Vers un apprentissage profondément plus économique

Tricks, Theory, Measures and Hardware

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31-08-2022

The computer bounce effect

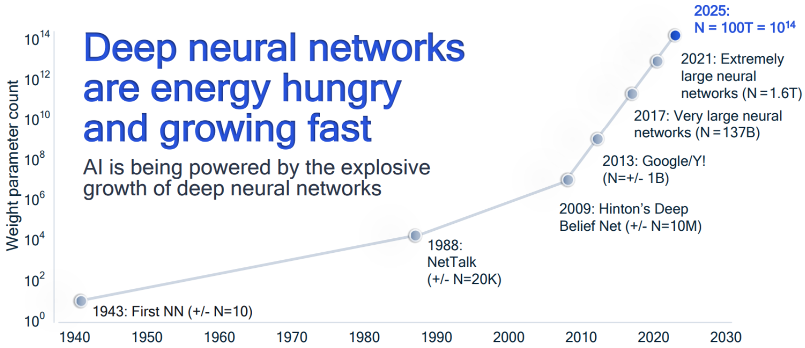


Figure 1: Exponential growth of Deep Learning models [Fournarakis, 2021a]

Impact on earth

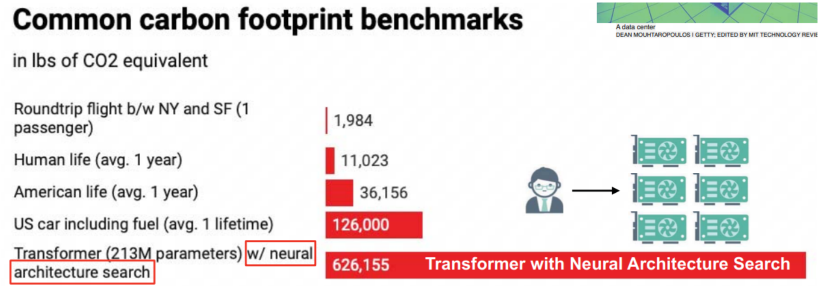


Figure 2: Carbon footprint comparative study between a neural network and activities [Han, 2021].

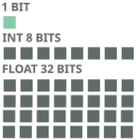
The impact of Machine Learning is non neglictible → Reduce the size of models !

1. Tricks and limits
   - Quantization
   - Pruning
   - Early Exits
2. More maths
3. AIPowerMeter
4. Tiny ML
5. Conclusion and Perspectives

Quantization

Low bitwidth approaches

- Originally from [Courbariaux et al., 2015] - BinaryConnect,
- Weights and I/O in [Bulat and Tzimiropoulos, 2019] - XNOR-nets ++,
- Quantization in [Zhou et al., 2016, Fournarakis, 2021a].



BNN's details

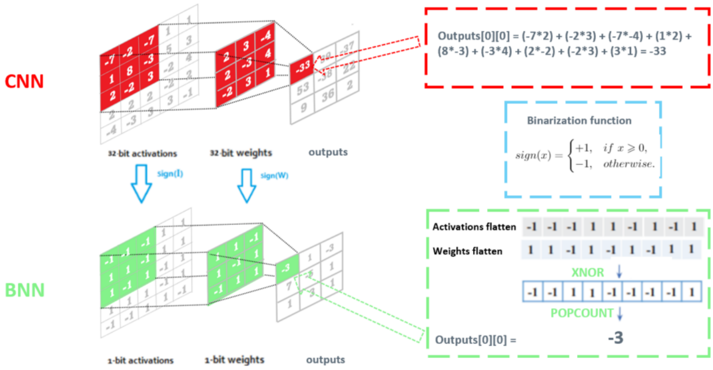


Figure 3: CNN and Binarization [Yuan and Agaian, 2021]

Backpropagation of a BNN

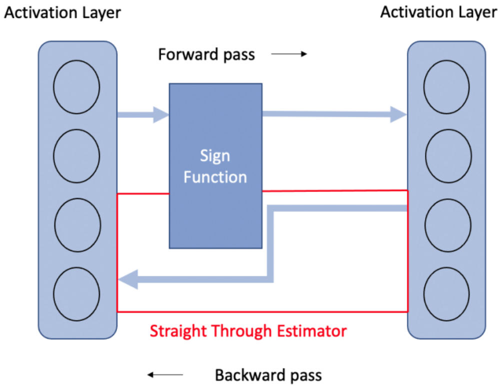


Figure 4: STE estimator in the backpropagation

Figure source :

Limits of BNN's

- STE estimator and continuous gradient accumulations,
- No gain observed in [Courbariaux et al., 2015] or [Bulat and Tzimiropoulos, 2019],

Limits of BNN's

- STE estimator and continuous gradient accumulations,
- No gain observed in [Courbariaux et al., 2015] or [Bulat and Tzimiropoulos, 2019],
- Larq Compute Engine to the rescue.

