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Forward and Backward Information Retention for Accurate Binary Neural Networks
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Outlines

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Forward and Backward Information Retention for Accurate Binary Neural Networks

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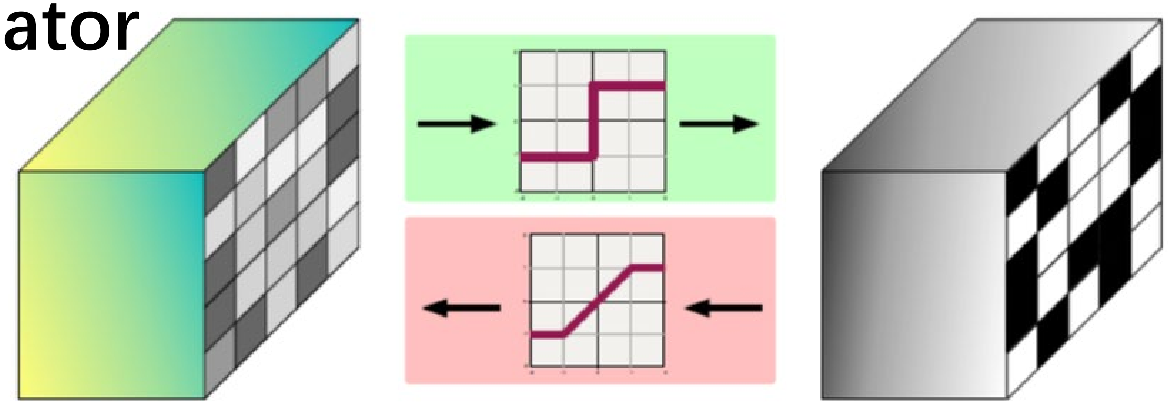
Overview of BNN

- 将权重和激活值进行二值化（-1，1）/（0，1）
- 二值化方法：符号函数、随机二值化
- 反向传播：计算梯度使用STE直通器
  STE：Straight-Through-Estimator

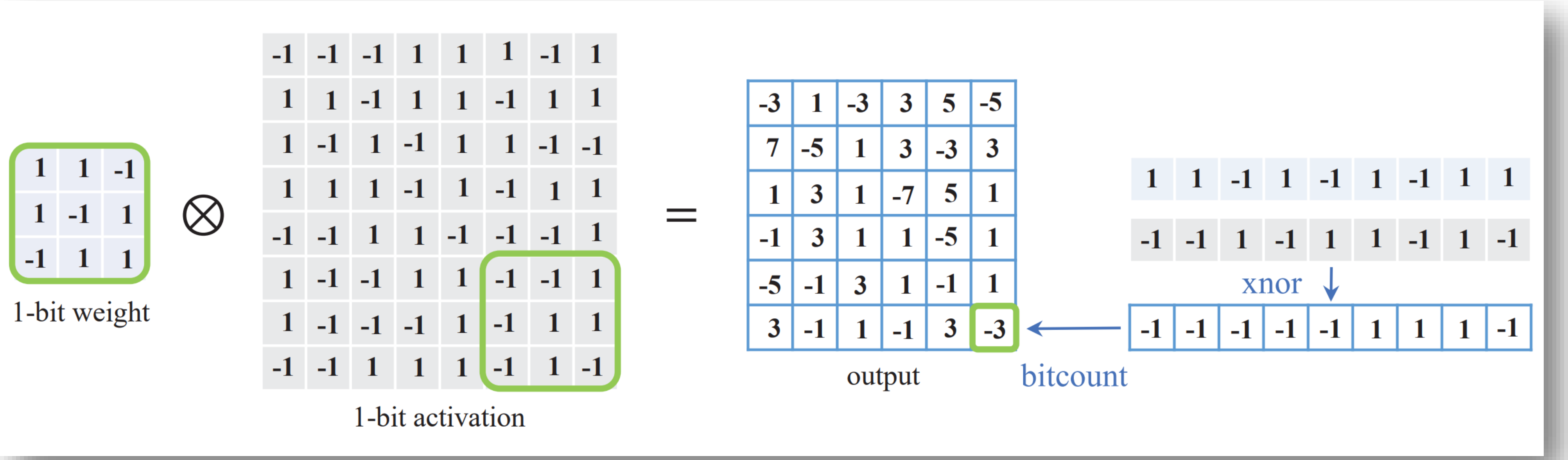


$$w_b = \begin{cases} +1 & \text{if } w \geq 0, \\ -1 & \text{otherwise.} \end{cases}$$

$$w_b = \begin{cases} +1 & \text{with probability } p = \sigma(w), \\ -1 & \text{with probability } 1 - p. \end{cases}$$

$$\sigma(x) = \text{clip}(\frac{x+1}{2}, 0, 1) = \max(0, \min(1, \frac{x+1}{2}))$$

