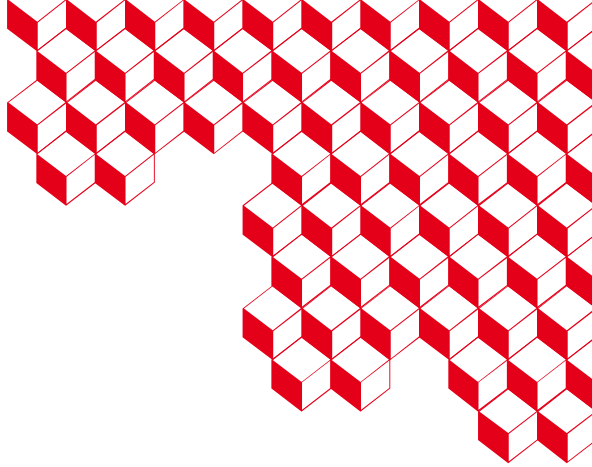


Quantized Neural Networks for edge implementation

Yannick Malot

JRAF 2023

Introduction

DNN, powerful but heavy models

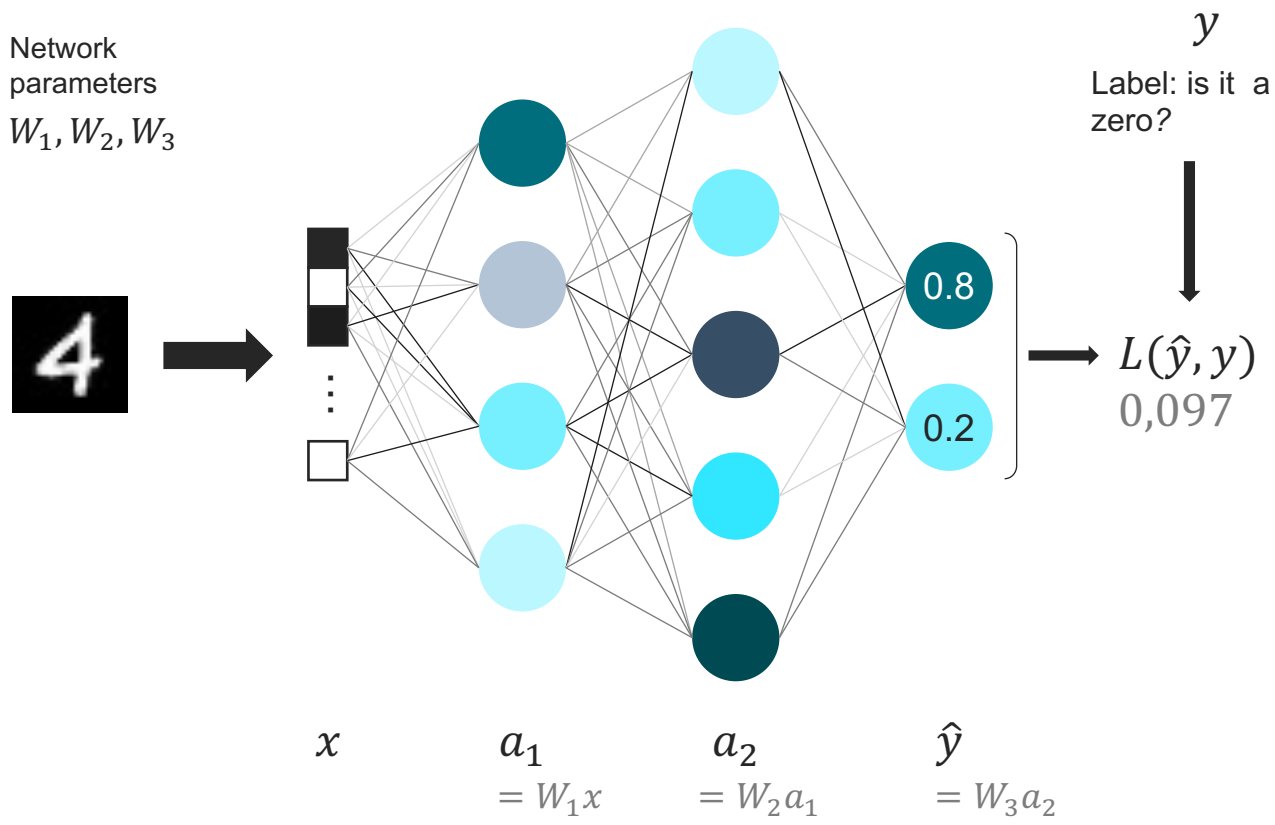
A neural network is a nesting of matrix products (parameters)

