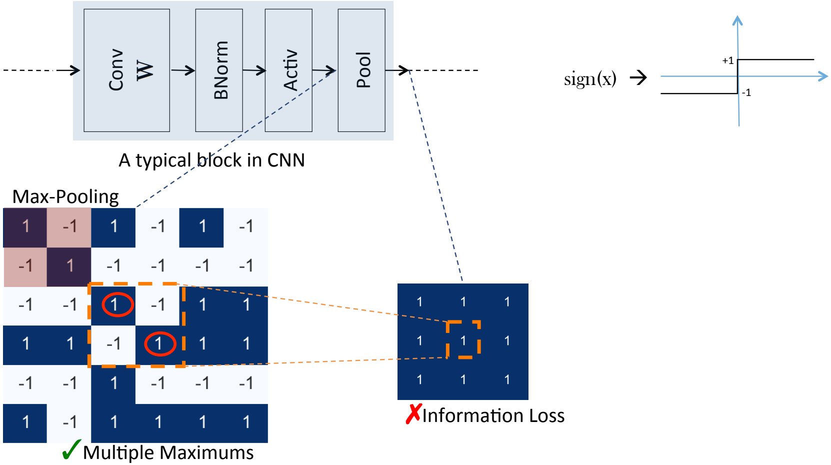


[1]

[1] Mohammad Rastegari et al. (2016). “XNOR-NET: Imagenet classification using binary convolutional neural networks”. In: *Proc. ECCV*, pp. 525–542.

Network Structure in XNOR-Networks



A typical block in CNN

1	-1	1	-1	1	-1
-1	1	-1	-1	-1	-1
-1	-1	1	-1	1	1
1	1	-1	1	1	1
-1	-1	1	-1	-1	-1
1	-1	1	1	1	1

✓ Multiple Maximums

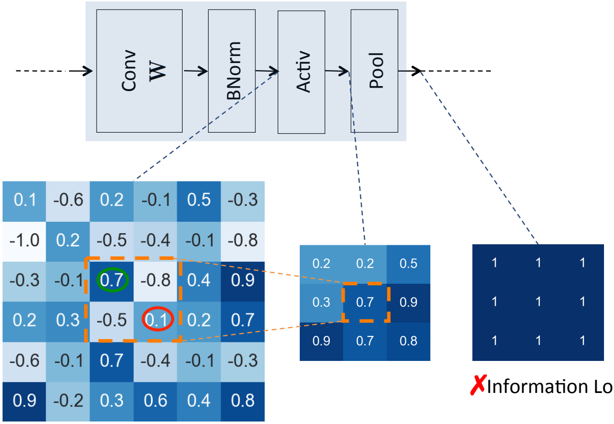
1	1	1
1	1	1
1	1	1

✗ Information Loss

1

[1] Mohammad Rastegari et al. (2016). "XNOR-NET: Imagenet classification using binary convolutional neural networks". In: *Proc. ECCV*, pp. 525–542.

Network Structure in XNOR-Networks



0.1	-0.6	0.2	-0.1	0.5	-0.3
-1.0	0.2	-0.5	-0.4	-0.1	-0.8
-0.3	-0.1	0.7	-0.8	0.4	0.9
0.2	0.3	-0.5	0.1	0.2	0.7
-0.6	-0.1	0.7	-0.4	-0.1	-0.3
0.9	-0.2	0.3	0.6	0.4	0.8

