Quantization Through Search: A Novel Scheme to Quantize Convolutional Neural Networks in Finite Weight Space

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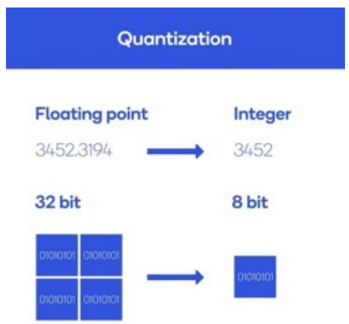
Quantization of Deep Neural Networks

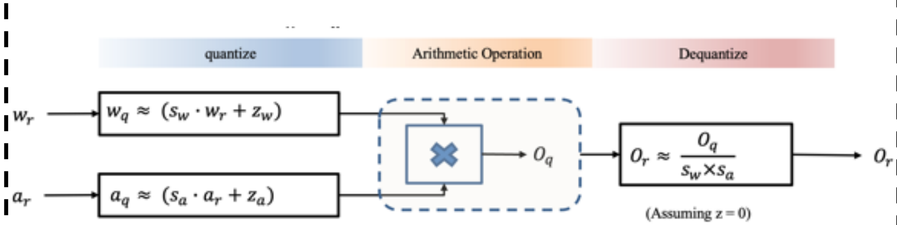
Growth of Interest



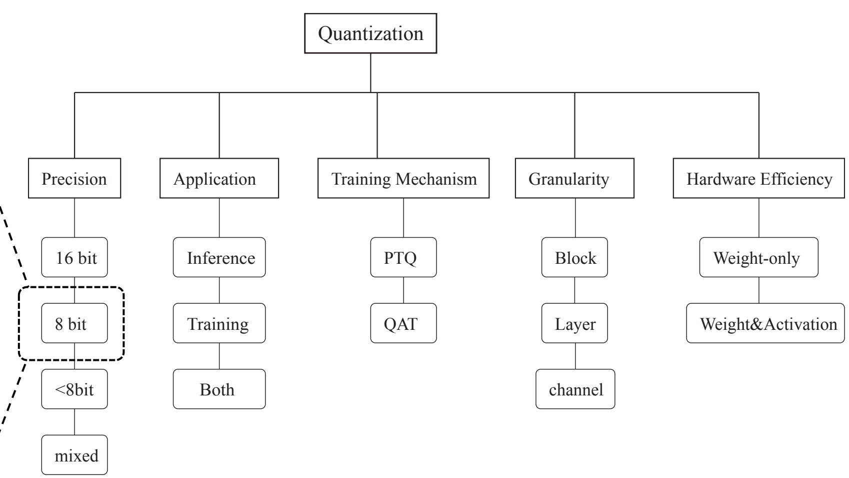
PyTorch → PyTorch

NVIDIA TAO

Taxonomy

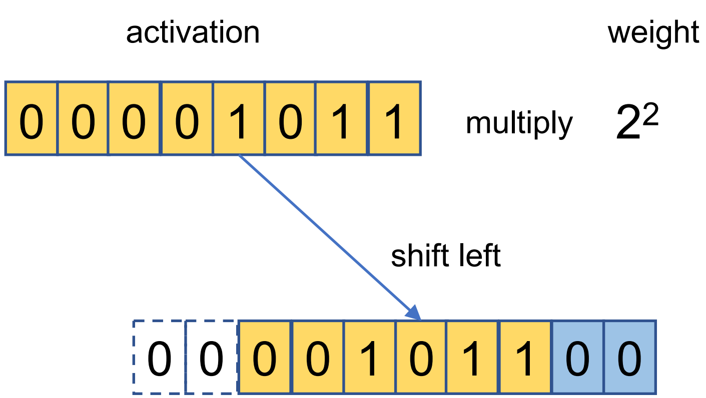


2x ~ 4x CPU inference speedup



Finite Weight Space Quantization