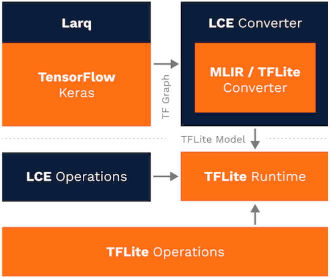


Figure 5: Larq Compute Engine workflow from training to deployment

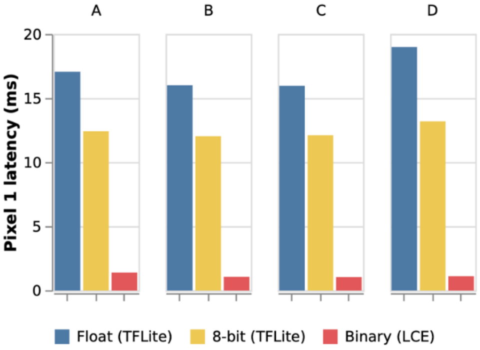
Larq Compute Engine of TFLite model

Principle

- train your model on a standard CPU/GPU,
- convert the model in tflite format,
- a python module (GitHub link here) based on a C++ routine is used (tiling, vectorization and parallelism) for fast inference.

More details on a blog post here.

Larq Compute Engine gain



h * w * in * out convolutions are:
(A)$56\times56\times64\times64$; (B) $28\times28\times128\times128$;
(C) $14\times14\times256\times256$; (D) $7\times7\times256\times256$

Pruning - origin

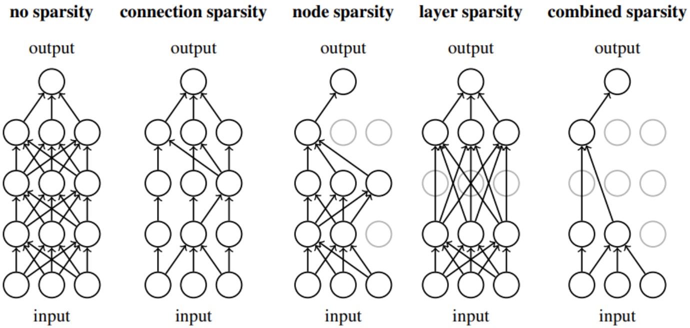
Originated in Leo Breiman's book Classification And Regression Tree (1984):

- build a maximal decision tree $\mathbb{T}_{\max}$
- solve the following optimization problem:

$$\arg \min_{\mathbb{T} \subset \mathbb{T}_{\max}} \left\{ \sum_{\text{node} \in \mathbb{T}} \sum_{x_i \in \text{node}} (y_i - \bar{y}_{\text{node}})^2 + \alpha \|T\|_0 \right\}$$

- goal: reduce overfitting !

Pruning NNs


no sparsity
connection sparsity
node sparsity
layer sparsity
combined sparsity
output
input

Pruning NNs - pruned literature

- originated in [Mozer and Smolensky, 1988] with relevance coefficients and Optimal Brain Damage in [LeCun et al., 1990] : **pruning after training**
- recent advances in [Lee et al., 2018], [de Jorge et al., 2020] : **pruning at init**
- statistical approach for layer sparsity or **pruning during training** in [Hebiri and Lederer, 2020, Bellec et al., 2018].

SNIP measures

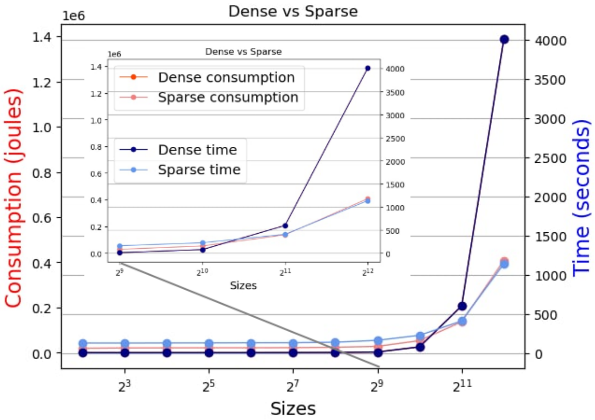
We test a Python implementation of SNIP.