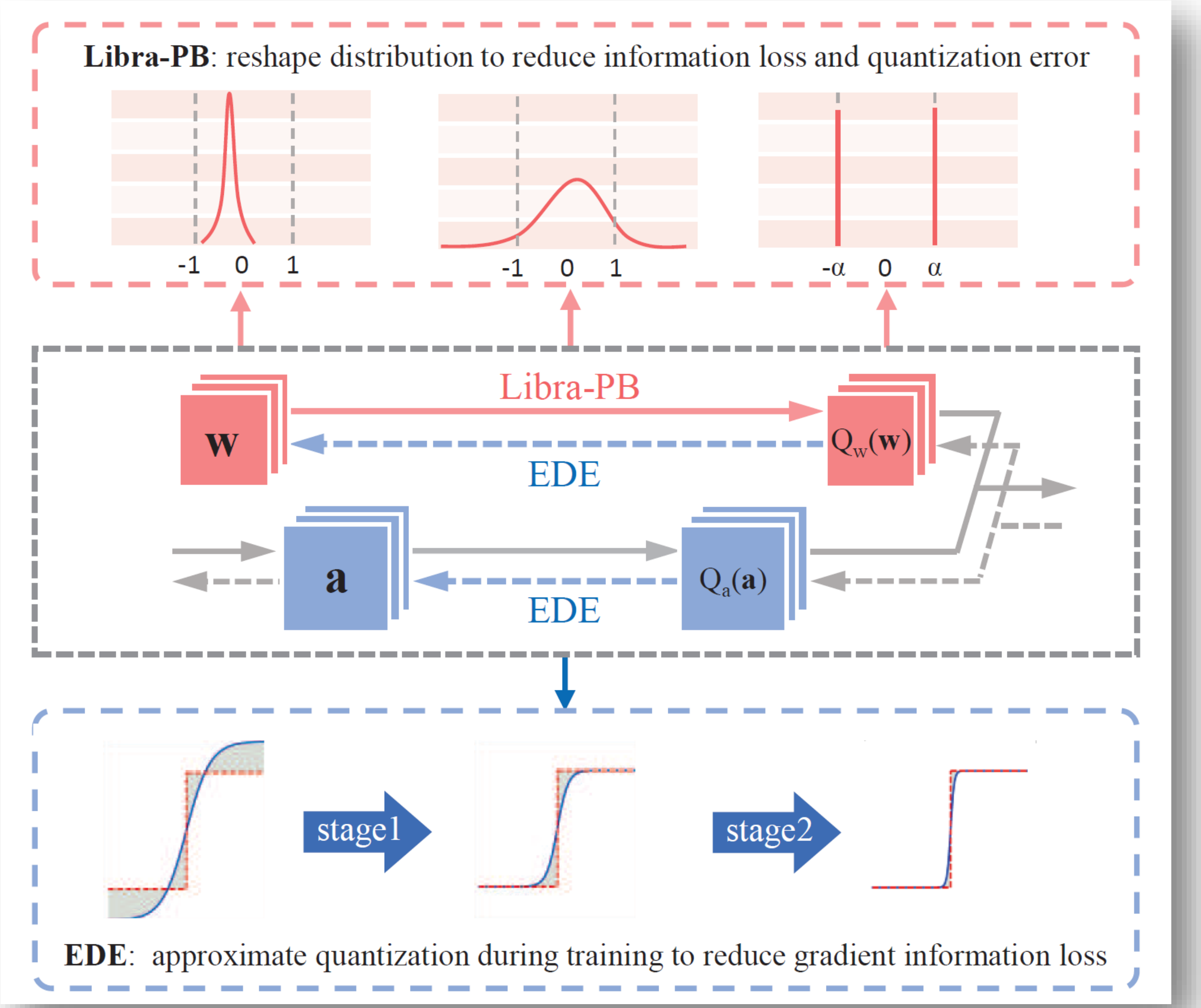
Overview of BNN



Motivations

- 减小二值化网络与全精度网络间的差距，提高性能
- 减小前向、后向传播过程中信息损失
- 解决STE带来不准确的梯度更新

Innovations



Information Retention Network (IR-Net)

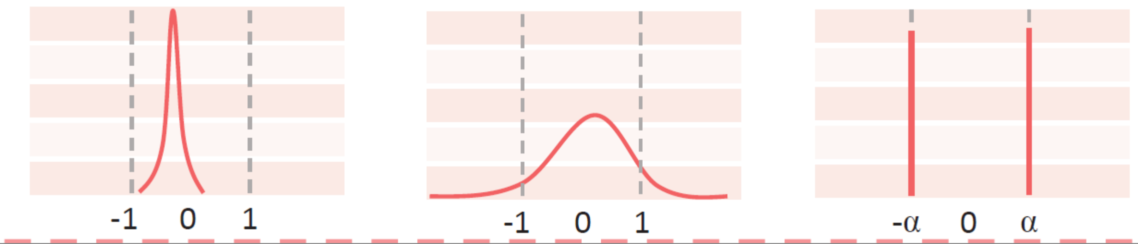
Innovations-Libra-PB

$$\min J(Q_x(\mathbf{x})) = \|\mathbf{x} - Q_x(\mathbf{x})\|^2 \qquad Q_x(\mathbf{x}) = \alpha \mathbf{B_x}$$

$$\mathcal{H}(Q_x(\mathbf{x})) = \mathcal{H}(\mathbf{B_x}) = -p\ln(p) - (1-p)\ln(1-p)$$

