CMSC 5743

Efficient Computing of Deep Neural Networks

Lecture 07: Binary/Ternary Network

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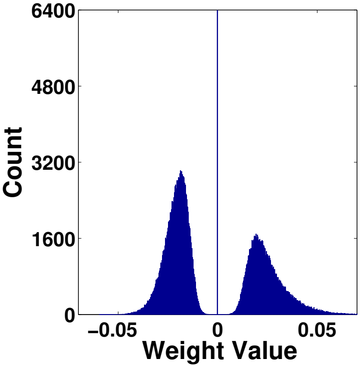
(Latest update: October 5, 2021)

Fall 2021

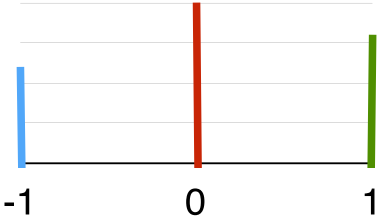
These slides contain/adapt materials developed by

- 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

Binary / Ternary Net: Motivation



=>



Binarized Neural Networks (BNN)

CNN

$$\begin{bmatrix} 2.4 & 6.2 & \dots \\ 3.3 & 1.8 & \\ \vdots & & \ddots \end{bmatrix} * \begin{bmatrix} 0.8 & 0.1 \\ 0.3 & 0.8 \end{bmatrix} = \begin{bmatrix} 5.0 & 9.1 & \dots \\ 4.3 & 7.8 & \\ \vdots & & \ddots \end{bmatrix}$$

Input Map · **Weights** · **Output Map**

Key Differences

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

BNN

$$\begin{bmatrix} 1 & -1 & \dots \\ 1 & 1 & \\ \vdots & & \ddots \end{bmatrix} * \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} = \begin{bmatrix} 1 & -3 & \dots \\ 3 & -7 & \\ \vdots & & \ddots \end{bmatrix}$$

Input Map (Binary) · **Weights** (Binary) · $\boldsymbol{x}_{ij}$ (Integer)

Batch Normalization

$$\boldsymbol{y}_{ij} = \frac{\boldsymbol{x}_{ij} - \mu}{\sqrt{\sigma^2 - \epsilon}}\gamma + \beta$$

↓

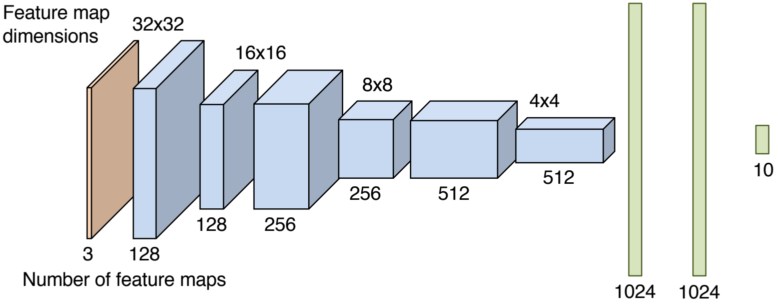
$$\boldsymbol{z}_{ij} = \begin{cases} +1 & \text{if } \boldsymbol{y}_{ij} \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

Binarization

$$\begin{bmatrix} 1 & -1 & \dots \\ 1 & -1 & \\ \vdots & & \ddots \end{bmatrix}$$

Output Map (Binary)

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!

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

Overview

1. Minimize the Quantization Error
2. Improve Network Loss Function
3. Reduce the Gradient Error

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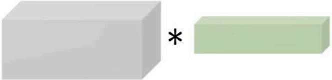	Operations	Memory	Computation
$\mathbb{R} * \mathbb{R}$	$+ \; - \; \times$	1x	1x

Binary Weight Networks

XNOR-Networks

[1]

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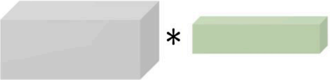

	Operations	Memory	Computation
$\mathbb{R} * \mathbb{R}$	+ − ×	1x	1x
$\mathbb{R} * \mathbb{B}$	+ −	~32x	~2x
$\mathbb{B} * \mathbb{B}$	XNOR Bit-count	~32x	~58x