Parameters:

- Numerous (deep networks)
- In high dimension

⇒ Important storage need

Scheme – Functioning of a neural network



Compress a DNN

Needed memory > memory available on edge devices

⇒ need for **compression**

Several possibilities:

- fewer parameters, smarter operations;
- pruning: remove nodes;
- **quantization**: reduce numerical precision of parameters

Model	Memory (parameters)
ResNet-18	45 MB
ResNet-50	98 MB
MobileNet-v2	14 MB
EfficientNet-b0	21 MB
Yolo v7	148 MB
RetinaNet	152 MB
GPT3-small	16 GB

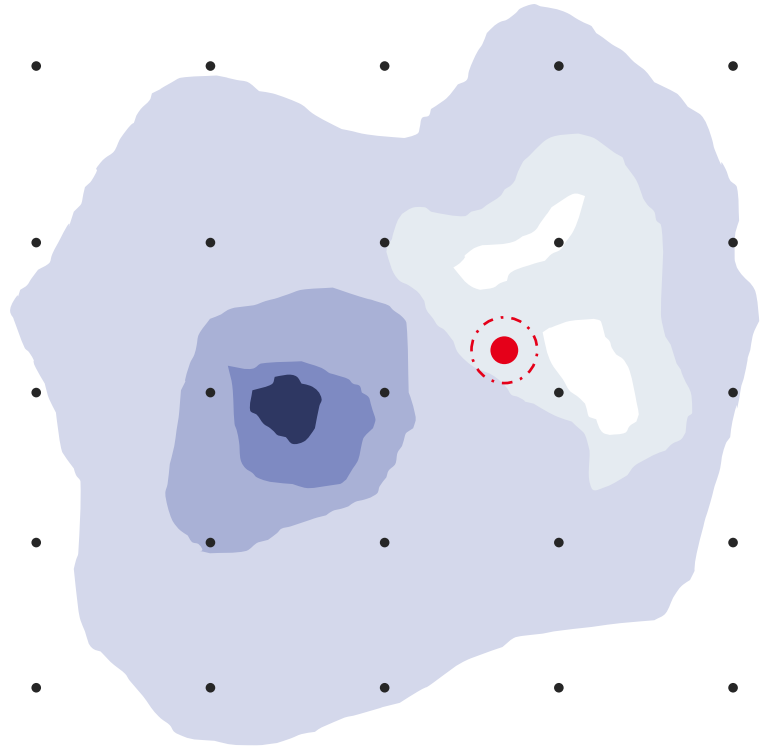
source: torchvision documentation

Quantization

A parameter is quantized if it lies in a **discrete** and **finite** set (vs. continu et infini)

- Quantization of a trained network (*Post Training Quantization*)
- Training iteratively with quantized weights (*Quantization Aware* Training)
- Integer-only training: parameters, activatoins and gradients

Scheme – Optimization of a function of a continuous parameter



1. Quantization Aware Training

Concepts and *benchmark*

Quantization Aware Training

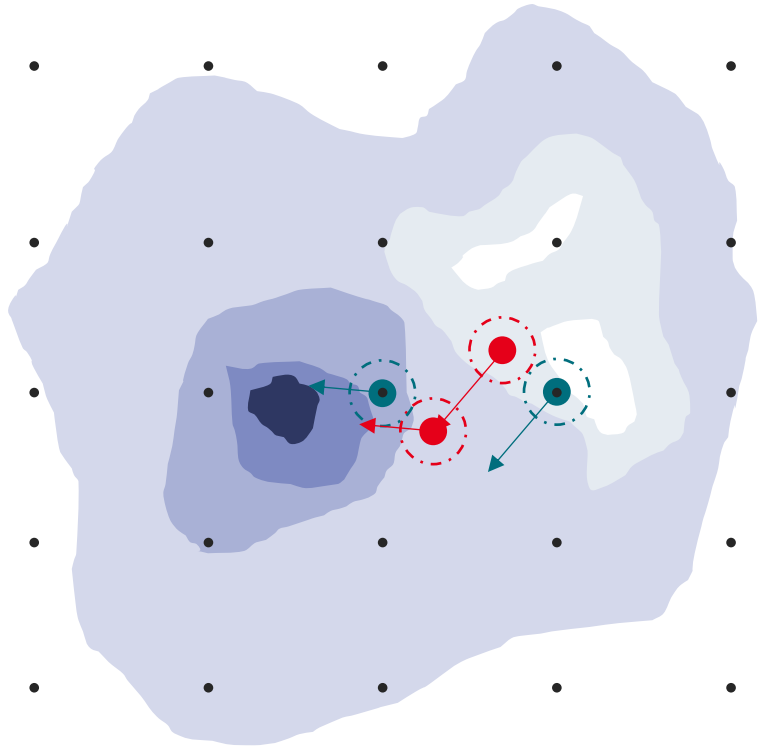
- Latent parameter

- Quantized parameter

  (iterative)