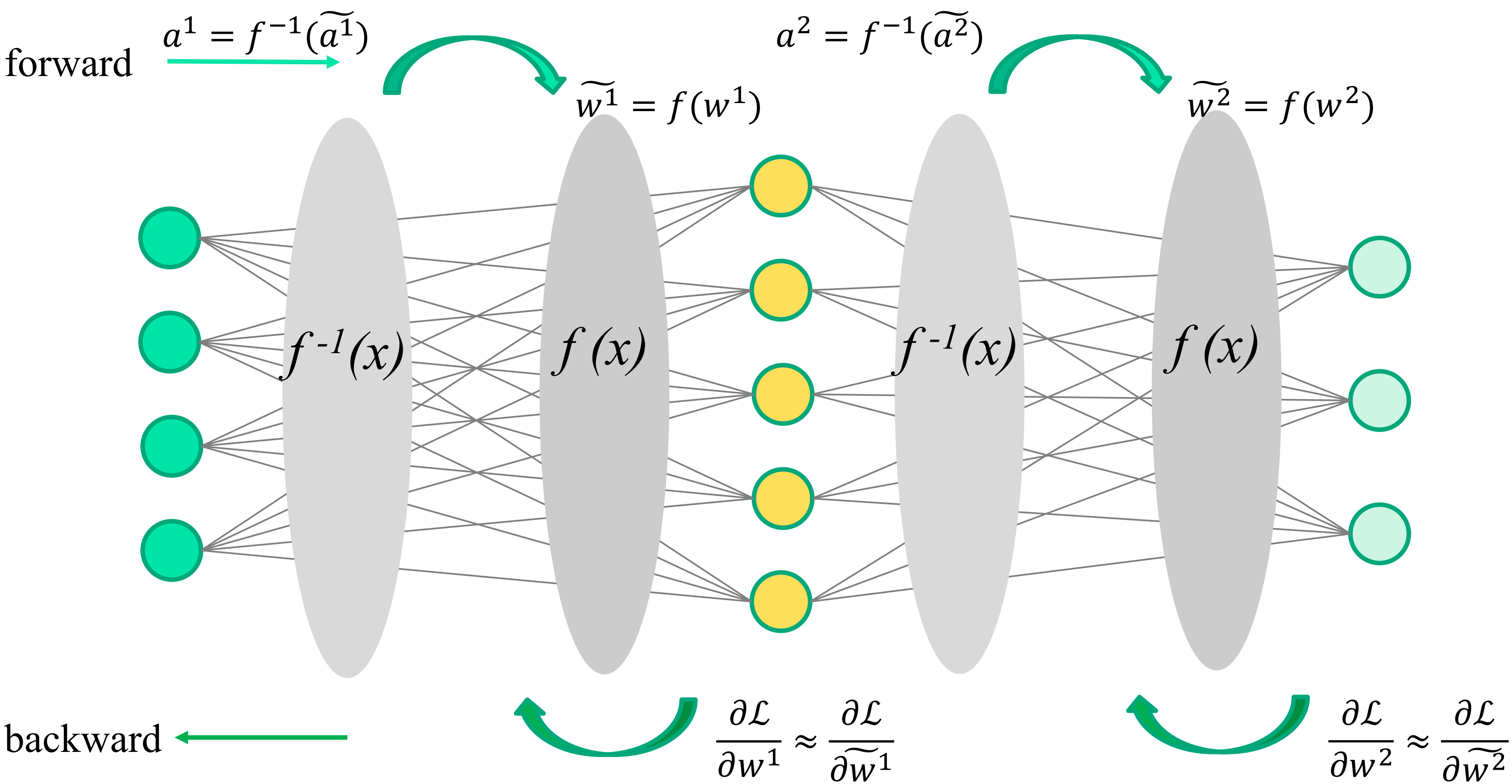
- Constraining weights into a definite set can maximize the execution efficiency
  - Memory is proportional to cardinality of value space;
  - Hardware-friendly value set lowers complexity;
  - Multiplication has equal instances to addition;



Operator	Logic Gates per Unit	Total Operations per Image
addition	~40	~37M
Multiplication	~320	~38M

8-bit quantization. Operations are profiled by assuming image of size 32x32 on ResNet18.