Architecture	Dataset	Pruning ?	Parameters	Time (hh:mm:ss)	Max precision (%)	Total consumption (Wh)
vgg-D	CIFAR-10	no	15,239,872	1:40:18	93.55	785
		yes (95%)	761,994	1:39:03	93.13	771
LeNet-5-Caffe	MNIST	no	430,500	30:18	99.42	145.5
		yes (98%)	8,610	28:26	99.15	145.28

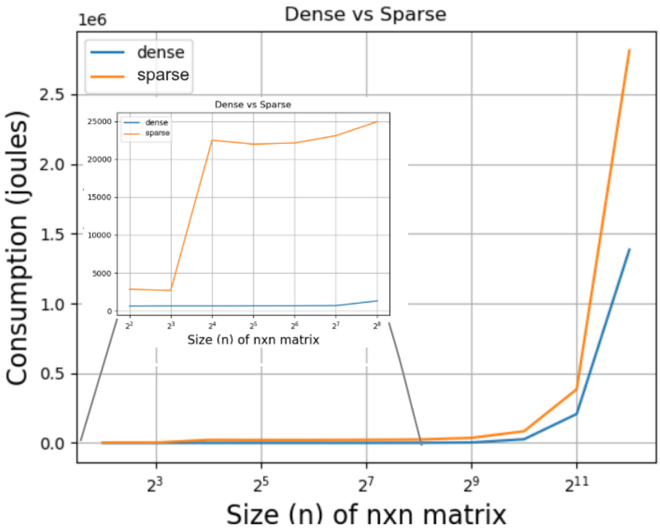
No gain since units are zeroing.

Pytorch Sparse with $1/n$ sparsity index

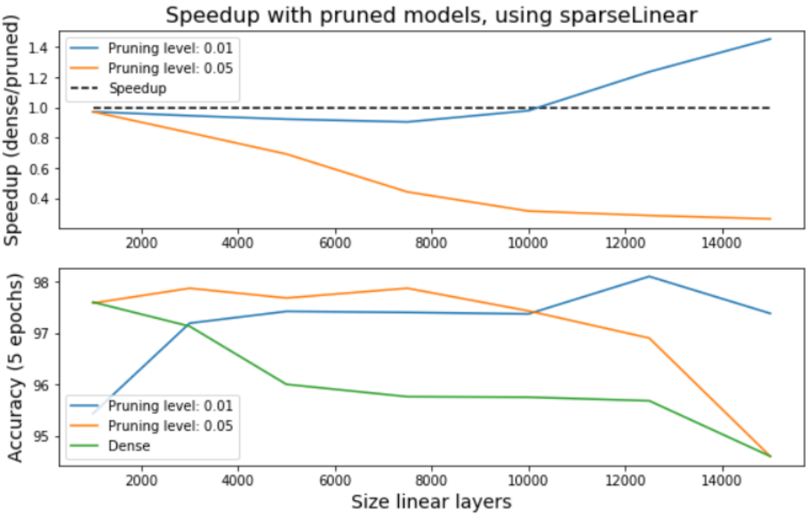
We test PyTorch Sparse library for sparse matrix multiplication.