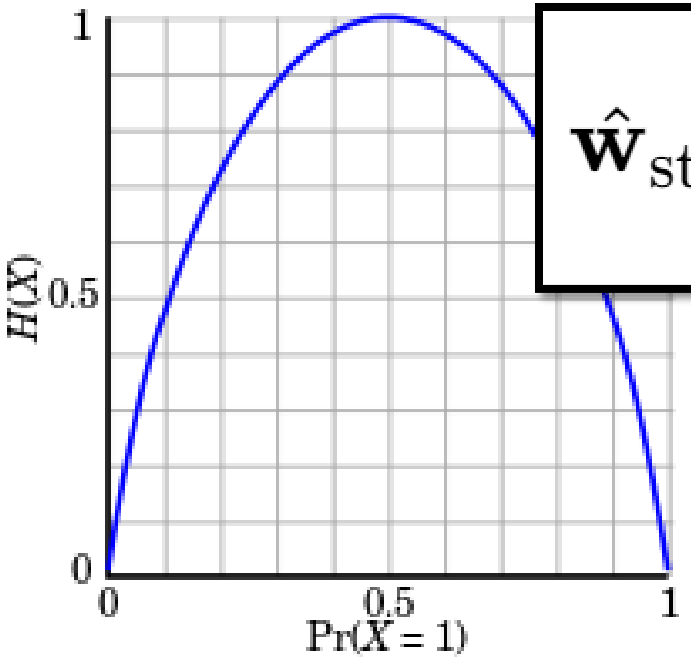
$$\min J(Q_x(\mathbf{x})) - \lambda \mathcal{H}(Q_x(\mathbf{x}))$$

Libra-PB: reshape distribution to reduce information loss and quantization error

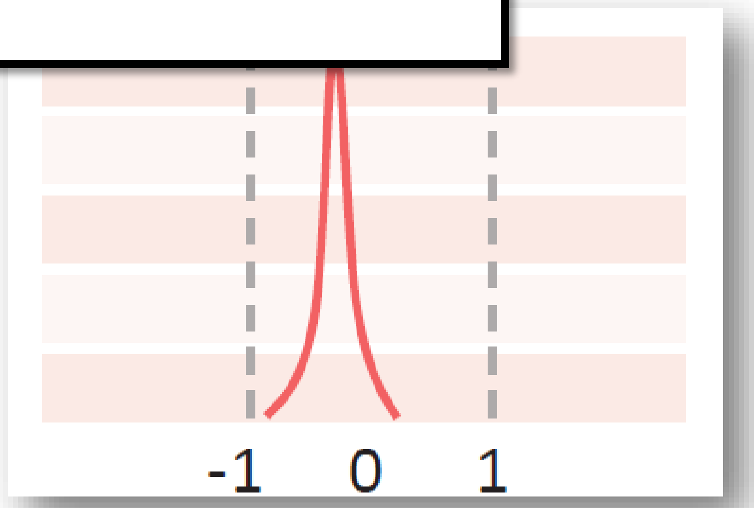


Innovations-Libra-PB

$$\mathcal{H}(Q_x(\mathbf{x})) = \mathcal{H}(\mathbf{B}_\mathbf{x}) = -p\ln(p) - (1-p)\ln(1-p)$$



