Training Multi-bit Quantized and Binarized Networks with A Learnable Symmetric Quantizer

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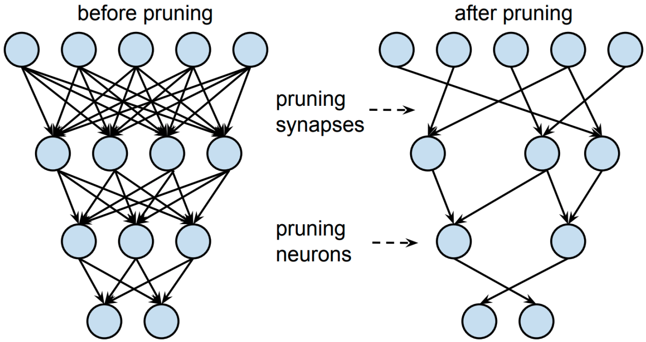
Neural network compression

Problem of the computational complexity and memory size.
Examples of methods for neural network compression:

- Pruning
- Quantization

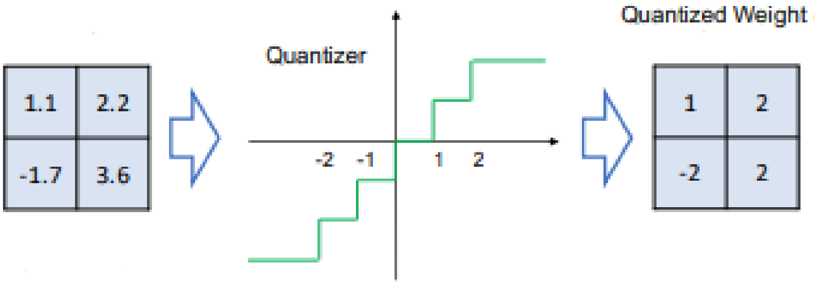
Pruning

Pruning removes redundant parameters or neurons that do not significantly contribute to the accuracy of results.



Quantization

Quantization is known as the process of approximating a continuous signal by a set of discrete symbols or integer values.



Learnable Symmetric Quantizer

The end points of the intervals are referred to as decision levels, the output is called the reconstruction level.
Δ (step size) - the length of the intervals, N - the total number of reconstruction levels.
$clip_N(x) = min(max(x, 0), N-1)$ - clip function

Uniform symmetric quantizer:
$Q_w(x) = [clip_N((x+\alpha)/\Delta)]\Delta - \alpha$, where $\alpha = \Delta(N-1)/2$

Q_w can be rewritten as:
$Q_w(x) = q_w(\Delta/2)$, where $q_w = 2[clip_N((x+\alpha)/\Delta)] - N + 1$;
q_w can be encoded into $[log_2(N)]$ bits using ± 1 encoding.

Learnable Symmetric Quantizer

The authors make the step size Δ a learnable parameter.
How to calculate gradient:

$$\frac{\partial Q_w(x)}{\partial \Delta} = \begin{cases} -\frac{x}{\Delta} + [\frac{x}{\Delta} - 0.5] + 0.5 & |x| < \alpha \\ sign(x)\alpha & \text{otherwise.} \end{cases}$$

Optimal MSE Initialization

Let X be the random variable for a quantizer input and its pdf is denoted by p(x). The optimal step size for Qw is defined in the mean squared error (MSE) sense by
$\Delta_w^* = argmin_\Delta D_w(\Delta)$, where
$D_w(\Delta) = E[(x - Q_w(x, \Delta))^2]$

$\frac{dD_w}{d\Delta} = -\sum_{i=1}^{N/2-1}(2i-1)\int_{(i-1)\Delta}^{i\Delta} 2(x - [\frac{2i-1}{2}]\Delta)p(x)dx$ -

- $(N-1)\int_{(N/2-1)\Delta}^{\infty} 2(x - [\frac{N-1}{2}]\Delta)p(x)dx$

ImageNet

Method	ResNet-18 (FP: 71.57)				ResNet-34 (FP: 75.11)				MobileNet-V2 (FP: 71.53)			
	Bit-width (W/A)											
	4/4	3/3	2/2	1/1	4/4	3/3	2/2	1/1	4/4	3/3	2/2	1/1
PACT [5]	69.2	68.1	64.4	-	-	-	-	-	61.4	-	-	-
DoReFa-Net [55]	68.1	67.5	62.6	-	-	-	-	-	-	-	-	-
DSQ [16]	69.6	68.7	65.2	-	72.8	72.5	70.0	-	-	-	-	-
QIL [14]	70.1	69.2	65.7	-	73.7	73.1	70.6	-	64.8	-	-	-
LSQ [11]	71.1	70.2	67.6	-	74.1	73.4	71.6	-	-	-	-	-
LSQ+ [2]	70.8	69.3	66.8	-	-	-	-		-	-	-	-
SAT [26]	70.3	69.3	65.5	-	-	-	-	-	-	-	-	-
QKD [29]	71.4	70.2	67.4	-	74.6	73.9	71.6	-	67.4	62.6	45.7	-
UniQ (Ours)	**71.5**	**70.5**	**67.8**	**60.5**	**75.0**	**74.2**	**72.1**	**65.8**	**68.2**	**65.0**	**50.5**	**23.2**

Рис. 1: Top-1 accuracy (%) on ImageNet dataset

Binarization

Network	Method	Acc(%)	Original
ResNet-18 (FP: 71.57)	ABC-Net [34]	42.7	
	XNOR-Net [42]	51.2	
	BNN+ [9]	53.0	✓
	DoReFa-Net [55]†	53.4	✓
	Bi-Real [36]	56.4	
	XNOR-Net++ [3]	57.1	
	IR-Net [41]	58.1	✓
	ProxyBNN [20]	58.7	✓
	RBNN [33]	59.9	✓
	BinaryDuo [28]	60.4	
	UniQ (Ours)	**60.5**	✓
ResNet-34 (FP: 75.11)	ABC-Net	52.4	
	Bi-Real	62.2	
	IR-Net	62.9	✓
	RBNN	63.1	✓
	UniQ (Ours)	**65.8**	✓

Рис. 2: Top-1 accuracy comparison to the existing stateof-the-art binarization methods on ImageNet.

Step Size Initialization

Bit-width	Step Size Initialization			
(W/A)	0.1	0.2	LSQ Init	Our Init
2/2	67.1	68.6	68.3	**69.3**
3/3	70.7	70.9	71.0	**71.4**

Рис. 3: Comparison of different methods for step size initialization.

References

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