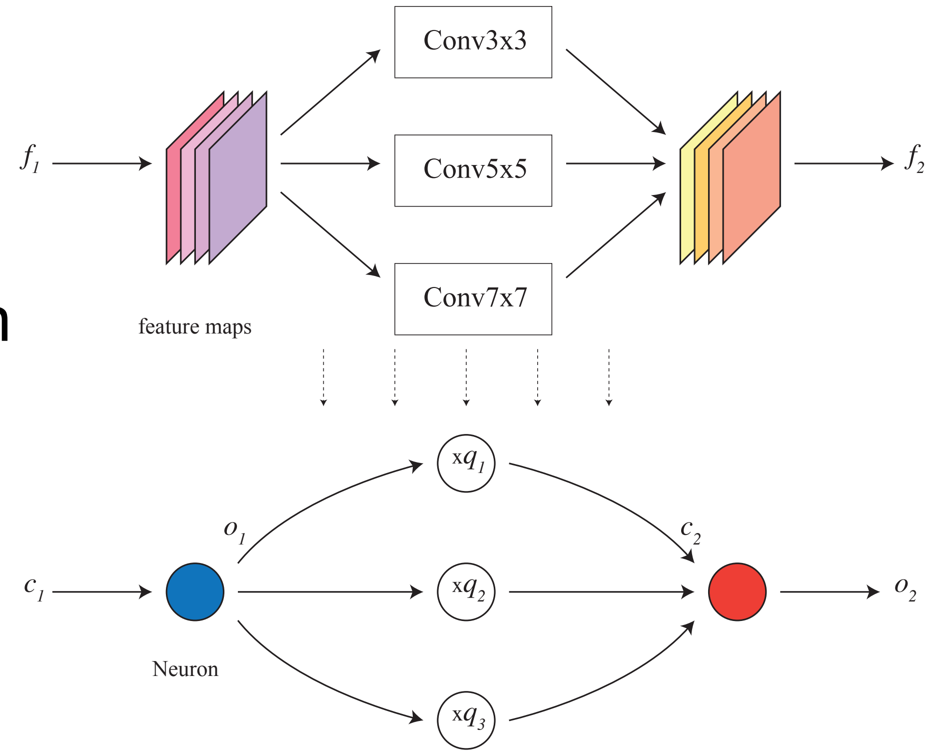
Quantization Through Approximated Function