Pytorch Sparse with 1% of sparsity

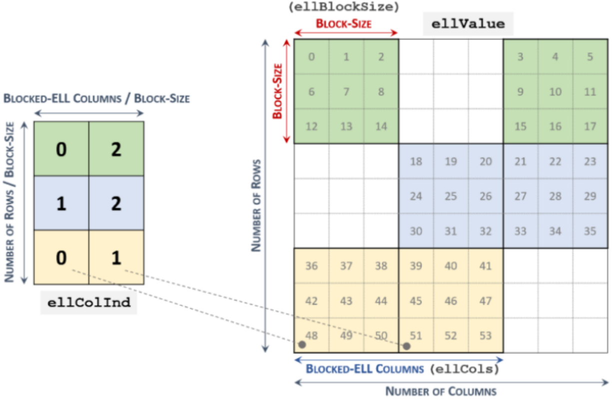


SNIP with PyTorch.Sparse



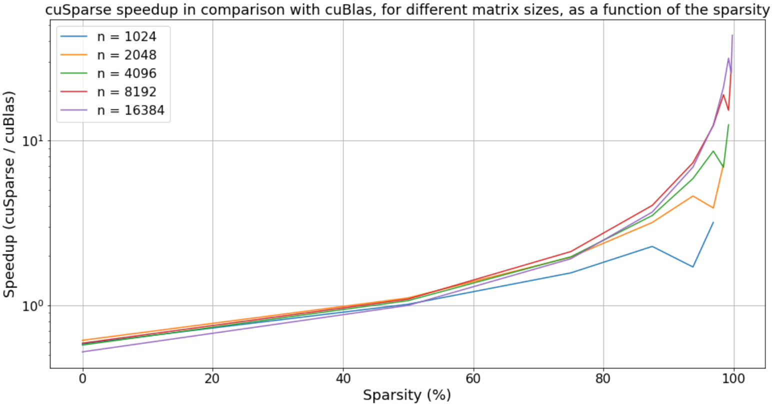
cuSparse

The cuSparse 11.4.0 release provides "a new high-performance block sparse matrix multiplication routine" for newer GPUs, with the help of the **Blocked-ELL format**.



read the cuSPARSE Library doc from Nvidia.

Comparison between cuSparse SpMM and cuBlas hGeMM



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   - Pruning
   - **Early Exits**
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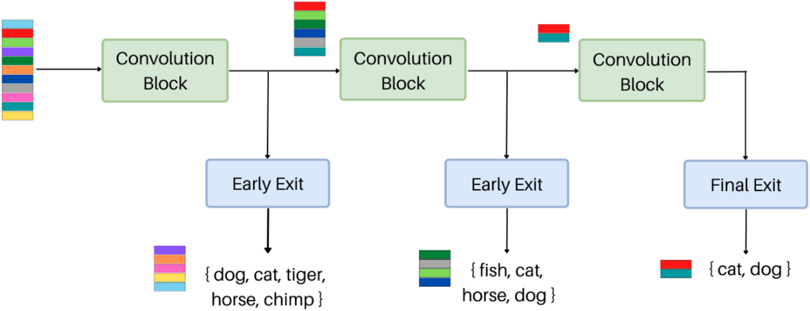
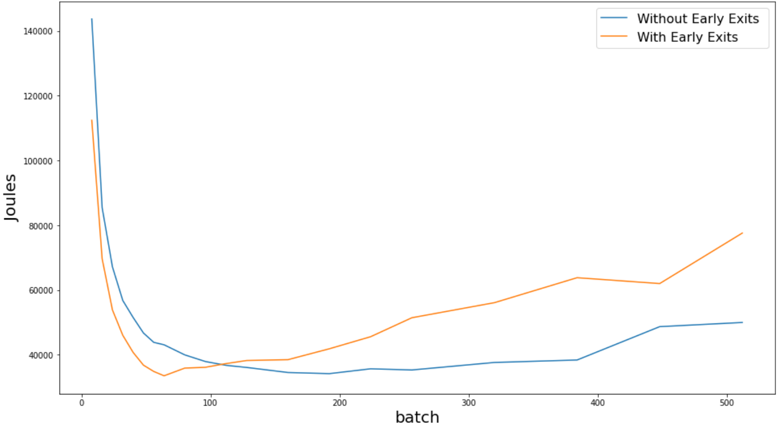
Early Exits - motivation

Figure 6: Easy and hard image from [Huang et al., 2017], Copyright Pixel Addict and Doyle