- Learning signal: gradient at the quantized point

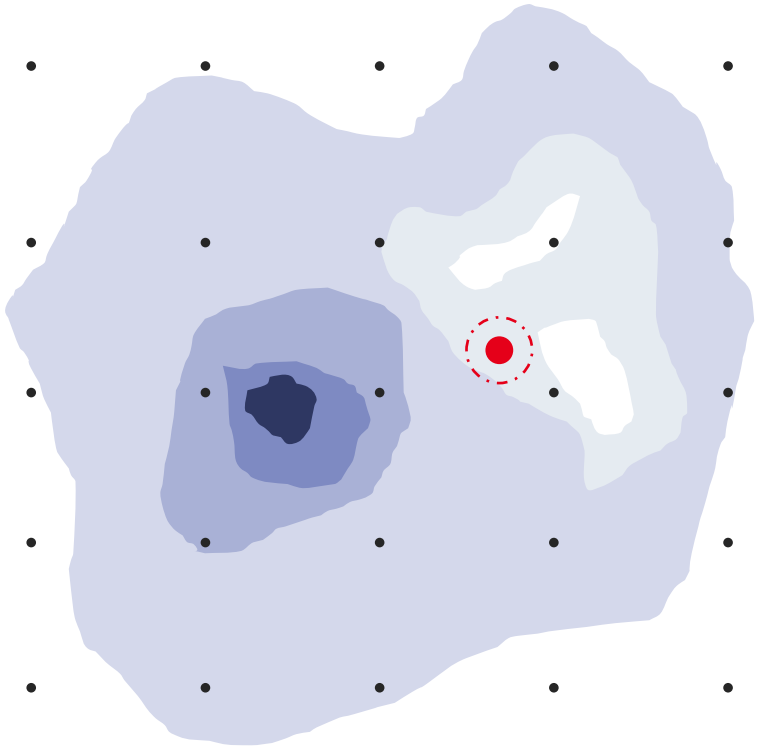
Scheme – QAT Learning



Diversity of QAT approaches

- Discretization set
  - Linear / uniform
  - Logarithmic
  - Any centroids

Scheme – QAT Learning



Diversité des approches

- Discretization set
  - Linear / uniform
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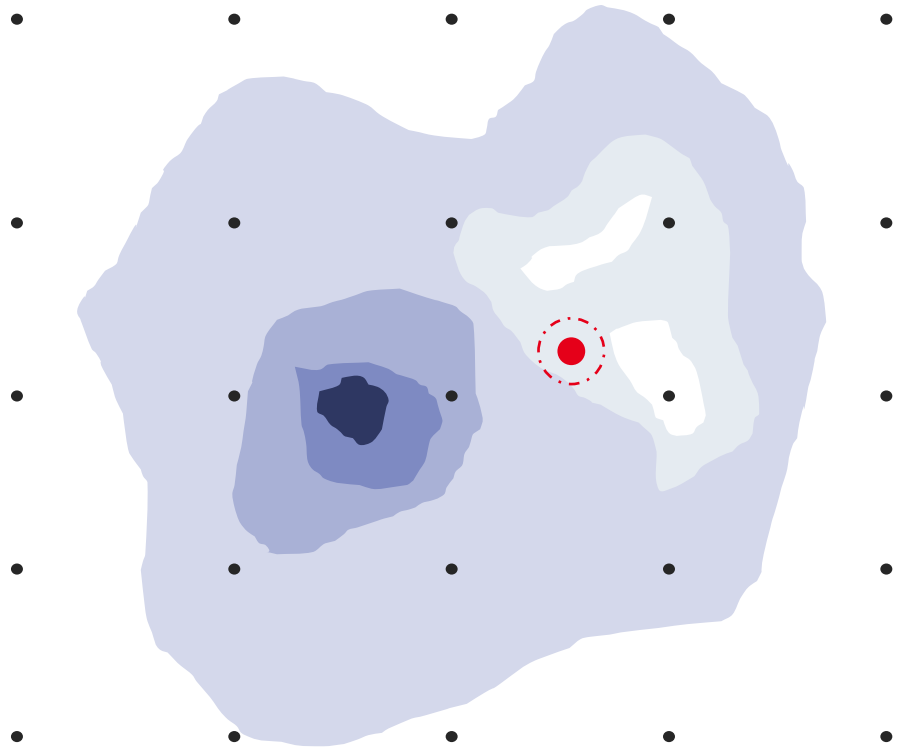
Scheme – QAT Learning