0.2	0.2	0.5
0.3	0.7	0.9
0.9	0.7	0.8

1	1	1
1	1	1
1	1	1

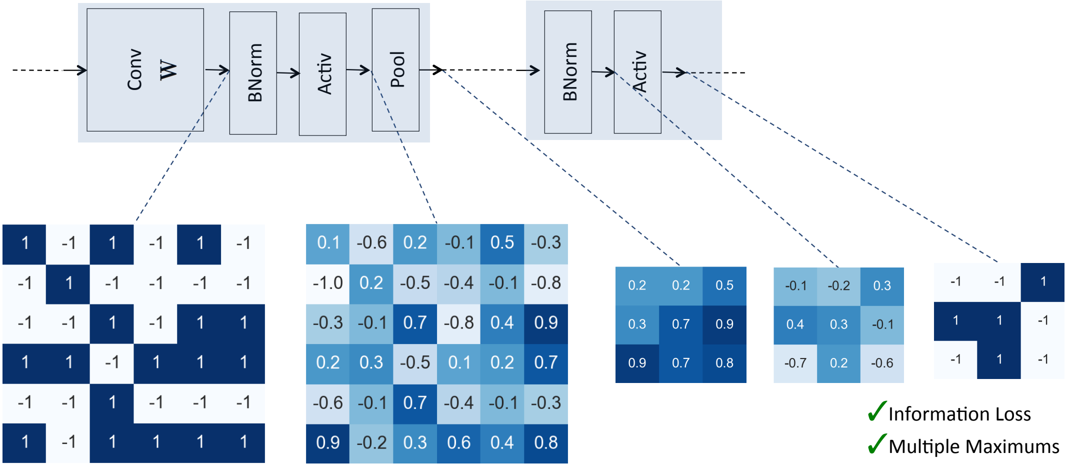
✗Information Loss

✓Multiple Maximums

[1]

[1] Mohammad Rastegari et al. (2016). “XNOR-NET: Imagenet classification using binary convolutional neural networks”. In: *Proc. ECCV*, pp. 525–542.

Network Structure in XNOR-Networks



1	-1	1	-1	1	-1
-1	1	-1	-1	-1	-1
-1	-1	1	-1	1	1
1	1	-1	1	1	1
-1	-1	1	-1	-1	-1
1	-1	1	1	1	1

0.1	-0.6	0.2	-0.1	0.5	-0.3
-1.0	0.2	-0.5	-0.4	-0.1	-0.8
-0.3	-0.1	0.7	-0.8	0.4	0.9
0.2	0.3	-0.5	0.1	0.2	0.7
-0.6	-0.1	0.7	-0.4	-0.1	-0.3
0.9	-0.2	0.3	0.6	0.4	0.8

0.2	0.2	0.5
0.3	0.7	0.9
0.9	0.7	0.8

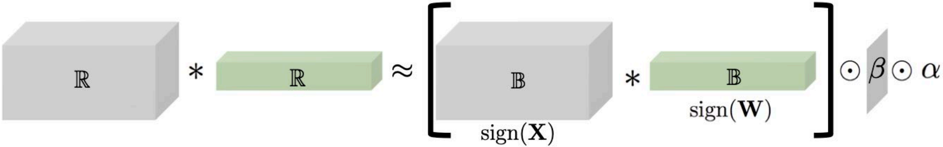
-0.1	-0.2	0.3
0.4	0.3	-0.1
-0.7	0.2	-0.6

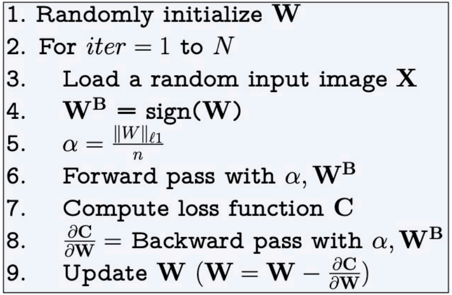
-1	-1	1
1	1	-1
-1	1	-1

✓Information Loss

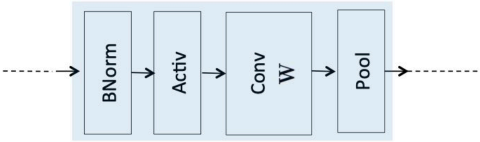
✓Multiple Maximums [1]

[1] Mohammad Rastegari et al. (2016). "XNOR-NET: Imagenet classification using binary convolutional neural networks". In: *Proc. ECCV*, pp. 525–542.


