Manage your neural network energy budget with LaNMax !

CMC Microsystems Workshop @Montréal

Accelerating AI – Challenges and Opportunities in Cloud and Edge Computing

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March 6, 2020

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This work is supported by IVADO and ReSMiQ

Outline

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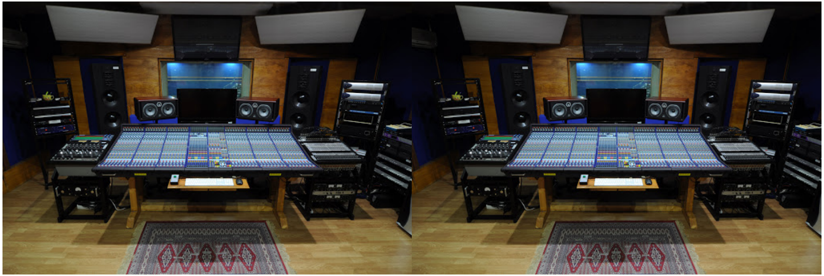
Parametric ML 101

Figure 1: Knobs

- Learning = finding the right knobs settings
- "Regular ML" with thousands parameters



(a) Layer 1 (b) Layer 2

Figure 2: Knobs everywhere

- Learning = finding the right knobs settings
- Millions, billions of parameters (NLP mostly)

Storing the parameters

As is, millions of parameters would be quite the burden on any hardware. We have leeway to reduce this burden through e.g.:

- Less degrees of freedom per parameter : quantization (well studied)
- Clever network designs (tricky !)
- Pruning (care of sparse network, specific hardware is needed for full advantage)
- Lately Hacene et al. (2019); Hirtzlin et al. (2019) were reducing supply voltage to the memory with interesting results

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On CMOS supply voltage

The dynamic energy consumption formula

$$C \times V^2 = \text{number of parameters} \times \text{number of bits} \times V^2 \times \text{technology dependent constant}$$

- The capacitance C is a constant depending on circuit area
- Static consumption = system online time, proportional to circuit area, i.e. number of parameters
- Dynamic consumption = number of memory accesses. No writes, only reads. Each parameters is read once
- Play with V and achieves quadratic savings !

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An optimisation problem

No free lunches, sorry

Reducing voltage as in near threshold CMOS will increase the fault rate p when reading bits (Dreslinski et al. (2010))

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We seek to jointly optimize an energy-capability trade-off through a fault rate parameter p that (i) degrades the capability when going up and (ii) reduces the energy when going up; while retaining the maximum capability for the lowest energy.
We exploit the known relationship between p and η (and *in fine* V) to measure the trade-off.

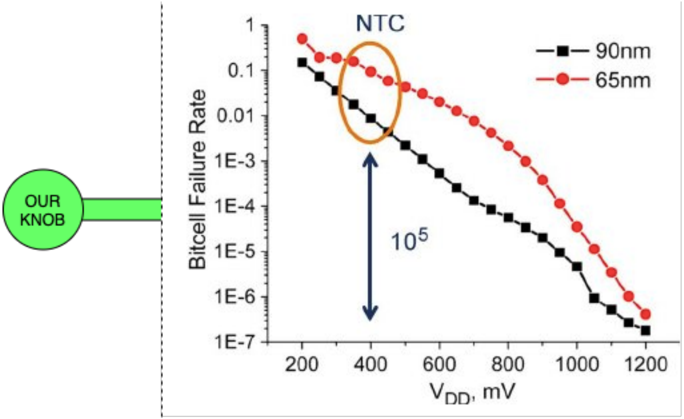
Our work

Hyp.: we can improve the supply voltage idea by letting the network find its own "best" supply voltage

Outline

Problem statement

We want to find *efficiently* the fault rate p that gives the best capability to the neural network for the lowest energy *without additional mechanisms*.



Adapted from Dreslinski et al. (2010)

Efficiently

- Finding the fault rate should have a small training overhead, idealy not at the cost of more training epochs

Implication

Make use of each existing epoch to gain information on the energy-capability trade-off

- **Why ?** Here are the existing training time for large NLP models as reported by Nvidia.