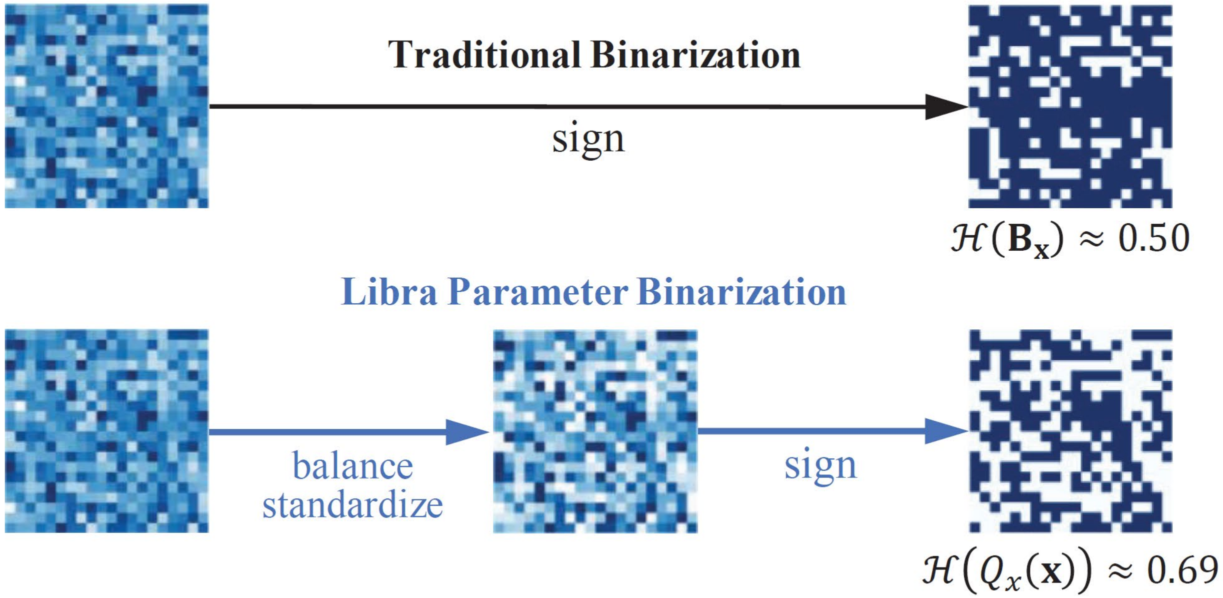
$$\hat{\mathbf{w}}_{\mathrm{std}} = \frac{\hat{\mathbf{w}}}{\sigma(\hat{\mathbf{w}})}, \hat{\mathbf{w}} = \mathbf{w} - \overline{\mathbf{w}}$$

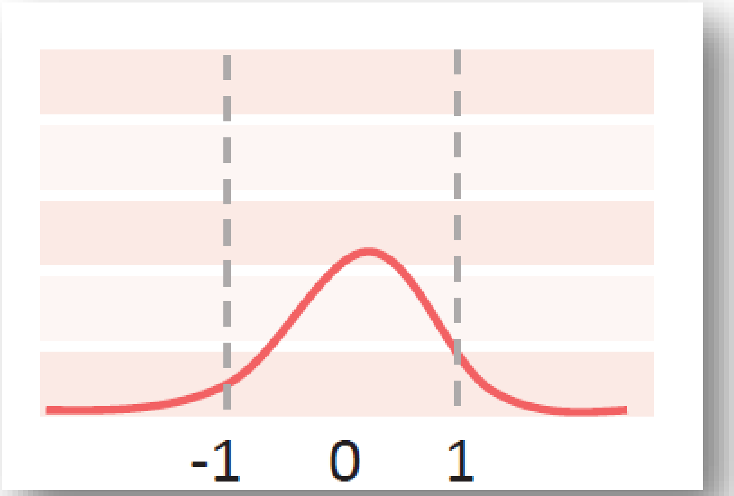


Bernoulli distribution

Innovations-Libra-PB

$$\hat{\mathbf{w}}_{\text{std}} = \frac{\hat{\mathbf{w}}}{\sigma(\hat{\mathbf{w}})}, \hat{\mathbf{w}} = \mathbf{w} - \overline{\mathbf{w}}$$