Quantization Through Search

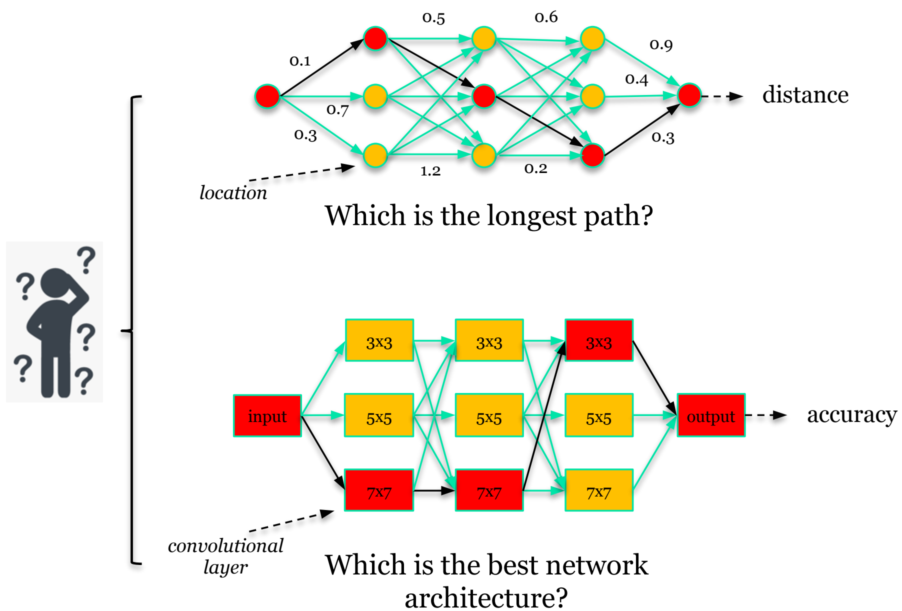
Problem Formulation

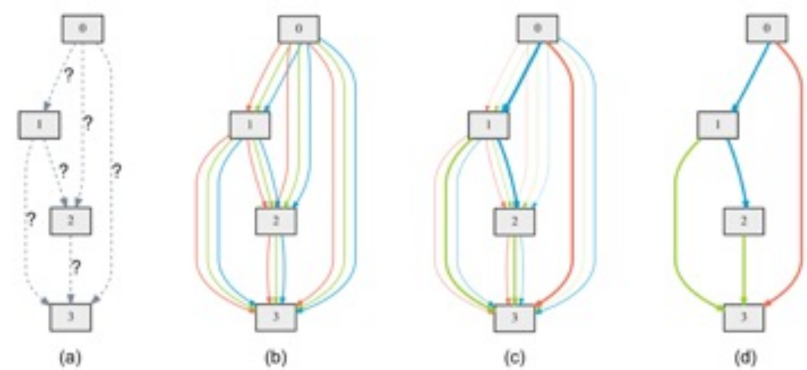
- Discrete search space $\{q^{(m)}\}^n$;
- Splitting path between each connected pair of neurons;
- Selecting weight value is effectively selecting operations as in NAS.



Neural Architecture Search Methods

Considering the huge search space ($\{q^{(m)}\}^n$), differentiable search algorithm is required.





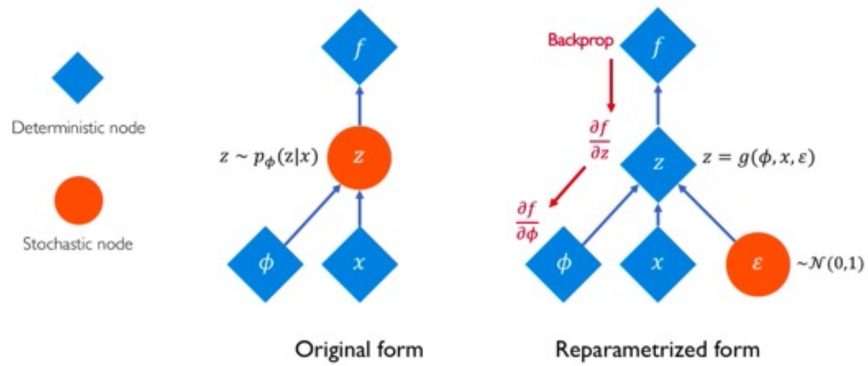
$$\bar{o}^{(i,j)}(x) = \sum_{o\in\mathcal{O}} \frac{\exp(\alpha_o^{(i,j)})}{\sum_{o'\in\mathcal{O}}\exp(\alpha_{o'}^{(i,j)})} o(x)$$

RL-NAS: Markov decision process

Differentiable NAS

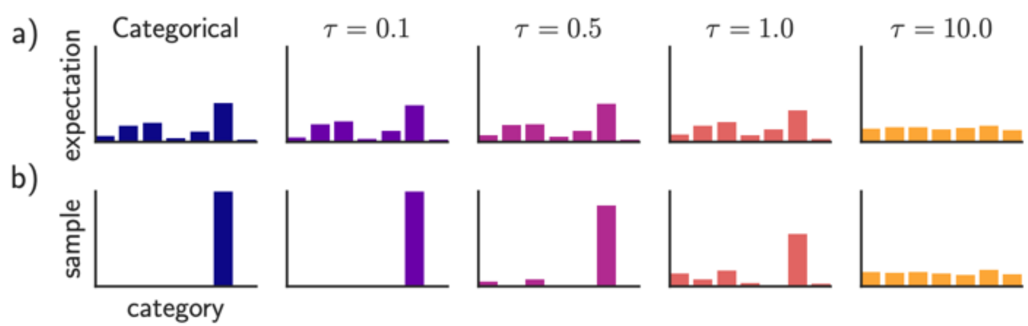
Indifferentiable Node in Networks

Gumbel Softmax



Reparameterization

$$y_i = \frac{\exp((\log(\pi_i) + g_i)/\tau)}{\sum_{j=1}^{k} \exp((\log(\pi_j) + g_j)/\tau)} \qquad \text{for } i = 1, ..., k.$$