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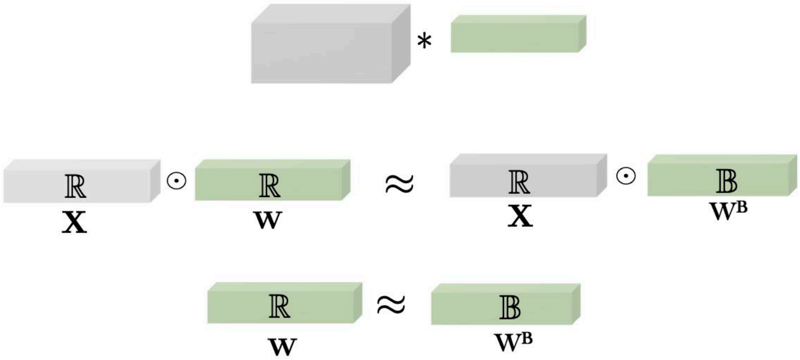

$$\mathbf{W}^{\mathbf{B}} = \mathrm{sign}(\mathbf{W})$$

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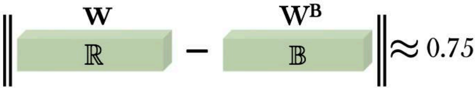
Quantization Error

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



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Optimal Scaling Factor

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

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

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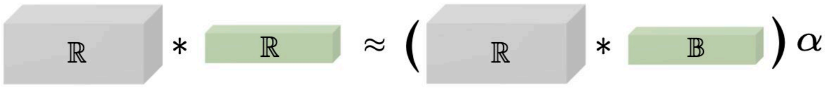
How to train a CNN with binary filters?



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Training Binary Weight Networks

Naive Solution:

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

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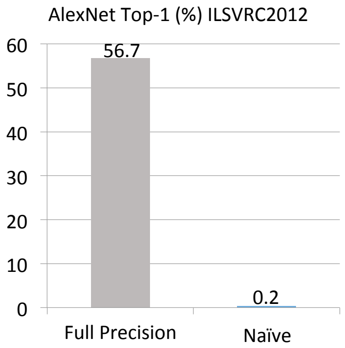

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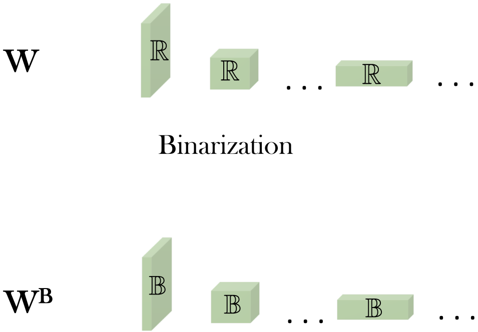

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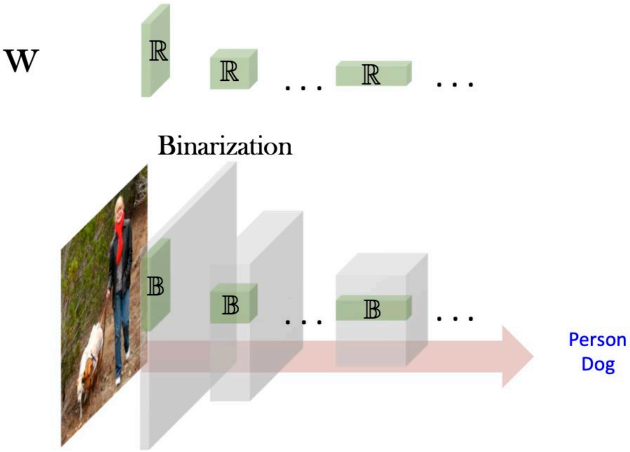

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Binary Weight Network

Train for binary weights:

1. Randomly initialize $\mathbf{W}$
2. For $iter = 1$ to N
3. Load a random input image $\mathbf{X}$
4. $\mathbf{W}^{\mathbf{B}} = \text{sign}(\mathbf{W})$
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 $\alpha, \mathbf{W}^{\mathbf{B}}$
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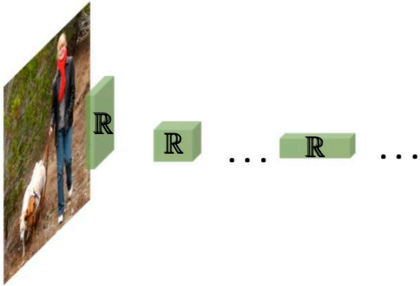