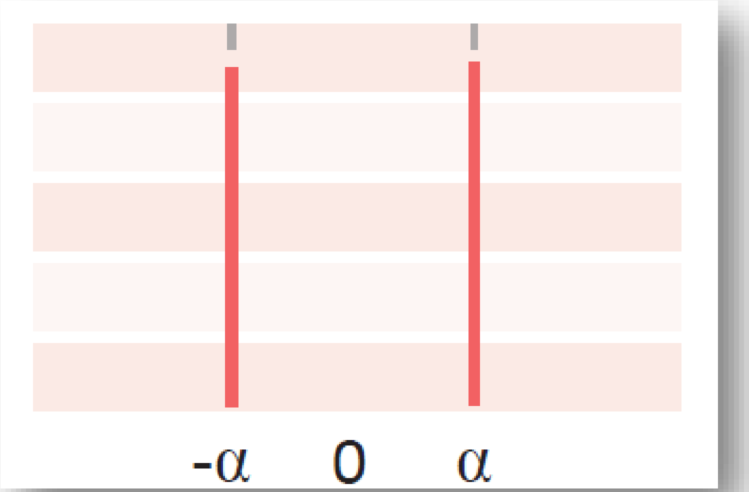


Innovations-Libra-PB

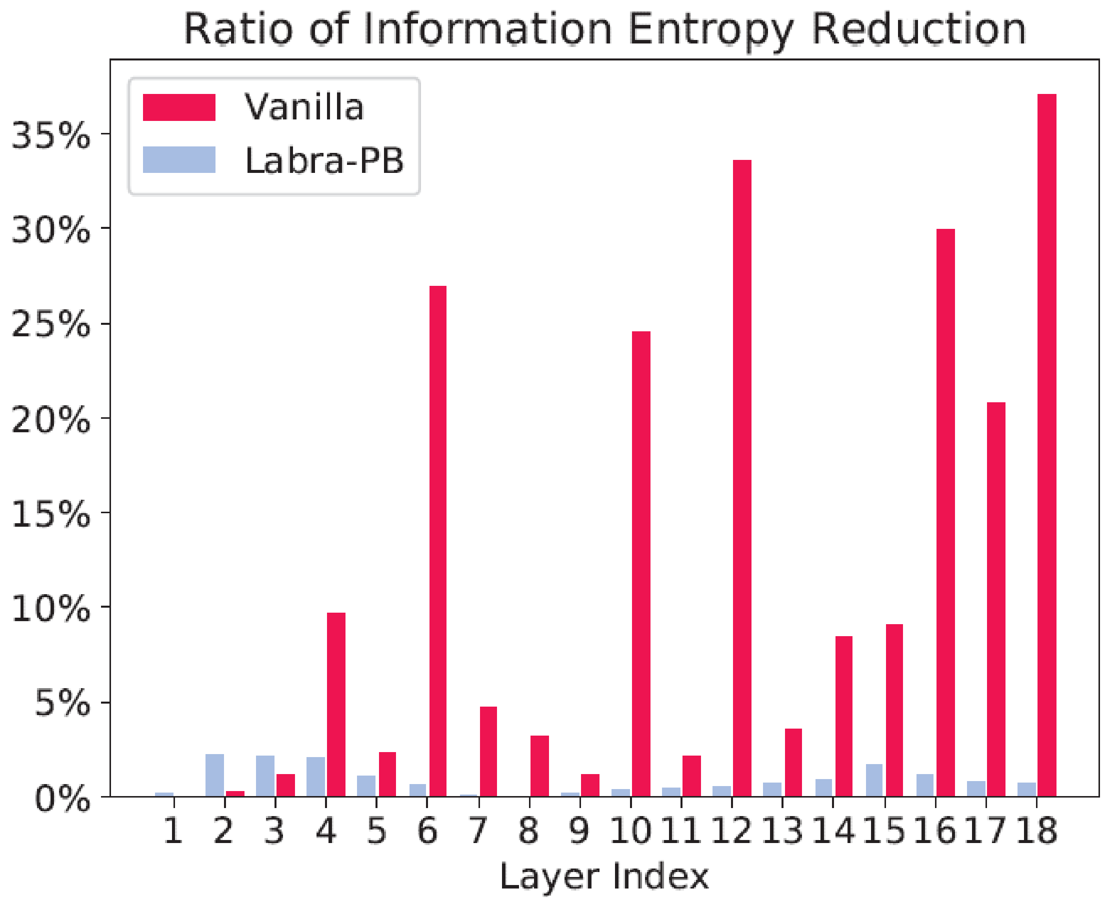
$$Q_w(\hat{\mathbf{w}}_{\text{std}}) = \mathrm{B}_{\mathbf{w}} \lll \ggg s = \operatorname{sign}(\hat{\mathbf{w}}_{\text{std}}) \lll \ggg s$$

$$Q_a(\mathbf{a}) = \mathbf{B_a} = \operatorname{sign}(\mathrm{a})$$

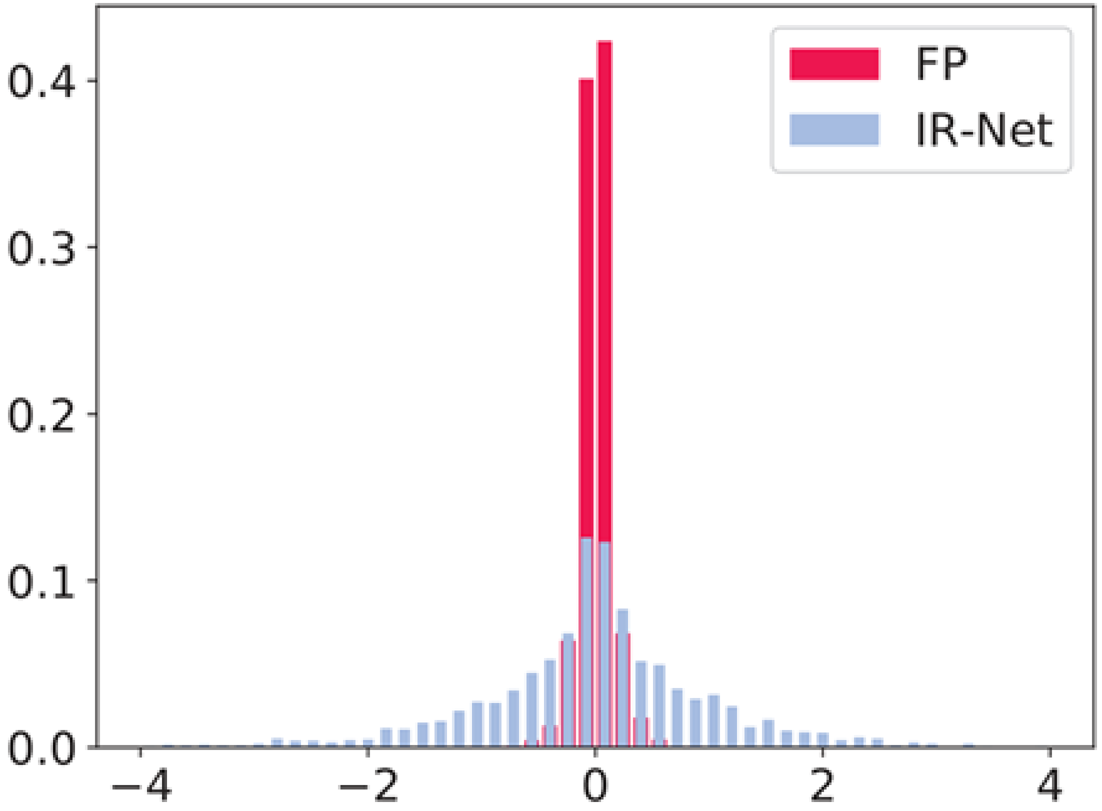
$$z = (\mathbf{B_w} \odot \mathbf{B_a}) \lll \ggg s$$