Diversité des approches

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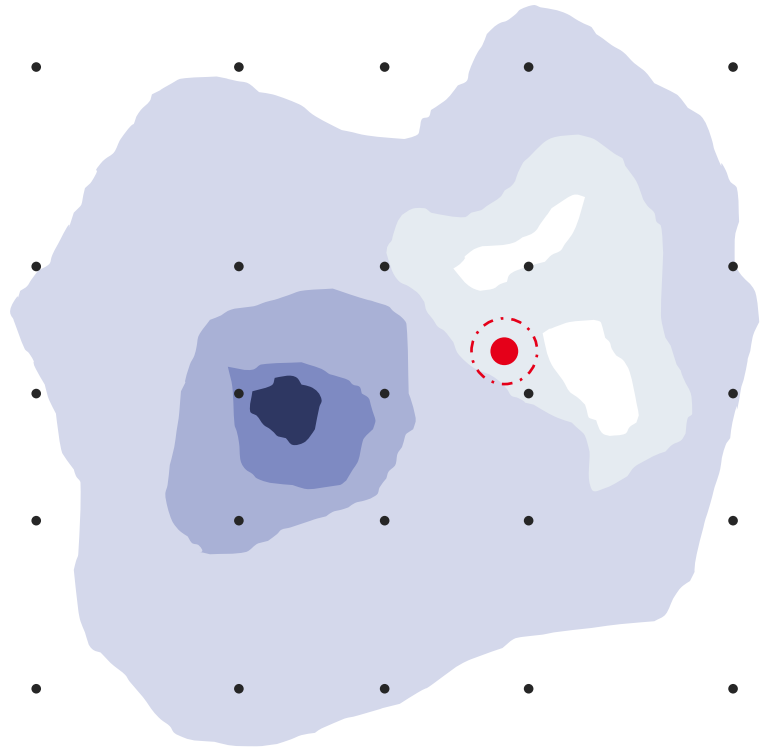
Scheme – QAT Learning



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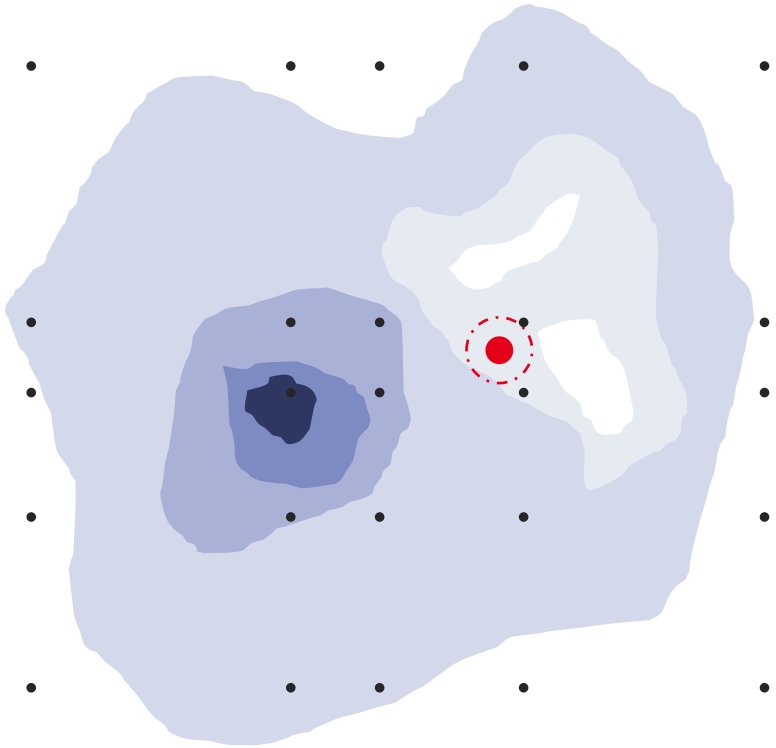
Scheme – QAT Learning