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BERT-Large Training Times on GPUs

Time	System	Number of Nodes	Number of V100 GPUs
47 min	DGX SuperPOD	92 x DGX-2H	1,472
67 min	DGX SuperPOD	64 x DGX-2H	1,024
236 min	DGX SuperPOD	16 x DGX-2H	256

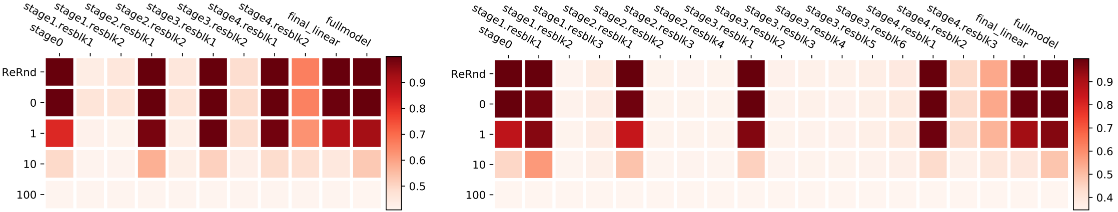
Without additional mechanism

Explored in Hacene et al. (2019) is the use of circuit-level error detection which zero-out faulty weights. This kind of Error-Correction mechanism is known and usable !
But this adds up hardware complexity.

Implication

No ECC or such mechanism, the bits are used by the network as they are read.

With a small training overhead constraint, we could easily add degrees of freedom to the storage energy optimisation : e.g. a fault rate per layer of the neural network.
This would concur with Zhang et al. (2019) (see below): layers don't share the same sensitivity to randomness.



Imagenet trained ResNet 18 and 50 layerwise sensibility to weights rewinding

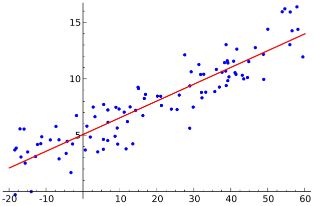
How-to

Usually, the fault rate is an hyperparameter : we propose to learn it with numerical gradients on a per-epoch basis.

Numerical gradient components

$$\nabla_p = \mathrm{OLS}_p(\{\alpha \sum_\ell E_{i,\ell} + \mathrm{loss}_i \,|\forall i \in \text{mini-batch}\}) \text{ coefficients}$$

Moreover, the trade-off is controlled by a parameter α: the bigger α the more emphasis on energy reduction there will be.



Layerwise Noise Maximisation

Algorithm overview

1. Initialize a fault rate p_ℓ per ℓ layer of the network
2. Begin an SGD like-optimization algorithm, for all epochs
    1. Sample neural network's weights at the current fault rate + some randomness
    2. Forward the current mini-batch
    3. Store the current energy-capability trade-off
    4. Do the usual backpropagation and gradient descent
    5. When all mini-batches have been done : linear regression on the trade-off points and numerical gradient descent
    6. Next epoch
3. Return the neural network weights and the layerwise fault rate

Outline

An optimisation scenario

- Moons et al. (2018) proposed that quantized network may be optimal in the energy-capability trade-off. Thus we test our method on a 1-bit weighted Wide Residual Network (Zagoruyko and Komodakis (2016)) that has shown good results in previous works.
- The net is binarized with Binary Connect Courbariaux et al. (2015) on the Conv. and FC layers. These layers have the additional trainable fault rate !
- The faults are uniformly drawn at the rate p each time a *forward* pass is done.
- We use CIFAR-10 dataset with Adam and standard hyperparameters.

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Comparing at isoaccuracy

- Can LaNMax provide efficient nets with higher accuracy than reliable smaller networks ?
- As we vary the size of the network, we note ρ the nb. of params. w.r.t. reference network (36 millions parameters).

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A fair comparison

For our results to be relevant, we will only compare networks that achieve the same accuracy.

Beforehand: are All Layers Equals ?

Recall earlier : does our scenario verify the layerwise sensitivity to randomness?
Train with 1% fault rate on global, test with maximum fault rate per layer (i.e. 50%).