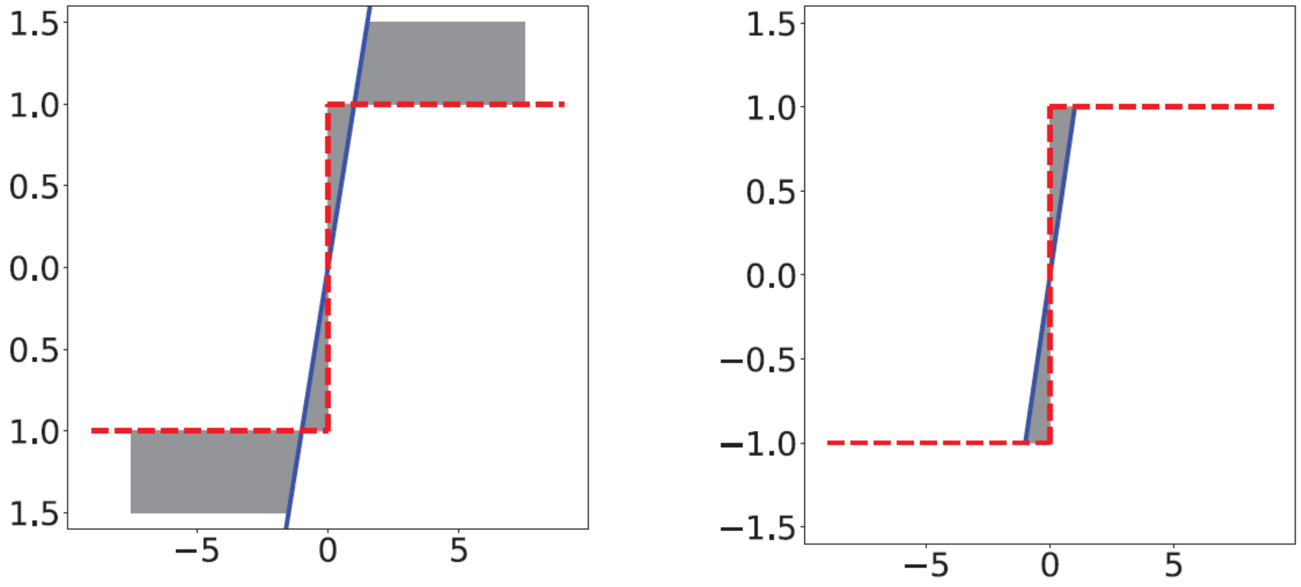
Innovations-Libra-PB



Innovations-Libra-PB



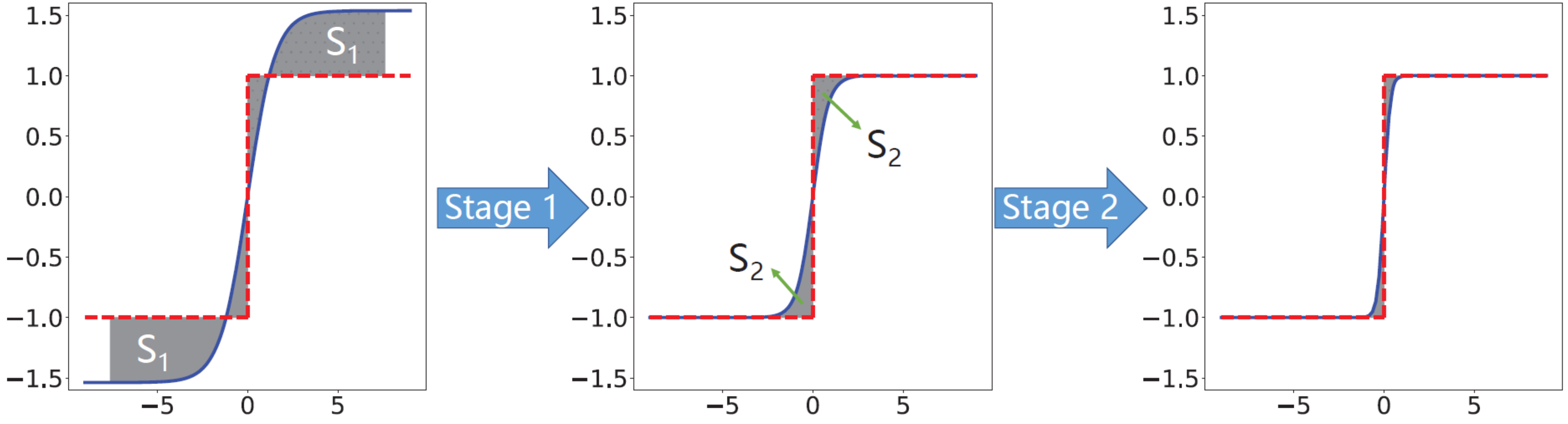
Innovations-EDE



(a) `Identity` (b) `Clip`

$$y = x \qquad y = \mathrm{clip}(x, -1, 1)$$

Innovations-EDE