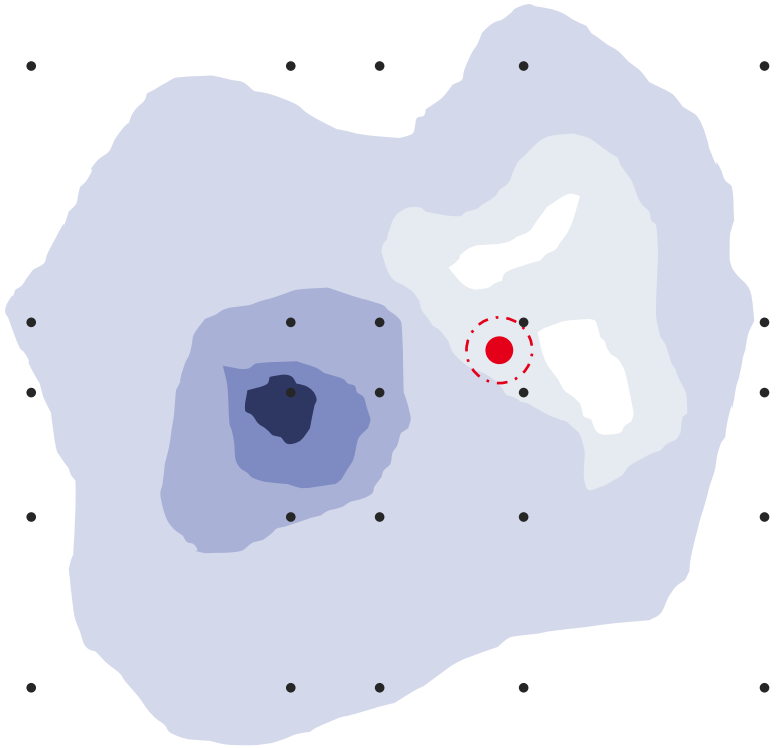
Diversité des approches

- Discretization set
  - Linear / uniform
  - Logarithmic
  - Any centroids

- Additional parameters
  - Scaling
  - Learnt discretization set

More complex approaches = additional settings to tune

Scheme – QAT Learning



QAT benchmark

Linear approaches can reach 90% accuracy, while more complicated approaches do not necessarily perform better

Test classification error on test data (W3A3)

ResNet20 network on CIFAR-10 data. Best epoch selected on 5% validation data, averaged over 10 runs. Optimizer SGD, lr 10^{-1}, 200 epochs

Méthode	**Taux d'erreur moyen**
Baseline (32 bits)	8.5%
Binarized NN (1 bit)	34%
Ternary Weight Net (2 bits)	27%
Quantized NN	19.5%
Learned Step Quantization	10%
DoReFa Net	12%
Scale Adjusted Training	11%
LQ-Net	11.5%
Scalar centroids	13%

2. Numerical precision

Which should we chose?

Number of parameters and memory

Model with N_p parameters and an activation with maximum size N_a

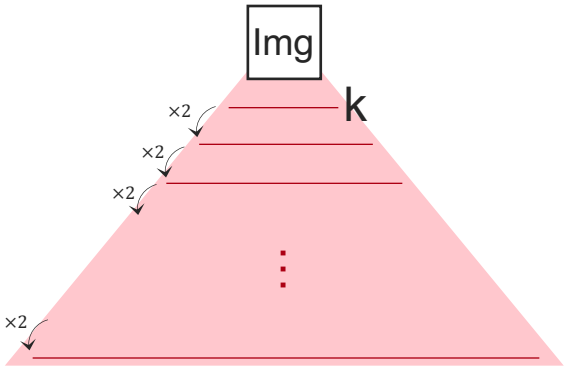
Memory needed for an inference:

parameters b_p bits, activations b_a bits

$$Mem = N_p \times b_p + N_a \times b_a$$

$$N_p = f(k)$$
$$N_a = g(k)$$

$$b_a = \begin{cases} b_p & if\ b_p > 3 \\ 4 & else \end{cases}$$



Number of parameters and memory

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$$N_p = f(k)$$
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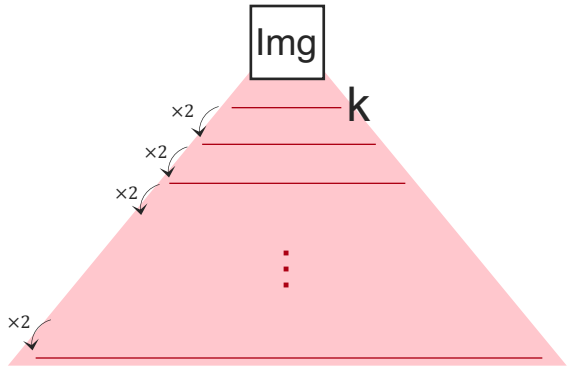
$$b_a = \begin{cases} b_p & if\ b_p > 3 \\ 4 & else \end{cases}$$