$\mathbb{R}$
$*$
$\mathbb{R}$
$\approx$
$\mathbb{B}$
$\text{sign}(\mathbf{X})$
$*$
$\mathbb{B}$
$\text{sign}(\mathbf{W})$
$\odot\, \beta \odot \alpha$

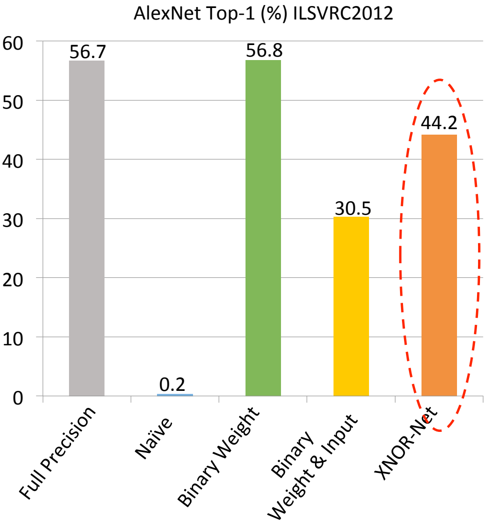


```
1. Randomly initialize $\mathbf{W}$
2. For $iter = 1$ to $N$
3.     Load a random input image $\mathbf{X}$
4.     $\mathbf{W}^{\mathbf{B}} = \text{sign}(\mathbf{W})$
5.     $\alpha = \frac{\|W\|_{\ell 1}}{n}$
6.     Forward pass with $\alpha, \mathbf{W}^{\mathbf{B}}$
7.     Compute loss function $\mathbf{C}$
8.     $\frac{\partial \mathbf{C}}{\partial \mathbf{W}} =$ Backward pass with $\alpha, \mathbf{W}^{\mathbf{B}}$
9.     Update $\mathbf{W}$ $(\mathbf{W} = \mathbf{W} - \frac{\partial \mathbf{C}}{\partial \mathbf{W}})$
```

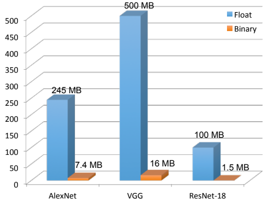


[1]

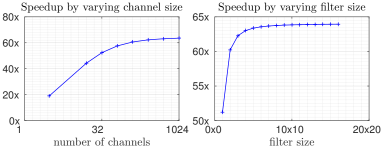
[1] Mohammad Rastegari et al. (2016). "XNOR-NET: Imagenet classification using binary convolutional neural networks". In: *Proc. ECCV*, pp. 525–542.



✓ 32x Smaller Model

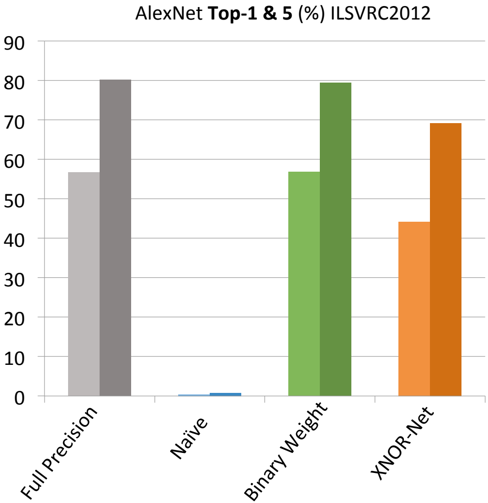


✓ 58x Less Computation



[1]

[1] Mohammad Rastegari et al. (2016). “XNOR-NET: Imagenet classification using binary convolutional neural networks”. In: *Proc. ECCV*, pp. 525–542.



[1]

[1] Mohammad Rastegari et al. (2016). “XNOR-NET: Imagenet classification using binary convolutional neural networks”. In: *Proc. ECCV*, pp. 525–542.

Motivation and Intuition

Motivation

- Naive methods (Matthieu Courbariaux, Yoshua Bengio, and Jean-Pierre David (2015). "Binaryconnect: Training deep neural networks with binary weights during propagations". In: *Advances in neural information processing systems*, pp. 3123–3131, Matthieu Courbariaux, Itay Hubara, et al. (2016). "Binarized neural networks: Training deep neural networks with weights and activations constrained to+ 1 or-1". In: *arXiv preprint arXiv:1602.02830*) suffer the accuracy loss

Intuition

- Quantized parameter should approximate the full precision parameter as closely as possible

ABC-Net

Towards Accurate Binary Convolutional Neural Network

ABC-Net

Contribution

- Approximate full-precision weights with the linear combination of multiple binary weight bases
- Introduce multiple binary activations