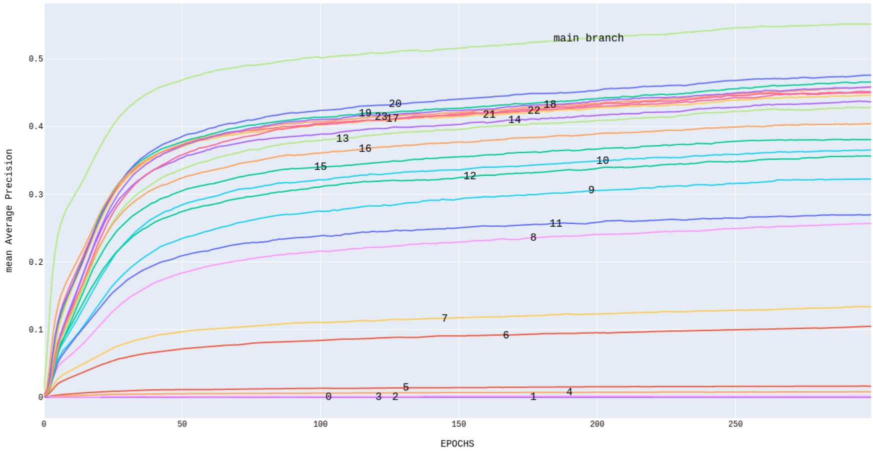
Early Exits - principle



Early Exists - Measure



Early Exists - Yolo v5



Tricks and limits - Conclusion

- BNN: real gain with Larq (see details here)
- Pruning: real gain with block-sparsity (see details here)
- Early Exits: some gain observed here, nice for model parallelism (work in progress).

Tricks and limits - Conclusion

- Difficult to observe real gain,
- Hardware dependent, model parallelism,
- SGD dependent.

Deep Learning is an optimization problem

- Optimization problem to deal with:

$$\min_{W=(W_1,\ldots,W_L)\in\mathbb{R}^p} \sum_{i=1}^{n} \ell(g_W(X_i), Y_i),$$

where the number of parameters p is huge and n is big.

- Solved by Stochastic Gradient descent:

$$\boxed{W^{(t+1)} = W^{(t)} - \alpha \nabla_W \left(\sum_{i=1}^{n} \ell(g_W(X_i), Y_i) \right) [W^{(t)}]}$$

SGD - Origin

A convex function is dually defined as:

$$f(y) \geq f(x) + \nabla f(x) \cdot (y - x), \forall x, y.$$

For $y = \arg\min f(x)$, we have:

$$\boxed{-\nabla f(x) \cdot (y - x) \geq 0}.$$

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WARNING : No constraint about energy consumption

Gradient to Mirror descent

Gradient descent can be written as:

$$W^{(t+1)} := \arg\min_{W \in \mathbb{R}^p} \left\{ \eta \nabla f(W^{(t)}) \cdot W + \frac{\|W - W^{(t)}\|^2}{2} \right\}.$$

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$\Rightarrow$ no localization and pure Euclidean setting

Gradient to Mirror descent

Mirror descent solves:

$$W^{(t+1)} := \arg\min_{W} \left\{ \eta \nabla f(W^{(t)}) \cdot W + \mathcal{B}_{\Phi}(W, W^{(t)}) \right\},$$

where $\mathcal{B}_{\Phi}(W, W^{(t)}) = \Phi(W) - \Phi(W^{(t)}) - \nabla\Phi(W^{(t)}) \cdot (W - W^{(t)})$ is a Bregman divergence.

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Sparsity induced NNs

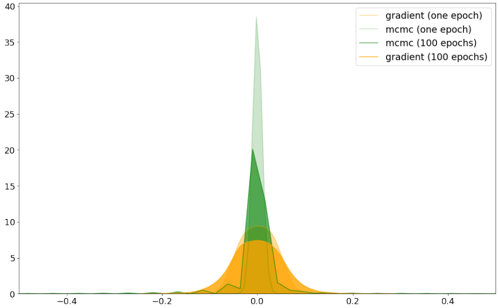
We are looking for a distribution ρ solution of:

$$\min_{\rho} \sum_{i=1}^{n} \mathbb{E}_{W\sim\rho} \ell(g_W(X_i), Y_i).$$

- For an entropy potential $\Phi(\rho) = \int \rho \log \rho$, we have $\mathcal{B}_\Phi(\rho, \pi) = \mathcal{K}(\rho, \pi)$,
- By chosen $\rho^{(n)}$ a sparsity prior, we get the following risk bound:

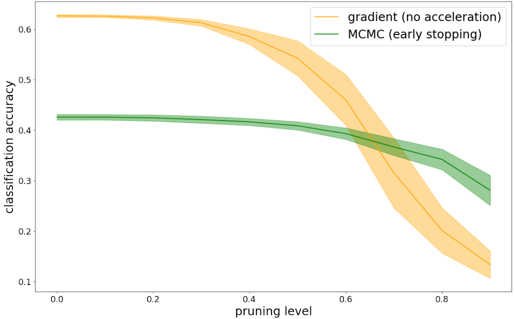
$$\sum_{i=1}^{n} \mathbb{E}_{W\sim\rho^{(n)}} \ell(g_W(X_i), Y_i) \leq \inf_{W\in\mathbb{R}^p} \left\{ \sum_{i=1}^{n} \ell(g_W(X_i), Y_i) + \alpha \|W\|_0 \right\}.$$

Resistence to pruning on CIFAR-10



- CNN with 60,000 params,
- SGD with batch size 256 and no acceleration,
- MCMC with 200 iterations by epoch.

Resistence to pruning on CIFAR-10



- CNN with 60,000 params,
- SGD with batch size 256 and no acceleration,
- MCMC with 200 iterations by epoch.

Greedy (RJ)-MCMC algorithm

Initialization : $\mathbf{w}_1 \sim \pi$. Parameter $\lambda > 0$.

For $m = 1, \dots M$ **do**

For $k = 1, \dots, N$ **do**

- Pick a layer $\ell \in \{1, \dots, L\}$ at random,
- Propose $\tilde{\mathbf{w}} \sim p(\cdot|\mathbf{w}_k)$,
- Accept $\mathbf{w}_{k+1} = \tilde{w}$ with proba:

$$\rho = \frac{\exp\{-\lambda \sum_{t \in \mathcal{I}_m} \ell(y_t, g_{\tilde{\mathbf{w}}}(x_t))\}}{\exp\{-\lambda \sum_{t \in \mathcal{I}_m} \ell(y_t, g_{\mathbf{w}_k}(x_t))\}} \frac{\pi(\tilde{\mathbf{w}})}{\pi(\mathbf{w}_k)}.$$

More maths - conclusion

With another mathematical framework, we get a simple Accept/Reject optimizer with several nice conclusion:

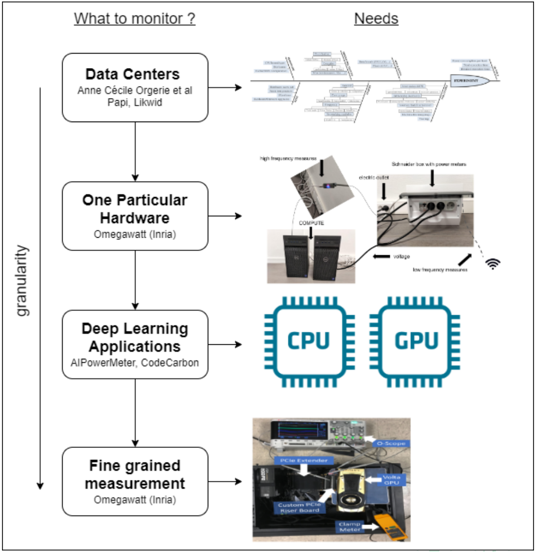
- (block)-sparsity induced NNs is easy,
- hybrid optimization is possible,
- model parallelism is easier,
- fast training $\Leftrightarrow$ fast inference.

Energy

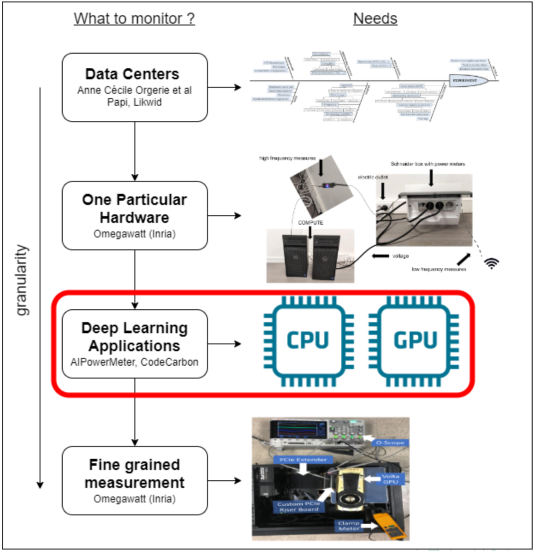
"You can't improve what you don't measure"

