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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Learning = finding the right knobs settings

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

- Millions, billions of parameters (NLP mostly)
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)

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Storing the parameters

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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 parameter 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))

$$\eta(p) = -\frac{\log(p)}{a}$$

with $\eta$ the normalized consumption and $a$ a technology dependent parameter
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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 $\eta$ (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

1. Introduction

2. LaNMax

3. Results on image classification

4. Wrap-up
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, ideally 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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<table>
<thead>
<tr>
<th>Time</th>
<th>System</th>
<th>Number of Nodes</th>
<th>Number of V100 GPUs</th>
</tr>
</thead>
<tbody>
<tr>
<td>47 min</td>
<td>DGX SuperPOD</td>
<td>92 x DGX-2H</td>
<td>1,472</td>
</tr>
<tr>
<td>67 min</td>
<td>DGX SuperPOD</td>
<td>64 x DGX-2H</td>
<td>1,024</td>
</tr>
<tr>
<td>236 min</td>
<td>DGX SuperPOD</td>
<td>16 x DGX-2H</td>
<td>256</td>
</tr>
</tbody>
</table>
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
Usually, the fault rate is an hyperparameter: we propose to learn it with numerical gradients on a per-epoch basis.

**Numerical gradient components**

\[
\nabla p = \text{OLS}_p(\{\alpha \sum_{\ell} E_{i,\ell} + \text{loss}_i | \forall i \in \text{mini-batch}\}) \text{ coefficients}
\]

Moreover, the trade-off is controlled by a parameter \(\alpha\): the bigger \(\alpha\) the more emphasis on energy reduction there will be.
Algorithm overview

1. Initialize a fault rate $p_\ell$ per $\ell$ 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
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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 $p$.

- 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.
An optimisation scenario

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Can LaNMax provide efficient nets with higher accuracy than reliable smaller networks?

As we vary the size of the network, we note $\rho$ the nb. of params. w.r.t. reference network (36 millions parameters).
Comparing at isoaccuracy

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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 $p = 1\%$](image)
Comparing LaNMax VS net configs. relative energy

Difference in model size $\Leftrightarrow$ 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

Average accuracy (%)

5% 10% 30% 100% 400%

E

FP16, noiseless
BC, noiseless
BC ($\rho = 1$), uniform noise
BC ($\rho = 1$), LaNMax

LaNMax optimised memory reliability $\Leftrightarrow$ even less energy!
Comparing LaNMax VS net configs. relative energy

![Graph showing the average accuracy (%) of different configurations as a function of energy (E)].

Legend:
- **Green Circle**: FP16, noiseless
- **Red Square**: BC, noiseless
- **Brown Diamond**: BC ($\rho = 1$), uniform noise
- **Blue Circle**: BC ($\rho = 1$), LaNMax
- **Blue Diamond**: BC ($\rho = \frac{1}{4}$), LaNMax

Average accuracy (%) increases with energy (E) for all configurations, indicating an improvement in performance as energy consumption varies.
Comparing LaNMax VS net configs. relative energy

Average accuracy (%)

$\approx 2.5 \times E$

FP16, noiseless
BC, noiseless
BC ($\rho = 1$), uniform noise
BC ($\rho = 1$), LaNMax
BC ($\rho = \frac{1}{4}$), LaNMax
Comparing LaNMax VS net configs. relative energy

Average accuracy (%) vs. $E$

- Green circle: FP16, noiseless
- Red square: BC, noiseless
- Brown diamond: BC ($\rho = 1$), uniform noise
- Blue circle: BC ($\rho = 1$), LaNMax
- Blue diamond: BC ($\rho = \frac{1}{4}$), LaNMax

Approximately 3x improvement at 100% noise level.
Aftermatch : layerwise sensitivity

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!
1 Introduction

2 LaNMax

3 Results on image classification

4 Wrap-up
Neural nets are terribly good at learning robustness

- Binary neural nets are more robusts than people thought, 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
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
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This work will be presented at AICAS 2020 and is accessible on Arxiv for details (arXiv:1912.10764 [cs.LG]).