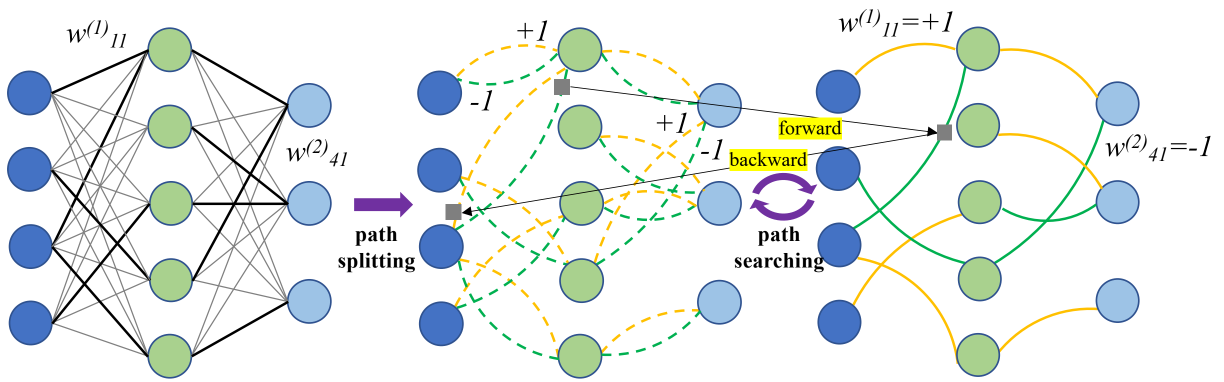
Problem Formulation

For each neuron pair <*i, j*>, we create *m* paths between them and:

- Associating probability variable;
- Define the forward selection mechanism;

$$f(q^1, q^2, \cdots q^m | \alpha_{i,j}^1, \alpha_{i,j}^2, \cdots \alpha_{i,j}^m) = q^k$$

- Derive the backward gradient $\frac{\partial \mathcal{L}}{\partial \boldsymbol{\alpha}_{i,j}}$



Method: RDHS

Reparameterization with deterministic hard-sampling

General form of sampling function with reparameterization trick

randomness

soft sample

$$y_{i,j}^k = \frac{exp((log(\alpha_{i,j}^k) + \mu n_{i,j}^k)/\tau)}{\sum_k exp((log(\alpha_{i,j}^k) + \mu n_{i,j}^k)/\tau)}$$

temperature

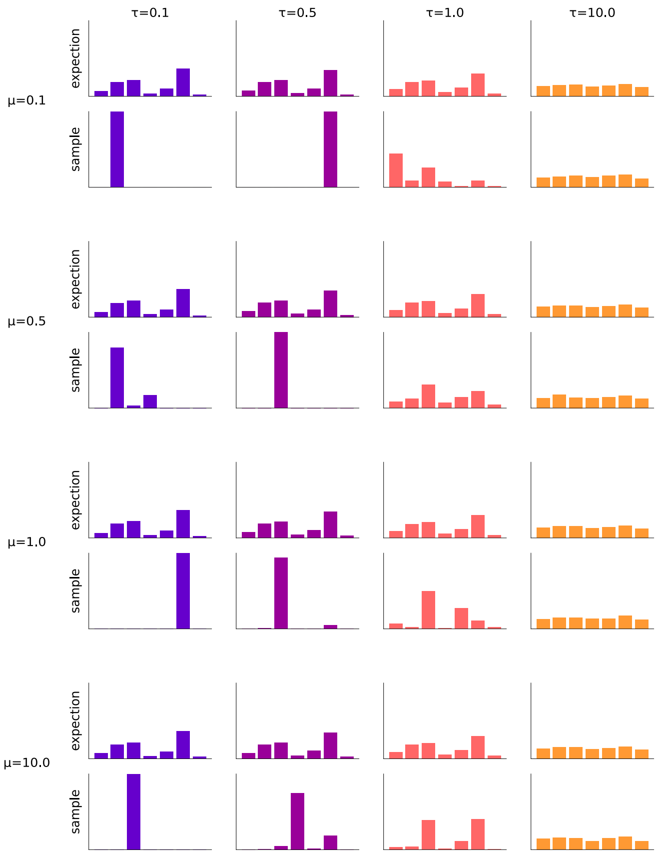
$$z_{i,j} = \text{one\_hot}\left(\arg\max_k \left(y_{i,j}^k\right)\right)$$