$$Mem = f(k) \times b_p + g(k) \times \max(b_p, 4)$$



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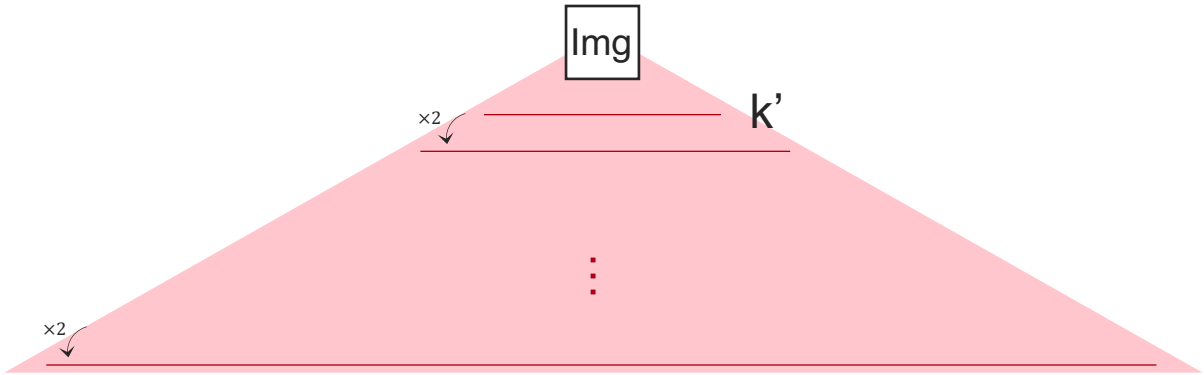


Tradeoff #parameters - precision

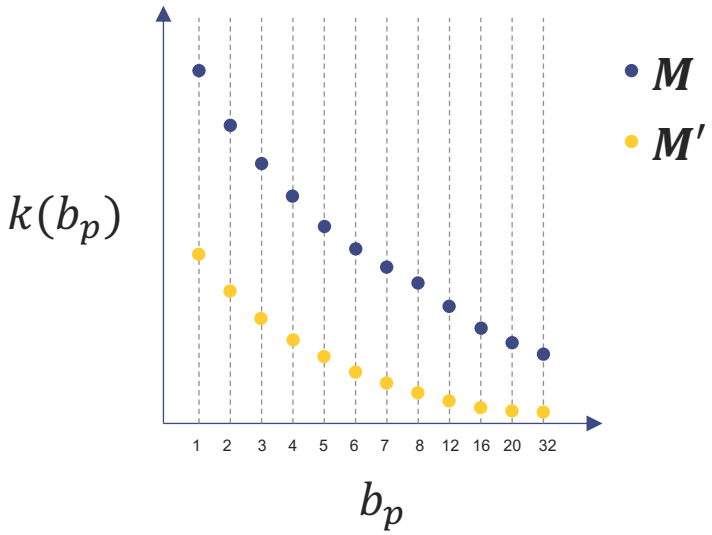
Fixed computational budget $\boldsymbol{M}$

Relation between the size of first convolutional filter and numerical precision:

$$k(b_p, \boldsymbol{M}) = \underset{k}{\operatorname{argmax}}\, Mem(k, b_p)$$
$$t.q.\ \ Mem(k, b_p) \leq \boldsymbol{M}$$

« take as many parameters as the memory budget $\boldsymbol{M}$ allows for with precision b_p »

$$Mem(k, b_p) = f(k) \times b_p + g(k) \times \max(b_p, 4)$$



Optimal numerical precision: 3-4 bits ?

Model: ResNet 20, CIFAR-10 data

Baseline memory of the model: $\boldsymbol{M_0}$

Observe model accuracy when the numerical precision varies (jointly with the number of parameters)

