

# Training Binarized Neural Networks the Easy Way

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# TOSHIBA

#### - Binarized Neural Networks

Binarized Neural Networks (BNN) are an extreme form of quantised neural networks. Specifically, where the majority of weights and activations are constrained to the set  $\{-1,1\}$ . BNN have the following advantages:

- Arithmetic operations can be replaced with faster bit-wise alternatives
- Lower computational and energy cost at inference
- Can be used on lightweight mobile hardware
- Up to 32 time less memory storage requirement
- Up to 58 time faster on the CPU [5]
- Around 5 time faster on the GPU [3]

## Existing Training Methods

**Notation.** Vector of all parameters  $\boldsymbol{w} \in \mathbb{R}^d$ . Vector of parameters to take binary values  $\boldsymbol{w}_t^b \in \mathbb{R}^p$ . Vector of parameters to retain real values  $\boldsymbol{w}_t^r \in \mathbb{R}^{d-p}$ .  $\tilde{\boldsymbol{w}}^r$  typically contains weights in the first and last layers, batch norm layers, biases, and bottleneck layers.

Straight Through Estimator Method [3] (STE)

$$egin{align} m{w}_t^b &= ext{sign}( ilde{m{w}}_t^b), \ m{ ilde{w}}_{t+1}^b &= \Pi( ilde{m{w}}_t^b - \eta_t \nabla \ell_{z_t}(m{w}_t^b)),. \end{aligned}$$

where  $\eta_t$  is the learning rate and  $\Pi$  is projection onto the interval [-1,1], and in practice Adam is used.

Mirror Descent View for BNN [1] (BMD)

$$m{w}_t^b = anh(eta_t ilde{m{w}}_t^b), \ m{\tilde{w}}_{t+1}^b = ilde{m{w}}_t^b - \eta_t \nabla \ell_{z_t}(m{w}_t^b), .$$

Again the Adam update is used in practice.

Binary Optimiser [2] (BOP)

$$\boldsymbol{m}_{t}^{b} = (1 - \eta_{t})\boldsymbol{m}_{t-1}^{b} - \eta_{t}\nabla\ell_{z_{t}}(\boldsymbol{w}_{t}^{b}), \quad \boldsymbol{m}_{0}^{b} = 0$$

$$\forall w^{b} \in \boldsymbol{w}^{b} : \mathbf{if} \mid m_{t+1}^{b} \mid > \tau \text{ and } \operatorname{sign}(m_{t}^{b}) = \operatorname{sign}(w_{t}^{b}):$$