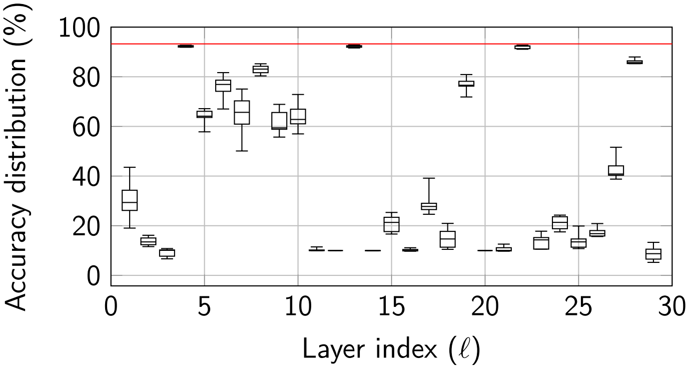
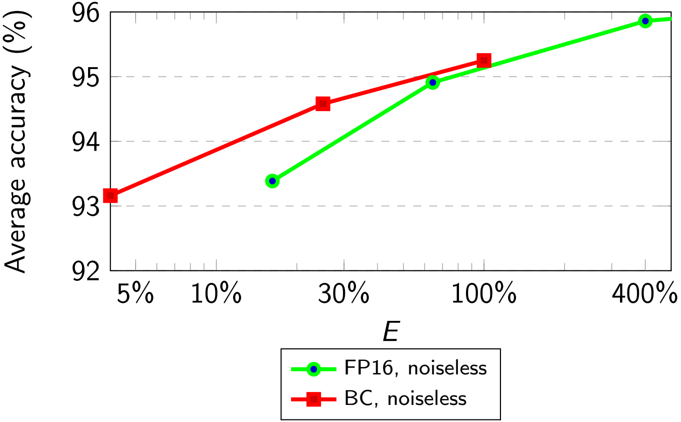


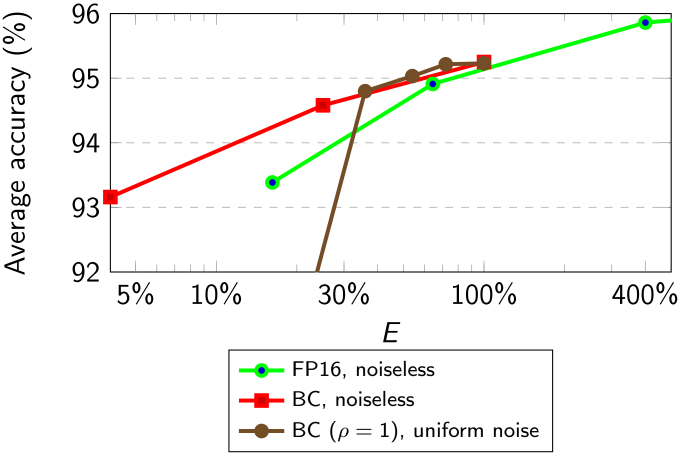
Figure 3: Sensitivity analysis under uniform noise $p = 1\%$

Comparing LaNMax VS net configs. relative energy



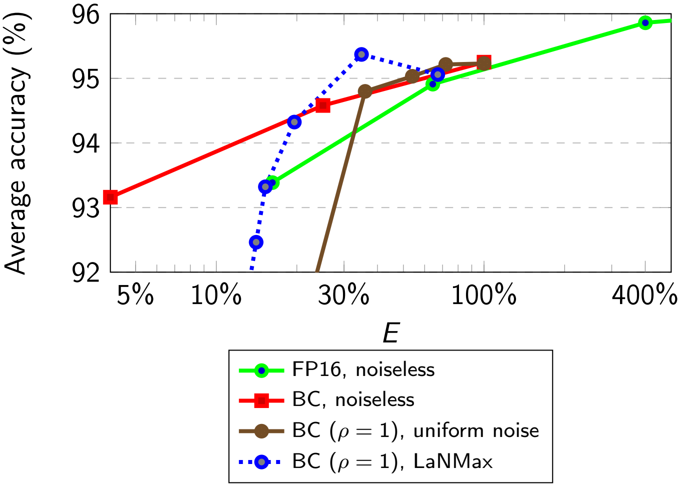
Difference in model size ⇔ difference in energy !

Comparing LaNMax VS net configs. relative energy



Difference in memory reliability $\Leftrightarrow$ difference in energy !

Comparing LaNMax VS net configs. relative energy



LaNMax optimised memory reliability ⇔ even less energy !

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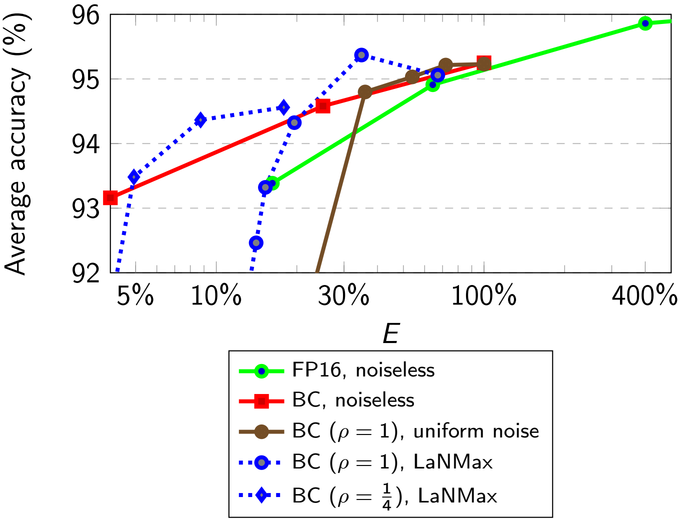