- What is energy ? Quantitative property that is transferred to to a physical system (through work, heat or light).
- Measured in Joules: $1J \rightarrow$ The energy dissipated as heat when an electric current of one ampere passes through a resistance of one ohm for one second.
- What is power ? $\rightarrow$ "The amount of energy transferred or converted per unit time" $\rightarrow$ J/s = W
- kWh ? $\rightarrow$ One kW sustained for one hour $\rightarrow$ $1kWh = 3.6MJ$

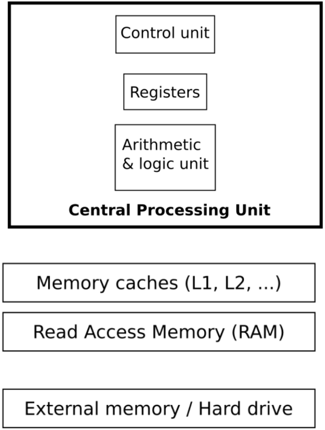
Energy consumption monitoring in IT



Energy consumption monitoring in IT

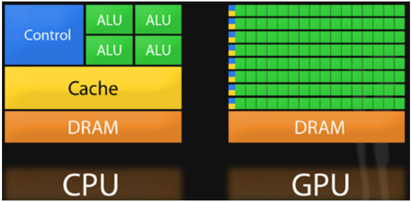


CPU



- Instructions set : boolean, floating operations
- Registers : fast memory used by the ALU (10-100 registers with 8-64 bits)
- Memory: Closer to the cpu $\rightarrow$ smaller and faster
- Moving data up and down the memory hierarchy costs time and power $\rightarrow$ optimizations

GPU



- GPU : Consumes more than the whole computer !
- Thousands of cores to enable parallelism
- Higher latency, Higher memory throughput

More power hungry and requires a CPU $\rightarrow$ BUT Energy efficient since the computations is faster

Monitoring the energy consumption of a Deep Learning algorithm

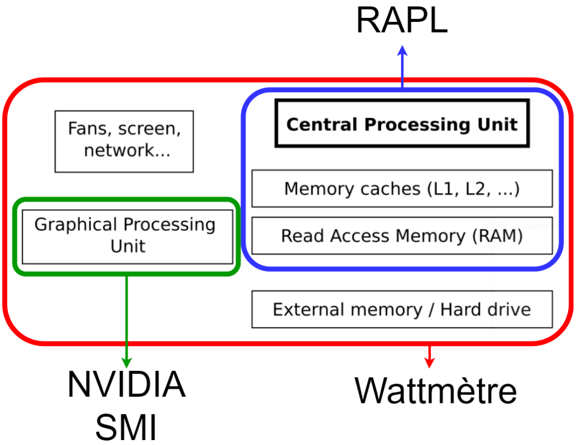


Figure 7: Different manners to monitor each components

RAPL for CPU energy consumption monitoring

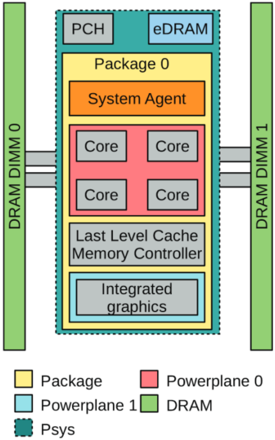


Figure 8: K. N. Khan et al. 2018

- Running Average Power Limit (Sandy bridge architecture in 2011)
- Reports the accumulated energy consumption recording at 1000Hz
- Monitor the energy consumption of different parts: CPU, RAM, System on Chip energy consumption, Processor graphics on the socket.
- Command:

```
sudo chmod -R 755 /sys/class/power
```