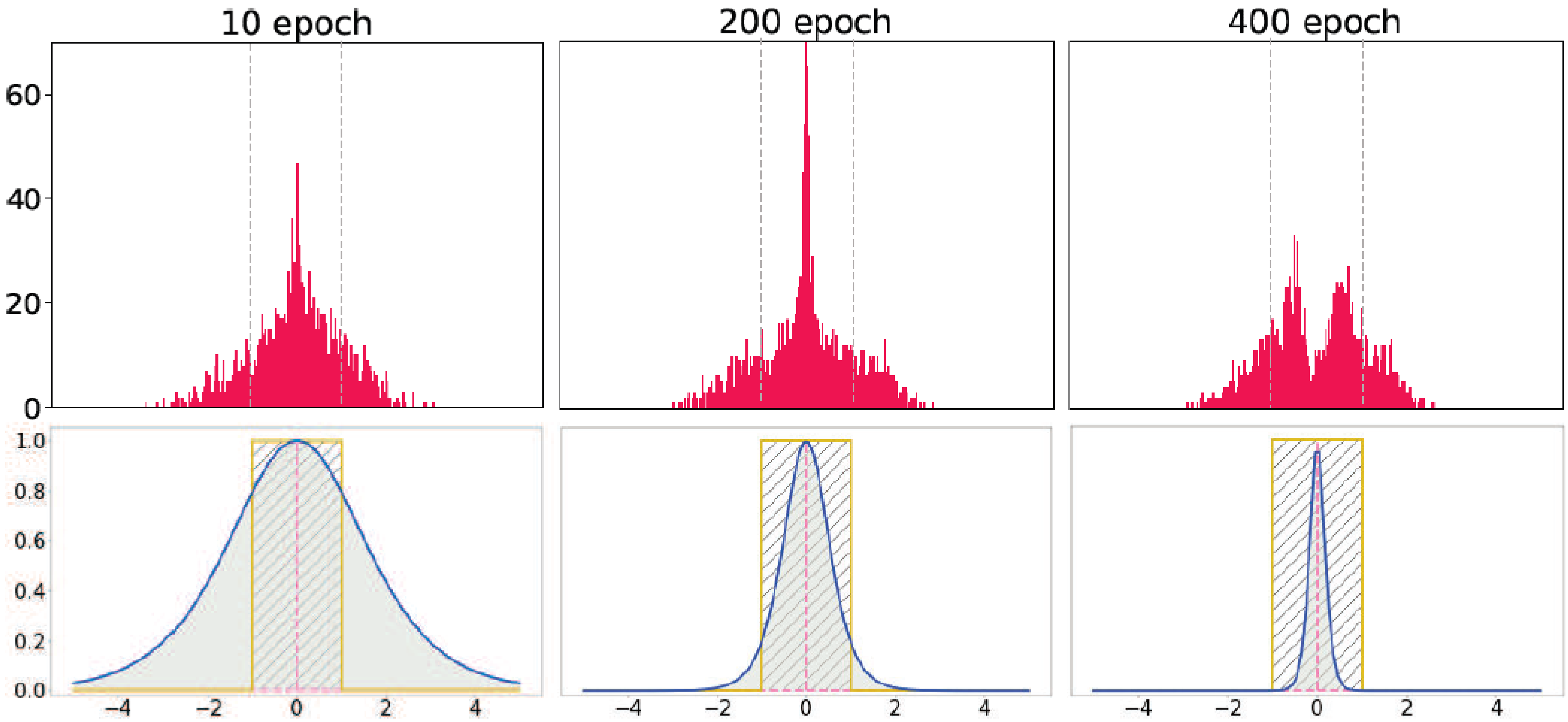


(c) EDE

$$g(x) = k \tanh tx$$

$$t = T_{\min} 10^{\frac{i}{N} \times \log \frac{T_{\max}}{T_{\min}}}, k = \max(\frac{1}{t}, 1)$$

Innovations-EDE



Experiments-Ablation Study

Table 2: Ablation study for IR-Net.