hard sample

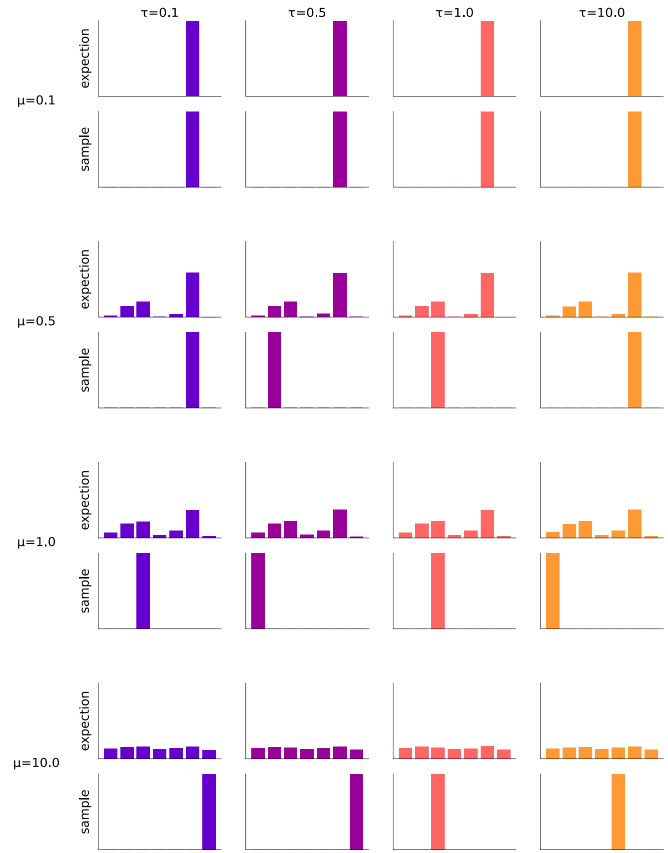
$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{y}_{i,j}} \approx \frac{\partial \mathcal{L}}{\partial z_{i,j}}$$

ST estimator

Hard-Sampling vs Soft-Sampling

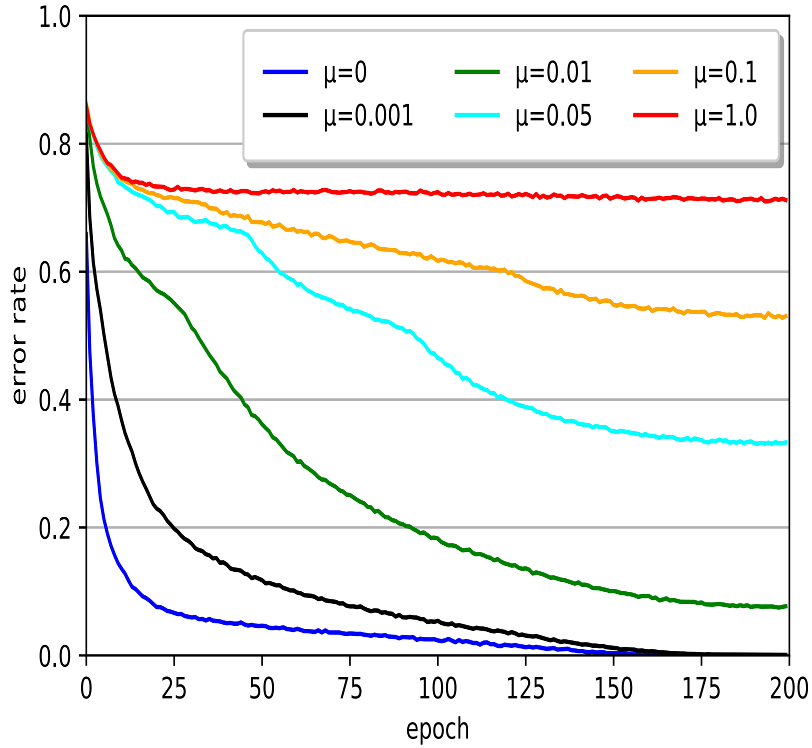


Gumbel-Softmax



Gumbel-Max

Error Rate Floor vs Randomness



Training VGG-small with binary weights ({-1, 1}).