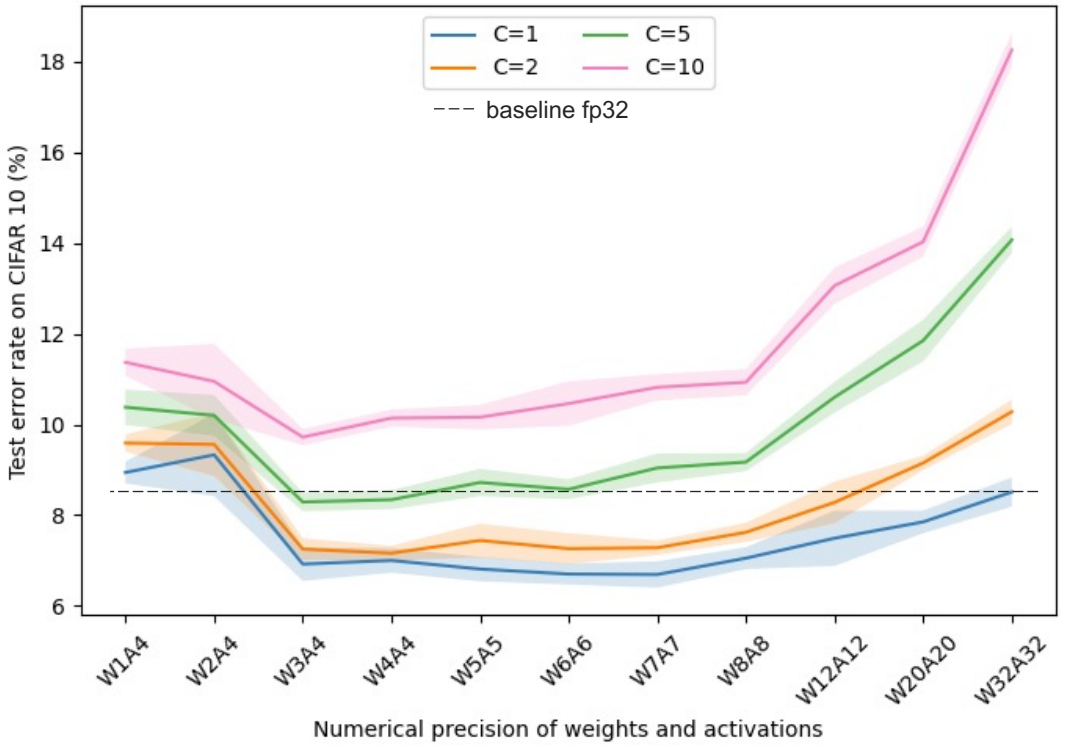
with memory budget $\boldsymbol{M_0}/C$

for given compression ratios C

Test classification error on test data (W3A3)

ResNet20 with fixed memory budget, for different compression ratios

CIFAR-10 data; Optimizer SGD, lr 10^{-1}, 200 epochs



3. Towards on-device training

Contraints for on-device training

more elements to keep in memory

In inference:

- quantized weights (*b* bits)
- activation (intermediary calculation, *b'* bits)

During training:

- latent parameters (32 bits)
- optimizer (32 bits)
- all activations (*b'* bits)

Table: Numerical precision of each element and needed memory
ResNet-20, CIFAR-10 data, batch size B

W32A32	Inférence	Mémoire (Mb)	Apprentissage	Mémoire (Mb)
Activations	+ grande	0,07	toutes	0,77 × B
Paramètres	tous	1,08	tous	1,08
Optimizer	N.A.	0	~paramètres	1,08
Total		**1,15**		**2,16 + 0,77 B**

W3A3	Inférence	Mémoire (Mb)	Apprentissage	Mémoire (Mb)
Activations	+ grande	0,006	toutes	0,07 × B
Paramètres	tous	0,10	Tous (32 bits)	1,08
Optimizer	N.A.	0	~paramètres	1,08
Total		**0,11**		**2,16 + 0,07 B**

All-integer training

Works well in 8 bits (see NITI)

How to go down to 4 bits?