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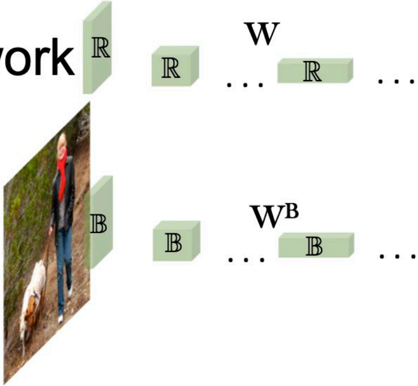

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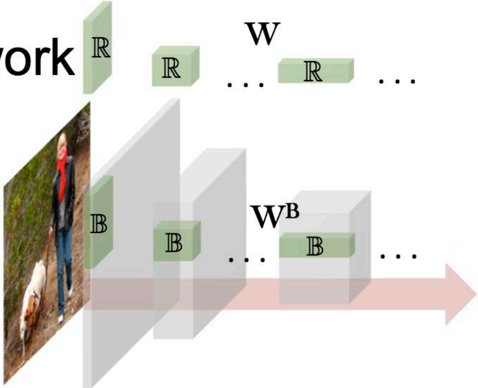

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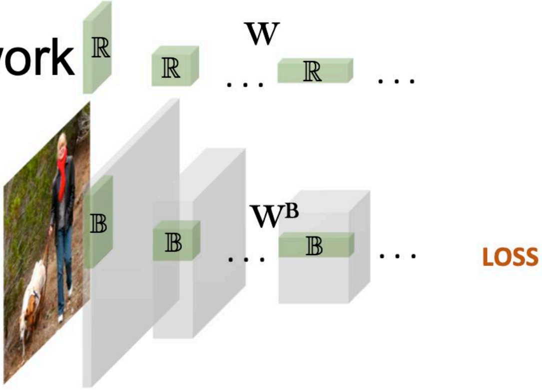

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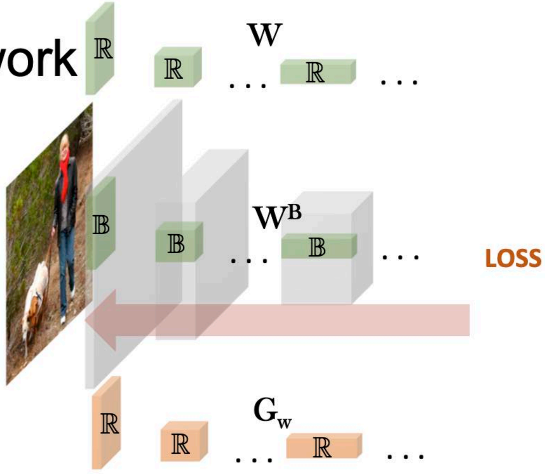

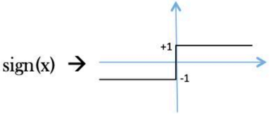

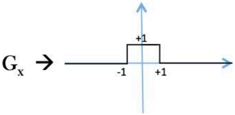

[Hinton et al. 2012]

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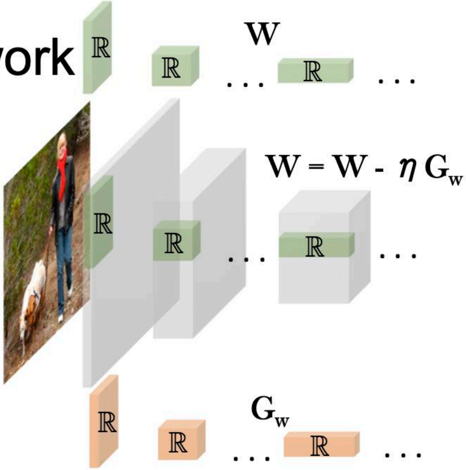