ABC-Net

Weights Binarization

- Weights tensors in one layer: $W \in \mathbb{R}^{w \times h \times c_{in} \times c_{\text{out}}}$

$$
\begin{aligned}
&B_1, B_2, \ldots, B_M \in \{-1, +1\}^{w \times h \times c_{in} x c_{out}} \\
&W \approx \alpha_1 B_1 + \alpha_2 B_2 + \ldots + \alpha_M B_M \\
&B_i = F_{u_i}(W) = \operatorname{sign}\left(\bar{W} + u_i \operatorname{std}(W)\right), i = 1, 2, \ldots, M
\end{aligned}
$$

where $\bar{W} = W - mean(W)$, u_i is a shift parameter(e.g. $u_i = -1 + (i-1)\frac{2}{M-1}$)
α can be calculated via $\min_a J(\alpha) = \|W - B\alpha\|^2$

ABC-Net

Forward and Backward

- Forward

$$B_1, B_2, \cdots, B_M = F_{u_1}(W), F_{w_2}(W), \cdots, F_{u,u}(W)$$

$$solve \min_{a} J(\alpha) = \|W - B\alpha\|^2 \, for \; \alpha$$

$$O = \sum_{m=1}^{M} \alpha_m \operatorname{Conv}(B_m, A)$$

- Backward

$$\frac{\partial c}{\partial W} = \frac{\partial c}{\partial O}\left(\sum_{m=1}^{M} \alpha_m \frac{\partial O}{\partial B_m}\frac{\partial B_m}{\partial W}\right) \overset{STE}{=} \frac{\partial c}{\partial O}\left(\sum_{m=1}^{M} \alpha_m \frac{\partial O}{\partial B_m}\right) = \sum_{m=1}^{M} \alpha_m \frac{\partial c}{\partial B_m}$$

ABC-Net

Multiple Binary Activations

- Bounded Activation Function

$$h(x) \in [0, 1]$$

$$h_r(x) = \mathrm{clip}(x + v, 0, 1)$$

where v is a shift parameter

- Binarization Function

$$H_v(\boldsymbol{R}) := 2\mathbb{I}_{h_v(\boldsymbol{R}) \geq 0.5} - 1$$

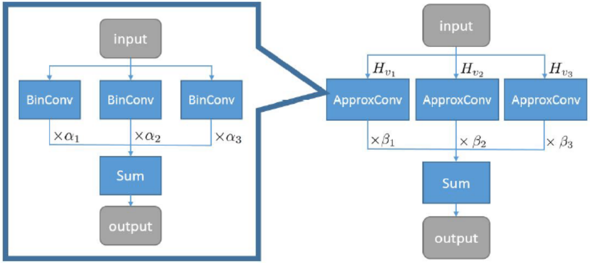
$$A_1, A_2, \ldots, A_N = H_{v_1}(R), H_{v_2}(R), \ldots, H_{v_N}(R)$$

$$R \approx \beta_1 A_1 + \beta_2 A_2 + \ldots + \beta_N A_N$$

where R is the real-value activation

- $A_1, A_2, \ldots, A_N$ is the base to represent the real-valued activations

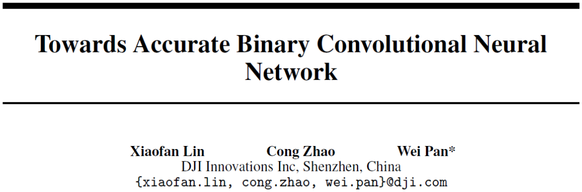
ABC-Net



- ApproxConv is expected to approximate the conventional full-precision convolution with linear combination of binary convolutions
- The right part is the overall block structure of the convolution in ABC-Net.The input is binarized using different functions H_v1,H_v2,H_v3
  $$\mathrm{Conv}(\boldsymbol{W},\boldsymbol{R}) \approx \mathrm{Conv}\left(\sum_{m=1}^{M}\alpha_m\boldsymbol{B}_m, \sum_{n=1}^{N}\beta_n\boldsymbol{A}_n\right) = \sum_{m=1}^{M}\sum_{n=1}^{N}\alpha_m\beta_n\,\mathrm{Conv}\left(\boldsymbol{B}_m,\boldsymbol{A}_n\right)$$

ABC-Net

Read the paper[2] if you want to learn the specific details of the algorithm



Towards Accurate Binary Convolutional Neural Network

Xiaofan Lin **Cong Zhao** **Wei Pan***
DJI Innovations Inc, Shenzhen, China
`{xiaofan.lin, cong.zhao, wei.pan}@dji.com`

[2] Xiaofan Lin, Cong Zhao, and Wei Pan (2017). "Towards accurate binary convolutional neural network". In: *Advances in Neural Information Processing Systems*, pp. 345–353.