- keep gradients in 8 bits
- random jumps from state to others

Figure: All-integer training
From NITI

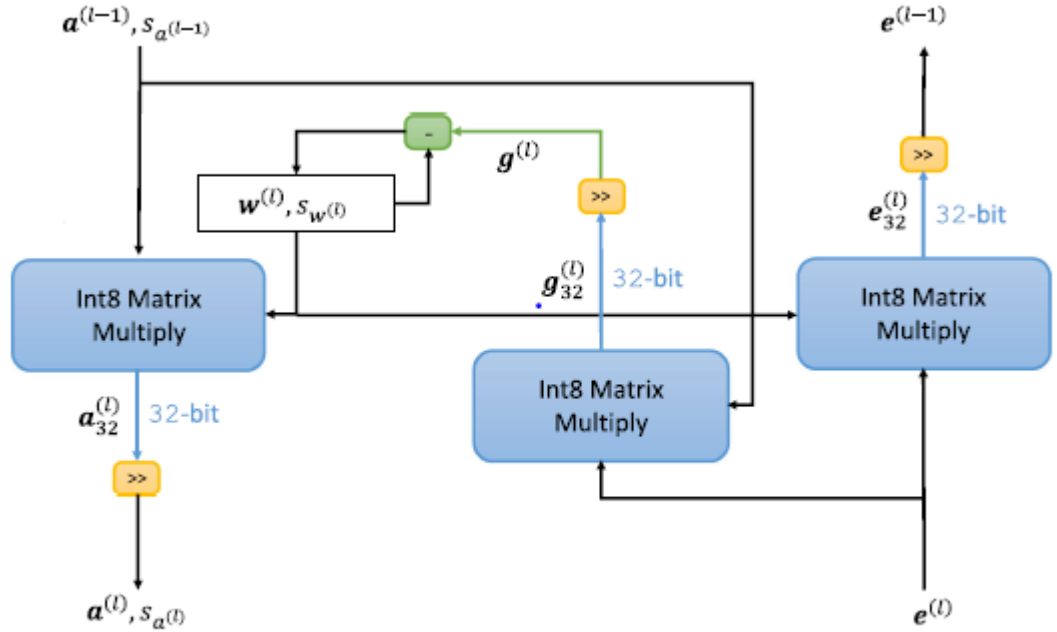


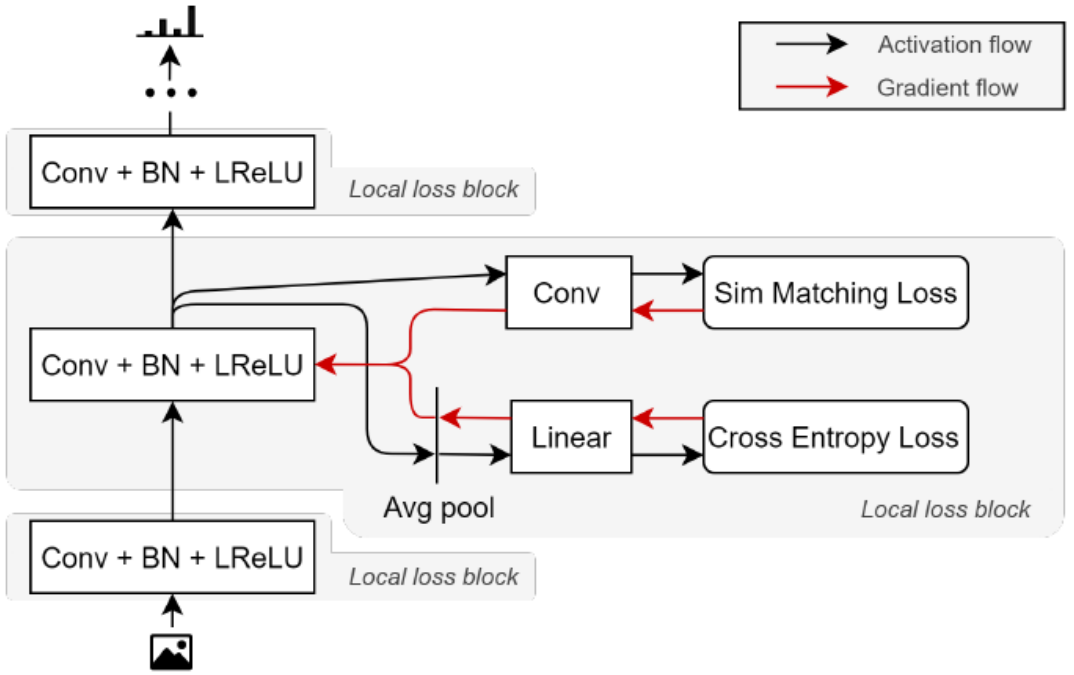
Fig. 1. Integer layer forward and backward pass.

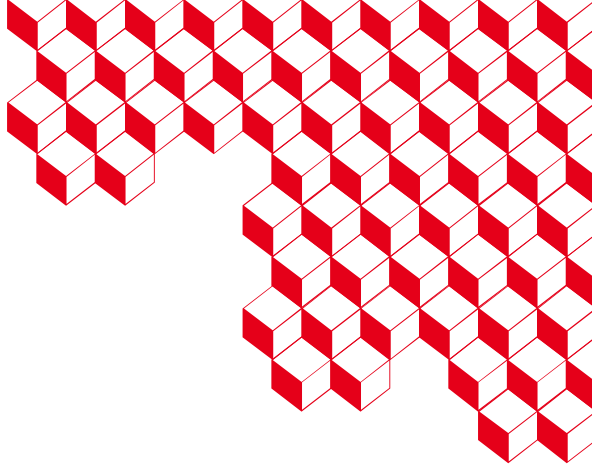
Local loss

Training with blocks

- No complete backpropagation
- QAT on the block being trained
- So far, 30% test error on Cifar-10

Figure: Training with local error signals
From Nokland et al.





Q&R

Direction: Kim Thang Nguyen (LIG)

Supervision: Thomas Mesquida (CEA), Sylvain Bouveret (LIG)

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