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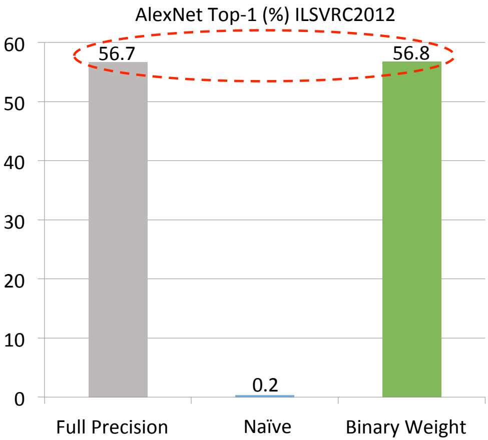

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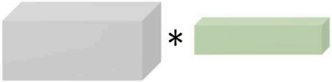	Operations	Memory	Computation
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Binary Input and Binary Weight (XNOR-Net) [1]

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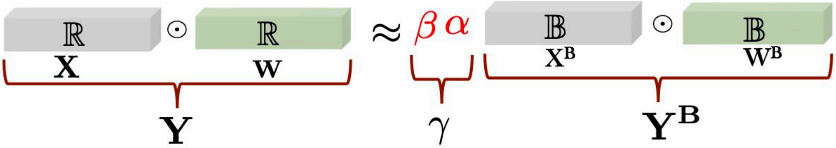

$$\mathbf{Y} \approx \gamma\, \mathbf{Y^B}$$

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

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

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

$$\alpha^* = \frac{1}{n}\|\mathbf{W}\|_{\ell 1} \qquad \beta^* = \frac{1}{n}\|\mathbf{X}\|_{\ell 1}$$

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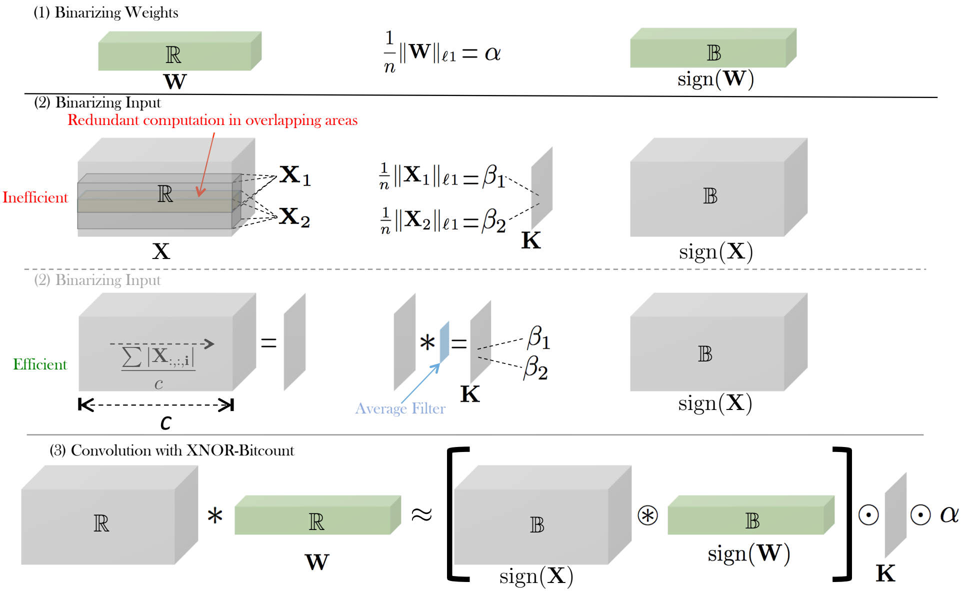

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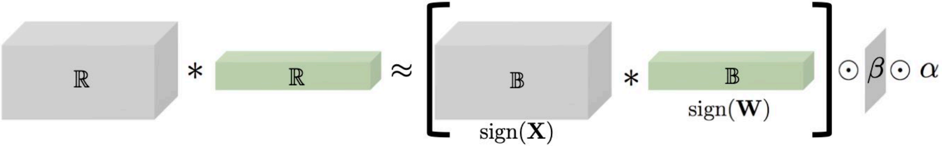