Table 3: Exploration of the relationship between accuracy and randomness in sampling. For all the test networks and bit-widths, the best accuracy occurs when deterministic sampling ($\mu = 0$) is adopted.

Network	#Bits	μ	Acc. (%)
VGG-small	1	0	93.6
		0.001	93.4
		0.01	85.6
ResNet20	1	0	90.9
		0.001	90.9
		0.01	90.7
		0.1	64.7
ResNet18	1	0	64.6/85.4
		0.001	64.1/84.1
		0.01	45.1/66.3
	2	0	67.4/87.5
		0.001	55.1/69.7
	3	0	68.1/88.2
		0.001	48.8/64.4

Method: SGT

Stochastic Gradient Transfer

- Hard-sampling: only one path needs to be involved in the computational graph.

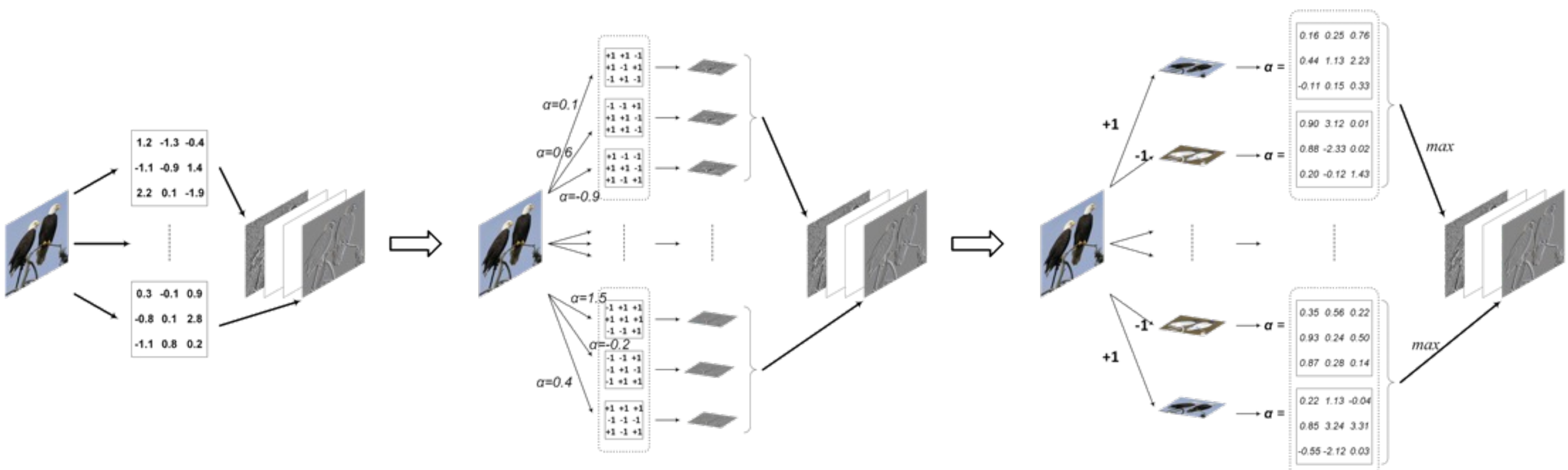
$$k = \arg\max_{r} \alpha_{i,j}^{r}.$$

- Heuristic: when the gradient of q^k is positive, it should decrease, other candidates should gain a higher odd, their associated parameters should increase; vice versa.

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\alpha}_{i,j}} = \frac{\partial \mathcal{L}}{\partial q_{i,j}^{k}} \cdot sign(\boldsymbol{q}_{i,j} - q_{i,j}^{k}) \qquad \text{where} \qquad \alpha_{i,j}^{k} = \max\{\alpha_{i,j}^{r}\}$$

Implementation Optimization for ConvNets

Neuron-to-neuron splitting requires exponentially increased parameters for updating, therefore we assign the associated parameters to the convolutional kernels scaled by each of *m* masks.