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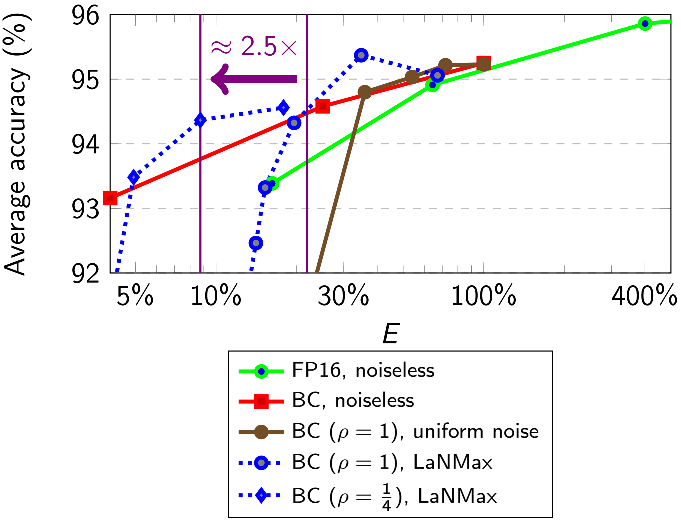

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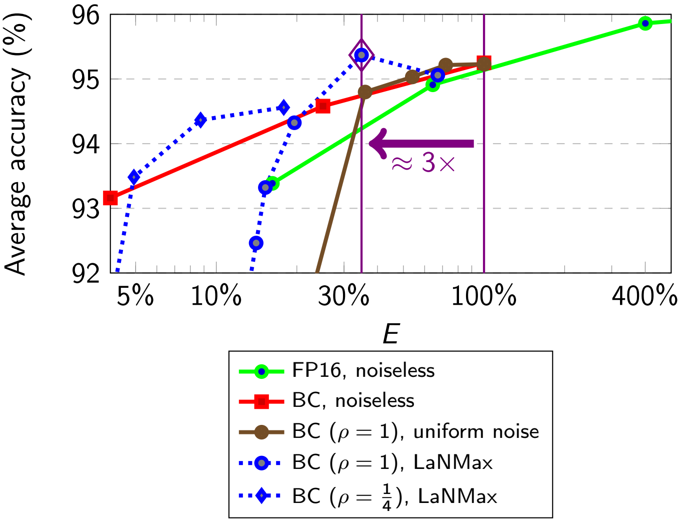
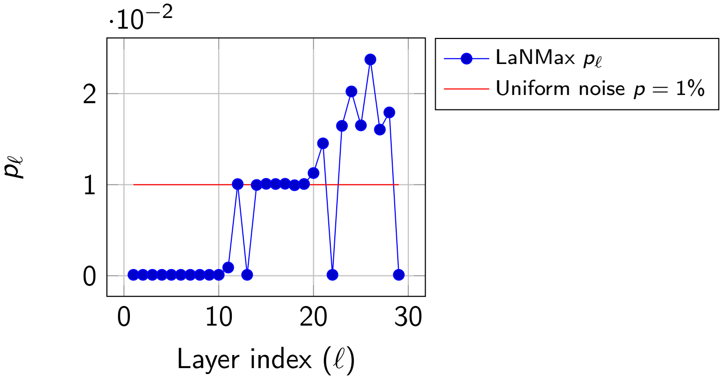


We can plot the learned fault rate at $\diamond$:



Instead of unreliable small layers from our layerwise sensitivity experiment, we have achieved a fault rate that prioritize unreliability on the largest layers. Good for E !

Outline

Take-away

- Neural nets are terribly good at learning robustness
- Binary neural nets are more robusts than people thoughts, with the adequate tools (not Dropout)
- Exploit this robustness by learning a layerwise fault rate during training
- Deploy a neural network on a server/embedded system at roughly a third of the storage energy cost

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This work will be presented at AICAS 2020 and is accessible on Arxiv for details (*arXiv:1912.10764 [cs.LG]*).

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