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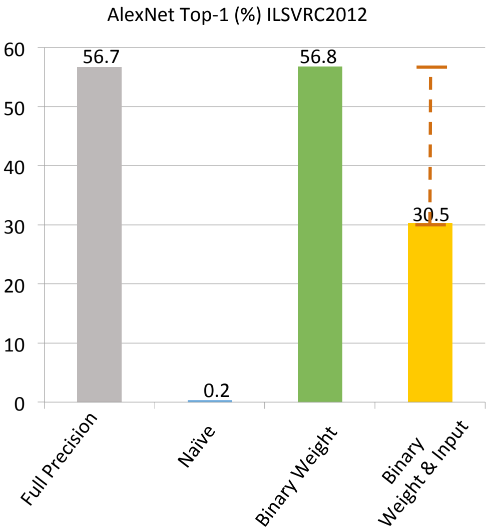

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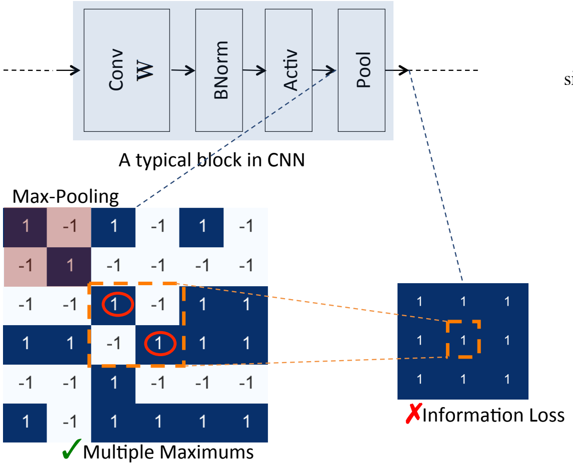
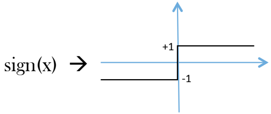
Network Structure in XNOR-Networks [1]





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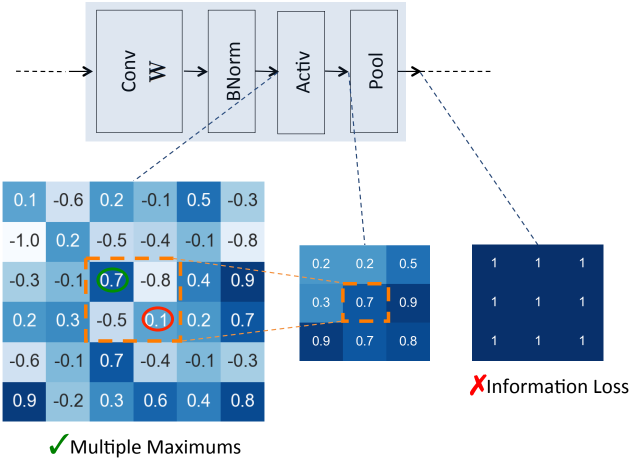

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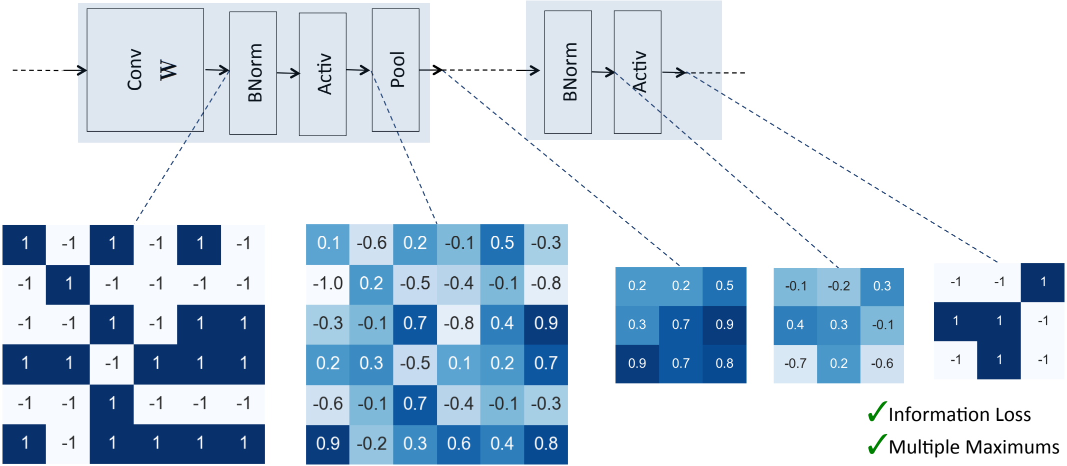