Overview

Minimize the Quantization Error

Reduce the Gradient Error

Motivation and Intuition

Motivation

- Although STE is often adopted to estimate the gradients in BP, there exists obvious gradient mismatch between the gradient of the binarization function
- With the restriction of STE, the parameters outside the range of $[-1 : +1]$ will not be updated.

Bi-Real

Bi-real net: Enhancing the performance of 1-bit CNNs with improved representational capability and advanced training algorithm

Bi-Real

Naive Binarization Function

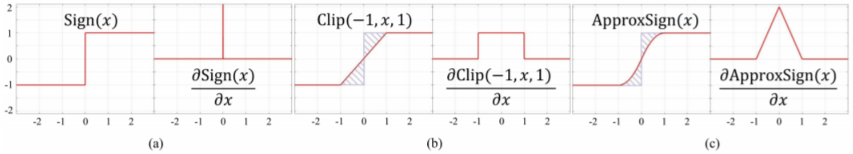
- Recall the partial derivative calculation in back propagation

$$\frac{\partial \mathcal{L}}{\partial \mathbf{A}_r^{l,t}} = \frac{\partial \mathcal{L}}{\partial \mathbf{A}_b^{l,t}} \frac{\partial \mathbf{A}_b^{l,t}}{\partial \mathbf{A}_r^{l,t}} = \frac{\partial \mathcal{L}}{\partial \mathbf{A}_b^{l,t}} \frac{\partial \operatorname{Sign}\left(\mathbf{A}_r^{l,t}\right)}{\partial \mathbf{A}_r^{l,t}} \approx \frac{\partial \mathcal{L}}{\partial \mathbf{A}_b^{l,t}} \frac{\partial F\left(\mathbf{A}_r^{l,t}\right)}{\partial \mathbf{A}_r^{l,t}}$$

- $Sign$ function is a non-differentiable function, so F is an approximation differentiable function of $Sign$ function

Bi-Real

$$\frac{\partial \mathcal{L}}{\partial \mathbf{A}_r^{l,t}} = \frac{\partial \mathcal{L}}{\partial \mathbf{A}_b^{l,t}} \frac{\partial \mathbf{A}_b^{l,t}}{\partial \mathbf{A}_r^{l,t}} = \frac{\partial \mathcal{L}}{\partial \mathbf{A}_b^{l,t}} \frac{\partial \operatorname{Sign}\left(\mathbf{A}_r^{l,t}\right)}{\partial \mathbf{A}_r^{l,t}} \approx \frac{\partial \mathcal{L}}{\partial \mathbf{A}_b^{l,t}} \frac{\partial F\left(\mathbf{A}_r^{l,t}\right)}{\partial \mathbf{A}_r^{l,t}}$$



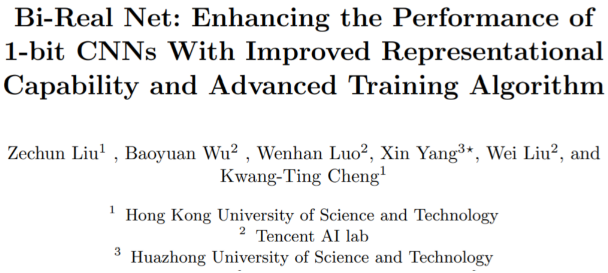
Approximation of *Sign* function

- Naive Approximation $F(x) = clip(x, 0, 1)$, see fig(b)
- More Precious Approximation in Bi-Real, see fig(c)

$$Approxsign(x) = \begin{cases} -1, & \text{if } x < -1 \\ 2x + x^2, & \text{if } -1 \leq x < 0 \\ 2x - x^2, & \text{if } 0 \leq x < 1 \\ 1, & \text{otherwise} \end{cases} \quad \frac{\partial Approxsign(x)}{\partial x} = \begin{cases} 2 + 2x, & \text{if } -1 \leq x < 0 \\ 2 - 2x, & \text{if } 0 \leq x < 1 \\ 0, & \text{otherwise} \end{cases}$$