Method	Bit-width (W/A)	Acc.(%)
FP	32/32	90.8
Binary	1/1	83.8
Libra-PB (without weight standardization)	1/1	84.3
Libra-PB (without bit-shift scales)	1/1	84.6
Libra-PB	1/1	84.9
EDE	1/1	85.2
IR-Net (Libra-PB & EDE)	1/1	**86.5**

ResNet-20 model on CIFAR-10

Experiments-CIFAR 10

Ours1: ResNet with normal structure

Ours2: ResNet with Bi-Real structure

Table 3: Accuracy comparison with SOTA methods on CIFAR-10.

Topology	Method	Bit-width (W/A)	Acc.(%)
ResNet-18	FP	32/32	93.0
	RAD	1/1	90.5
	Ours[1]	1/1	**91.5**
ResNet-20	FP	32/32	91.7
	DoReFa	1/1	79.3
	DSQ	1/1	84.1
	Ours[1]	1/1	**85.4**
	Ours[2]	1/1	**86.5**
	FP	32/32	91.7
	DoReFa	1/32	90.0
	LQ-Net	1/32	90.1
	DSQ	1/32	90.2
	Ours[1]	1/32	**90.8**
VGG-Small	FP	32/32	91.7
	LAB	1/1	87.7
	XNOR	1/1	89.8
	BNN	1/1	89.9
	RAD	1/1	90.0
	Ours	1/1	**90.4**

Experiments-ImageNet

Table 4: Accuracy comparison with SOTA methods on ImageNet.

Topology	Method	Bit-width (W/A)	Top-1(%)	Top-5(%)
ResNet-18	FP	32/32	69.6	89.2
	ABC-Net	1/1	42.7	67.6
	XNOR	1/1	51.2	73.2
	BNN+	1/1	53.0	72.6
	DoReFa	1/2	53.4	–
	Bi-Real	1/1	56.4	79.5
	XNOR++	1/1	57.1	79.9
	Ours[2]	1/1	**58.1**	**80.0**
	FP	32/32	69.6	89.2
	SQ-BWN	1/32	58.4	81.6
	BWN	1/32	60.8	83.0
	HWGQ	1/32	61.3	83.2
	TWN	2/32	61.8	84.2
	SQ-TWN	2/32	63.8	85.7
	BWHN	1/32	64.3	85.9
	Ours[1]	1/32	**66.5**	**86.8**
ResNet-34	FP	32/32	73.3	91.3
	ABC-Net	1/1	52.4	76.5
	Bi-Real	1/1	62.2	83.9
	Ours[2]	1/1	**62.9**	**84.1**
	FP	32/32	73.3	91.3
	Ours[1]	1/32	**70.4**	**89.5**

Experiments-Deployment

Raspberry Pi 3B

1.2 GHz 64-bit quad-core ARM Cortex-A53

Deploy with daBNN[1]

Table 5: Comparison of time cost of ResNet-18 with different bits (single thread).

Method	Bit-width (W/A)	Size (Mb)	Time (ms)
FP	32/32	46.77	1418.94
NCNN	8/8	–	935.51
DSQ	2/2	–	551.22
Ours (without bit-shift scales)	1/1	**4.20**	**252.16**
Ours	1/1	**4.21**	**261.98**

[1] Zhang, J., Pan, Y., Yao, T., Zhao, H., & Mei, T. (2019, October). dabnn: A super fast inference framework for binary neural networks on arm devices. In Proceedings of the 27th ACM international conference on multimedia (pp. 2272-2275).

Conclusion

- 从信息熵的角度出发，提出两个措施（Libra-PB、EDE）减少信息损失，极大保留原始权重与激活值的信息量
- 引入BitShift操作，减少乘法运算，进一步加速推理
- Libra-PB、EDE可以作为模块，方便的应用于其他网络的二值化中

Insights & Thoughts

- BNN加速效果明显，实际应用价值较高，可寻找其他应用场景，或者在实际部署上做文章

- 如何提高BNN的精度？---与其他网络结合（BinaryViT[1]、Bibert[2]等）、改进二值化方式、改进损失函数等

[1] Le, P. H. C., & Li, X. (2023). BinaryViT: Pushing Binary Vision Transformers Towards Convolutional Models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 4664-4673).
[2] Qin, H., Ding, Y., Zhang, M., Yan, Q., Liu, A., Dang, Q., ... & Liu, X. (2022). Bibert: Accurate fully binarized bert. *arXiv preprint arXiv:2203.06390*.

Thanks