✓ Information Loss
✓ Multiple Maximums [1]

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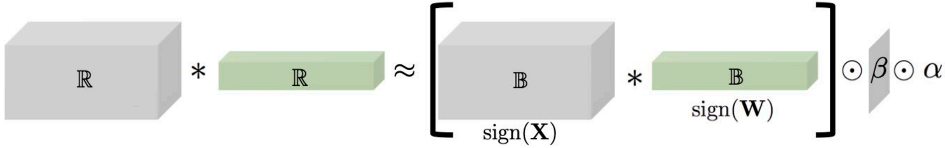

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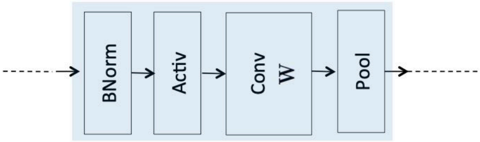
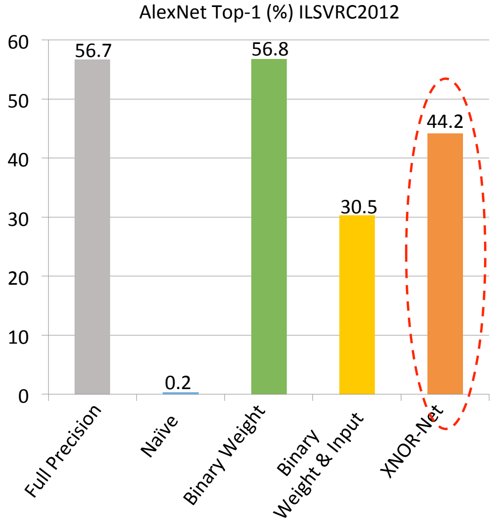
6. Forward pass with $\alpha, \mathbf{W}^{\mathrm{B}}$
7. Compute loss function $\mathbf{C}$
8. $\frac{\partial \mathrm{C}}{\partial \mathbf{W}} =$ Backward pass with $\alpha, \mathbf{W}^{\mathrm{B}}$
9. Update $\mathbf{W}$ $(\mathbf{W} = \mathbf{W} - \frac{\partial \mathrm{C}}{\partial \mathbf{W}})$

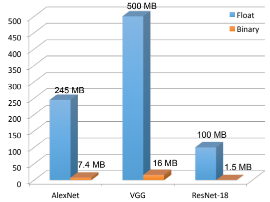


[1]

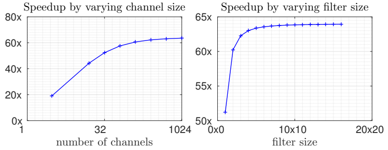
[1] Mohammad Rastegari et al. (2016). "XNOR-NET: Imagenet classification using binary convolutional neural networks". In: *Proc. ECCV*, pp. 525–542.



✓ 32x Smaller Model

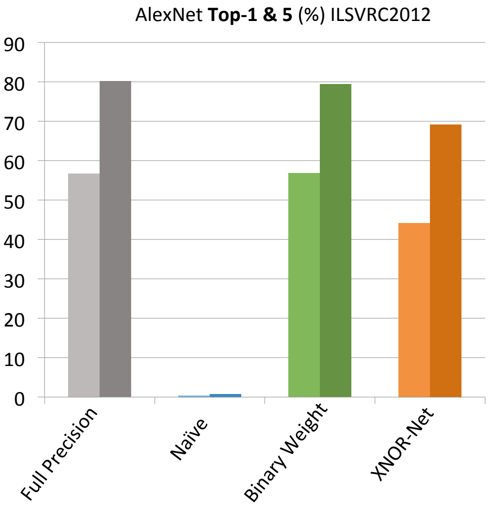


✓ 58x Less Computation



[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

- 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

DoReFa-net: Training low bitwidth convolutional neural networks with low bitwidth gradients

Contribution

- Succeeded in quantizing gradients to numbers with bitwidth less than 8 bits during the backward pass
- Creating DoReFa-Net which has arbitrary bitwidth in weights, activations and gradients
- Explore the the configuration space of bitwidth for weights, activations and gradients for DoReFa-Net