$$w_{t+1}^{b} = -w_{t}^{b}$$

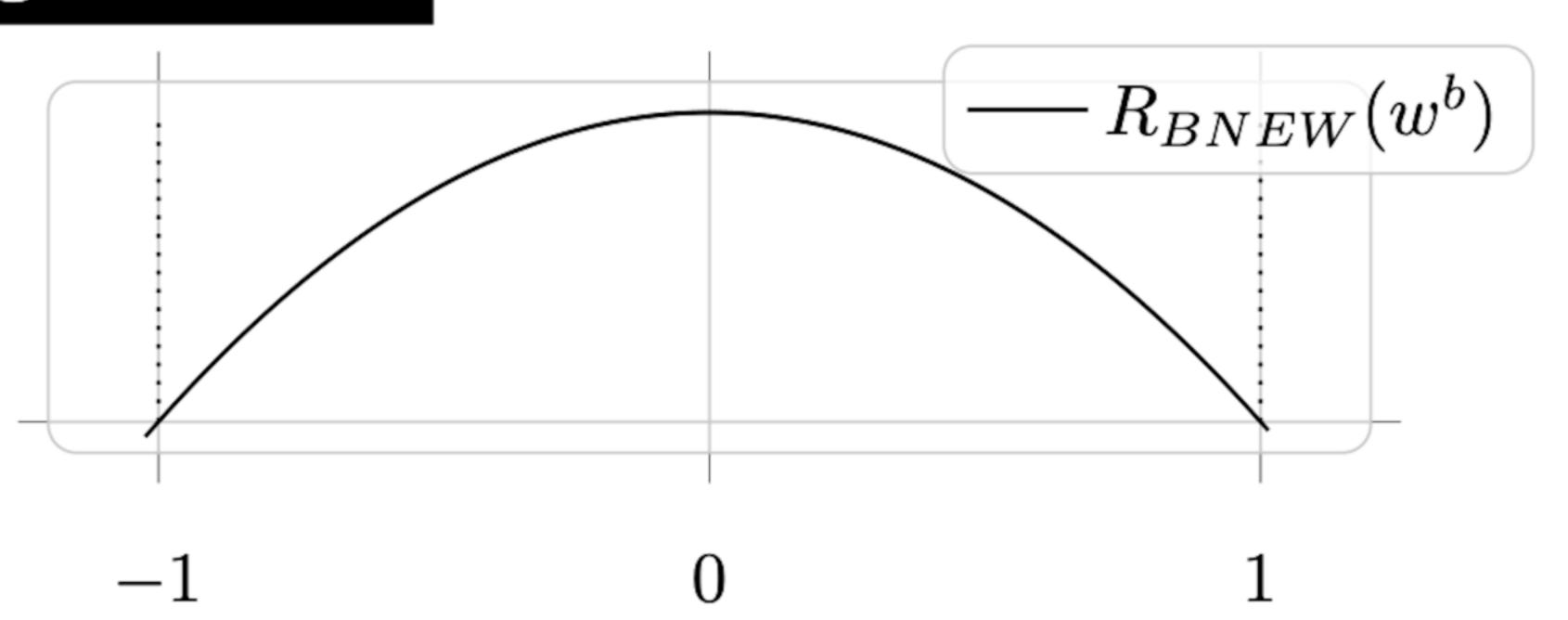
## Objective

Unlike most existing methods for optimising BNN we relax the constraint on the binary parameters to its convex hull and add a regulation function  $R_{BNEW}$  that penalises solutions with  $\boldsymbol{w}_{\star}^{b} \notin \{-1,1\}^{p}$ 

$$\boldsymbol{w}_{\star} \in \operatorname*{argmin}_{\boldsymbol{w} \in \Omega} F_{\lambda} \triangleq f(\boldsymbol{w}) + \lambda R_{BNEW}(\boldsymbol{w}),$$

where  $\Omega \triangleq [-1, 1]^p \cup \mathbb{R}^{d-p}$ .

#### Regularisation



We use the regularisation function  $R_{BNEW}(\boldsymbol{w}) \triangleq -\|\boldsymbol{w}^b\|^2 + p$ . This regularisation can be seen at negative weight decay.

## Update

The resulting algorithm which we name BNEW (Binarized Networks the Easy Way) uses the update:

$$oldsymbol{w}_{t+1}^b = \Pi\left((1+2\lambda_t\eta_t)(oldsymbol{w}_t^b - \eta_t 
abla \ell_{z_t}(oldsymbol{w}_t^b))
ight).$$

Again, the Adam update is used.  $\eta_t$  follows a linearly decaying schedule, that is reset after step 1 below.

## Training Procedure

We use the following training procedure:

- 1. Train the network to have binary activations and real valued parameters ( $\lambda_t = 0$ )
- 2. Slowly binarize the parameters  $\boldsymbol{w}^b$  by linearly increasing  $\lambda_t = \beta \cdot t$
- 3. Project  $\boldsymbol{w}_{t=t_{lock}}^b$  onto  $\{-1,1\}^p$ , set  $\nabla \boldsymbol{w}_{t>t_{lock}}^b = 0$
- 4. Fine-tune only the real valued parameters  $\tilde{\boldsymbol{w}}^r$ .

#### Results

Results training a small BNN architecture on CIFAR:

Data Set	CIFAR-10		CIFAR-100	
Distillation	No	Yes	No	Yes
Real Valued	$91.4\sigma 0.3$	_	$67.1\sigma 0.7$	_
STE	$84.3\sigma.3$	$85.1\sigma.4$	$55.0\sigma.5$	$56.8\sigma.3$
BMD	$84.0\sigma.4$	$84.9\sigma.3$	$54.8\sigma.5$	$56.8\sigma.5$
BOP	$84.5\sigma.2$	$85.2\sigma.4$	$55.3\sigma.4$	$57.7\sigma.4$
$\mathbf{BNEW}$	$84.5\sigma.3$	$85.1\sigma.4$	$55.0\sigma.3$	$57.5\sigma.3$

Training a ReActNet architecture [4] on ImageNet:

Optimiser	Accuracy	
STE	69.4 69.7	
DIVE VV	09.7	

### - Properties of BNEW

- Very simple
- Strong empirical results
- Strong theoretical justification
- Poor estimate of performance during training
- $\bullet$  Best results require long training time (large T)
- The optimal value of  $\beta$  depends on T

#### References

- [1] Thalaiyasingam Ajanthan, Kartik Gupta, Philip Torr, Richad Hartley, and Puneet Dokania. Mirror descent view for neural network quantization. International Conference on Artificial Intelligence and Statistics, 2021.
- [2] Koen Helwegen, James Widdicombe, Lukas Geiger, Zechun Liu, Kwang-Ting Cheng, and Roeland Nusselder. Latent weights do not exist: Rethinking binarized neural network optimization. Neural Information Processing Systems, 2019.
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