Results on CNN (CIFAR10, ImageNet)

Table 1: Results using different methods on CIFAR-10: accuracy (%), accuracy loss (%) against unquantized network (FP32), and whether multiplication is required are reported.

Network	Method	Value Space	Acc. (%)	ΔAcc. (%)	Req. Mult
VGG-small	BC [2]	$\{\pm 1\}$	91.7	2.1	N
	BWN [14]	$\mathbb{R}$	90.1	3.7	Y
	LAB [7]	$\{\pm 1\}$	89.5	4.3	N
	LQ-Net [17]	$\mathbb{R}$	93.5	0.3	Y
	Ours	$\{\pm 1\}$	**93.6**	**0.2**	N
ResNet-20	DoReFa [19]	$\mathbb{R}$	90.0	2.1	N
	LQ-Net [17]	$\mathbb{R}$	90.1	2.0	Y
	Ours	$\{\pm 1\}$	**90.9**	**0.9**	N
MobileNet	*ours*	$\{\pm 1\}$	93.78	0.3	N

Table 2: Results of ResNet18 quantized by different methods on ImageNet: Top-1/Top-5 accuracy (%) and accuracy loss (%) (shown in the parentheses) from the unquantized network.

#Bits	Method	Value Space	Top-1	Top-5	Req. Mult
1	BWN [14]	$\mathbb{R}$	60.8(8.5)	83.0(6.2)	Y
	ABC-Net [12]	$\mathbb{R}$	62.8(6.5)	84.4(4.8)	Y
	DSQ [5]	$\{\pm 1\}$	63.7(6.2)	-	N
	Ours	$\{\pm 1\}$	64.6(**4.5**)	85.4(**3.5**)	N
2	TWN [10]	$\mathbb{R}$	61.8(3.6)	84.2(2.6)	Y
	INQ [18]	$\{\pm 1/2^n\}$	66.0(2.3)	87.1(1.6)	N
	TTQ [20]	$\mathbb{R}$	66.6(3.0)	87.2(2.0)	Y
	ADMM [11]	$\mathbb{R}$	67.0(2.1)	87.5(1.5)	Y
	ABC-Net [12]	$\mathbb{R}$	63.7(5.6)	85.2(4.0)	Y
	LQ-Net [17]	$\mathbb{R}$	68.0(2.3)	88.0(1.5)	Y
	Ours	$\{\pm 1, \pm \frac{1}{2}\}$	67.4(**1.7**)	87.5(**1.4**)	N
3	INQ [18]	$\{\pm 1/2^n\}$	68.1(0.2)	88.4(0.3)	N
	ABC-Net [12]	$\mathbb{R}$	66.2(3.1)	86.7(2.5)	Y
	LQ-Net [17]	$\mathbb{R}$	69.3(1.0)	88.8(0.7)	Y
	Ours	$\{\pm 1, \pm \frac{1}{2}, \pm \frac{1}{4}, \pm \frac{1}{8}\}$	68.1(**1.0**)	88.2(**0.9**)	N

Performance of RDHS vs SGT

SGT

- Faster
- Less memory
- Higher variance

RDHS

- Slower
- Higher memory
- Lower variance

Table 4: Full comparison between RDHS and SGT in training ResNet18 on ImageNet. Training time and memory footprint are reported in relative to training in full precision.

#Bits	Method	Avg. Acc. (%)	Best Acc. (%)	Time	Memory
1	RDHS	64.3/83.9	64.6/85.4	1.47	1.34
	SGT	64.1/81.8	64.5/85.4	1.33	1.10
2	RDHS	67.5/87.0	67.4/87.5	1.66	1.48
	SGT	66.7/86.2	67.4/87.5	1.48	1.24
3	RDHS	67.9/88.1	68.1/88.2	1.96	1.73
	SGT	66.3/85.6	68.9/87.9	1.74	1.45

Conclusion

- Proposed to quantize deep neural networks from a "search" perspective.
- Identified the necessity of using deterministic hard-sampling in differentiable searching algorithm for quantization.
- Implemented and evaluated two methods for ConvNets with optimization tricks, achieving best trade-off between accuracy and execution efficiency.
- Our code is available at https://github.com/qinglu0330/DNN-weight-search

Thank You

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