Weights Quantization

- Weights binarization

Activations Quantization

- Assume the output of the previous layer has passed through a bounded activation function h, which ensures $r \in [0, 1]$

$$f_{\alpha}^{k}(r) = \text{quantize}_{\text{k}}(r)$$

Gradient Quantization

- Gradients are unbounded and may have significantly larger value range than activations

$$f_{\gamma}^{k}(\mathrm{d}r) = 2\max_{0}(|\mathrm{d}r|)[quantize_{k}[\frac{\mathrm{d}r}{2\max_{0}(|\mathrm{d}r|)} + \frac{1}{2} + N(k)] - \frac{1}{2}]$$

$$N(k) = \frac{\sigma}{2^{k}-1} where \sigma \sim Uniform(-0.5, 0.5)$$

DoReFa-Net

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

DOREFA-NET: TRAINING LOW BITWIDTH CONVOLUTIONAL NEURAL NETWORKS WITH LOW BITWIDTH GRADIENTS

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{zsc, wyx, nzk, zxy, wenhe, zouyuheng}@megvii.com

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

Towards Accurate Binary Convolutional Neural Network

Contribution

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

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 $\min_a J(\alpha) = \|W - B\alpha\|^2$

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

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

Multiple Binary Activations

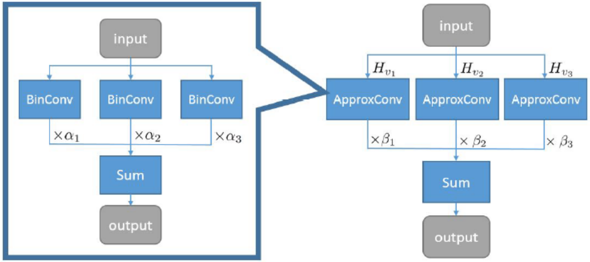
- Bounded Activation Function

$$h(x) \in [0, 1]$$
$$h_r(x) = \text{clip}(x + v, 0, 1)$$
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



- 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[3] 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

[3] 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

1. Minimize the Quantization Error
2. Improve Network Loss Function
3. Reduce the Gradient Error

Motivation

- Only focusing on the **local layers** can hardly promise the exact final output passed through a series of layers.
- It is highly required that the network training should **globally** take the **binarization** as well as the **task-specific objective** into account.

Intuition

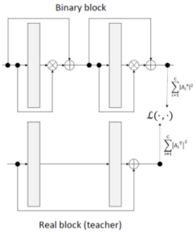
- Finding the desired loss function contribute to **guide the learning of parameter with restriction**

Training binary neural networks with real-to-binary convolutions

Contribution

- Use an attention matching strategy called ”a sequence of teacher-student pairs”, so that the real-valued network can more closely guide the binary network during optimization
- Use the real-valued activations of the binary network to compute scale factors that are used to re-scale the activations right after the application of the binary convolution.

- Proposed Real-to-Bin Block



Supervision is injected at the end of each binary block

Loss Term

- Compare attention maps between real-valued and binary network
- Gradients do not have to travel the whole network and suffer degradation

$$\mathcal{L}_{att} = \sum_{j=1}^{\mathcal{J}} \left\| \frac{Q_S^j}{\left\|Q_S^j\right\|_2} - \frac{Q_T^j}{\left\|Q_T^j\right\|_2} \right\| \text{ where } Q^j = \sum_{i=1}^{c} |A_i|^2$$

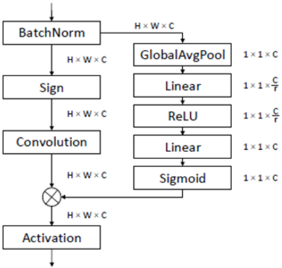
Progressive Teacher-Student

- Step1
  teacher: real-valued network with standard ResNet architecture
  student: real-valued network with the same architecture as the binary ResNet-18
- Step2
  teacher: student network from step1
  student: binary ResNet-18 with binary activations and real-valued weights
- Step3
  teacher: student network from step2
  student: binary ResNet-18 with binary activations and binary weights

Data-driven Channel Rescaling

- To solve limited representation problem
- Rely on the full-precision activation signal to predict the scaling factors used to re-scale the output of the binary convolution channel-wise

$$\mathcal{A} * \mathcal{W} \approx (\operatorname{sign}(\mathcal{A}) \bigotimes \operatorname{sign}(\mathcal{W})) \odot \alpha \odot G(\mathcal{A}; \mathcal{W}_G)$$



The proposed data-driven channel re-scaling approach.