Bi-Real

Read the paper[3] if you want to learn the specific details of the algorithm



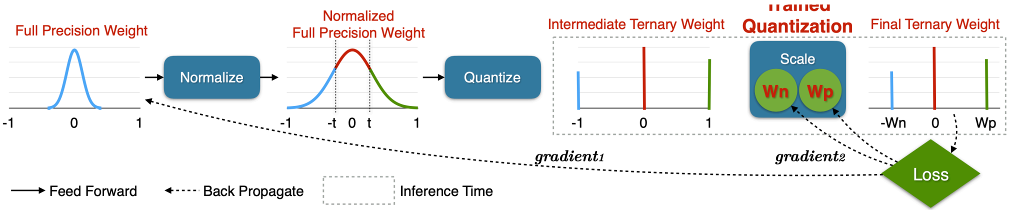
Bi-Real Net: Enhancing the Performance of 1-bit CNNs With Improved Representational Capability and Advanced Training Algorithm

Zechun Liu[1] , Baoyuan Wu[2] , Wenhan Luo[2], Xin Yang[3*], Wei Liu[2], and Kwang-Ting Cheng[1]

[1] Hong Kong University of Science and Technology
[2] Tencent AI lab
[3] Huazhong University of Science and Technology

[3] Zechun Liu et al. (2018). "Bi-real net: Enhancing the performance of 1-bit cnns with improved representational capability and advanced training algorithm". In: *Proceedings of the European conference on computer vision (ECCV)*, pp. 722–737.

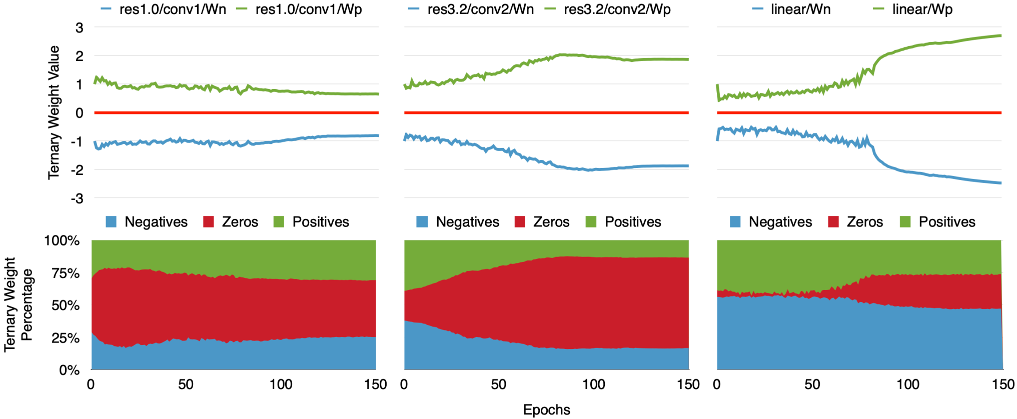
Trained Ternary Quantization[4]



Overview of the trained ternary quantization procedure.

[4] Chenzhuo Zhu et al. (2017). “Trained ternary quantization”. In: *Proc. ICLR*.

Trained Ternary Quantization[4]



Ternary weights value (above) and distribution (below) with iterations for different layers of ResNet-20 on CIFAR-10.

[4] Chenzhuo Zhu et al. (2017). "Trained ternary quantization". In: *Proc. ICLR*.

Reading List

- Hyeonuk Kim et al. (2017). "A Kernel Decomposition Architecture for Binary-weight Convolutional Neural Networks". In: *Proc. DAC*, 60:1–60:6
- Jungwook Choi et al. (2018). "Pact: Parameterized clipping activation for quantized neural networks". In: *arXiv preprint arXiv:1805.06085*
- Dongqing Zhang et al. (2018). "Lq-nets: Learned quantization for highly accurate and compact deep neural networks". In: *Proceedings of the European conference on computer vision (ECCV)*, pp. 365–382
- Aojun Zhou et al. (2017). "Incremental network quantization: Towards lossless cnns with low-precision weights". In: *arXiv preprint arXiv:1702.03044*
- Zhaowei Cai et al. (2017). "Deep learning with low precision by half-wave gaussian quantization". In: *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 5918–5926