Real-to-Bin

Read the paper[4] if you want to learn the specific details of the algorithm

TRAINING BINARY NEURAL NETWORKS WITH REAL-TO-BINARY CONVOLUTIONS

Brais Martinez[1], **Jing Yang**[1,2,*], **Adrian Bulat**[1,*] **& Georgios Tzimiropoulos**[1,2]
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[2] Computer Vision Laboratory, The University of Nottingham, UK
{brais.a,adrian.bulat,georgios.t}@samsung.com

[4]Brais Martinez et al. (2020). "Training binary neural networks with real-to-binary convolutions". In: *arXiv preprint arXiv:2003.11535*.

Overview

1. Minimize the Quantization Error
2. Improve Network Loss Function
3. Reduce the Gradient Error

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

Naive Binarization Function

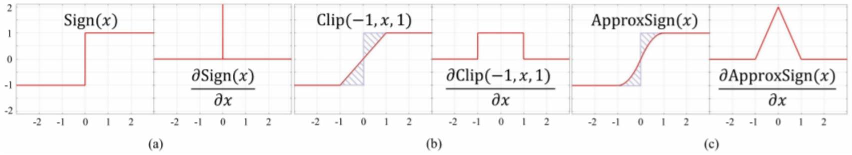
- Recall the partial derivative calculation in back propagation

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

- *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)

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

Read the paper[5] 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

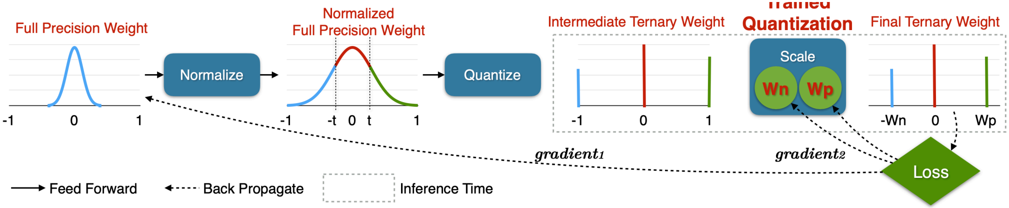
Zechun Liu[1] , Baoyuan Wu[2] , Wenhan Luo[2], Xin Yang[3⋆], Wei Liu[2], and Kwang-Ting Cheng[1]

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

[5]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

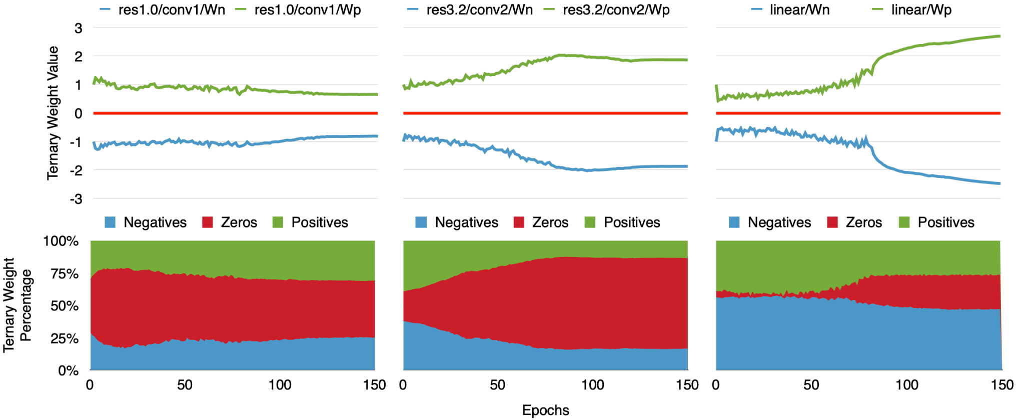
Trained Ternary Quantization[6]



Overview of the trained ternary quantization procedure.

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

Trained Ternary Quantization[6]



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

[6]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