NVIDIA-SMI to monitor GPU consumption

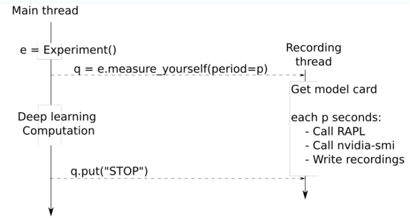
```
| NVIDIA-SMI 410.79       Driver Version: 410.79       CUDA Version: 10.0     |
|-------------------------------+----------------------+----------------------+
| GPU  Name        Persistence-M| Bus-Id        Disp.A | Volatile Uncorr. ECC |
| Fan  Temp  Perf  Pwr:Usage/Cap|         Memory-Usage | GPU-Util  Compute M. |
|===============================+======================+======================|
|   0  TITAN Xp            Off  | 00000000:01:00.0 Off |                  N/A |
|ERR!  54C    P2   ERR! / 250W |   1861MiB / 12194MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
|   1  TITAN Xp            Off  | 00000000:02:00.0 Off |                  N/A |
| 50%  69C    P2    74W / 250W |  11097MiB / 12196MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+
|   2  TITAN Xp            Off  | 00000000:05:00.0 Off |                  N/A |
| 62%  81C    P2    86W / 250W |  11299MiB / 12196MiB |      0%      Default |
+-------------------------------+----------------------+----------------------+

+-----------------------------------------------------------------------------+
| Processes:                                                       GPU Memory |
|  GPU       PID   Type   Process name                             Usage      |
|=============================================================================|
|    0      1535      C   -                                            617MiB |
|    0     17875      C   -                                            617MiB |
|    0     23889      C   -                                            617MiB |
```

Figure 9: K. N. Khan et al. 2018

- NVIDIA System Management Interface (CUDA)
- +/- 5% accuracy of current power draw. Memory usage per gpu and per process
- Command: $\boxed{\text{nvidia-smi -q -x}}$

In practice: AI PowerMeter

- Developed by GreenAI UPPA, to measure the efficiency of your deep learning recording CPU and GPU
- By and for data scientists
- It uses Nvidia-smi and RAPL as well as psUtil (to compute by program)



https://github.com/GreenAI-Uppa/AIPowerMeter

AIPowerMeter vs WattMetre

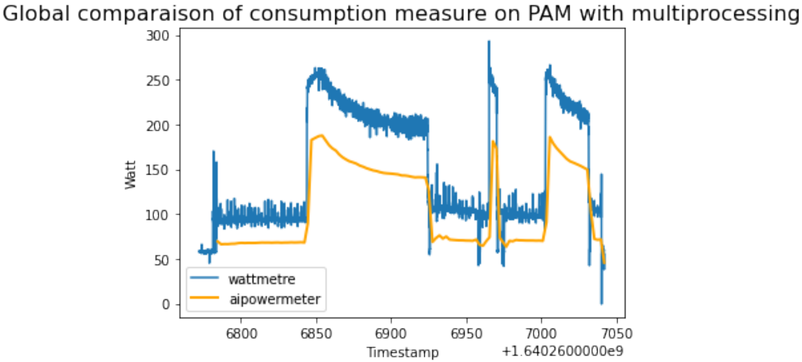
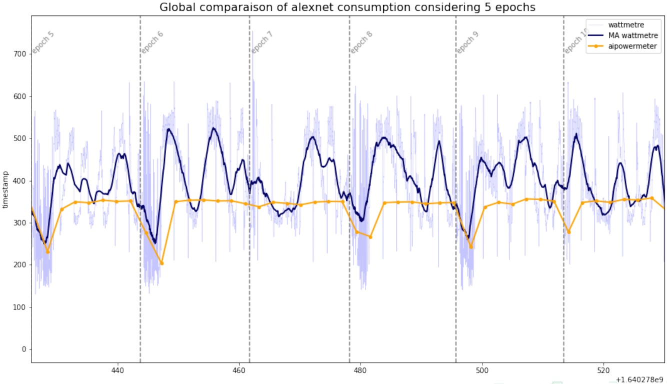


Figure 10: Wattmeter is more precise, but AiPowermeter permits to monitor the evolution of the power supply.

Application

- Example of the training of AlexNet for image classification.
- Energy consumed during training: $672kJ = 0.187kWh$ $(\simeq 11gCO2eq)$



Monitor smaller, optimized, hardwares

- In the lab, we are interested in embedded systems: Rasberrypi, Jetson Cards or micro-controllers
- Constraints exist to monitor (GPU, RAPL not available for ARM processors, Nvidia-SMI not working on Jetson...)

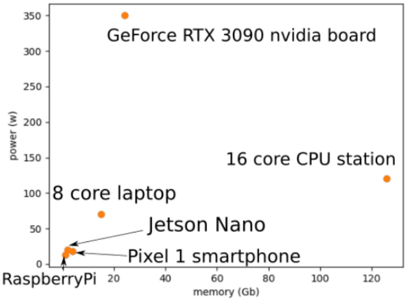


Figure 12: Find the better compromise between power and memory !

ML field

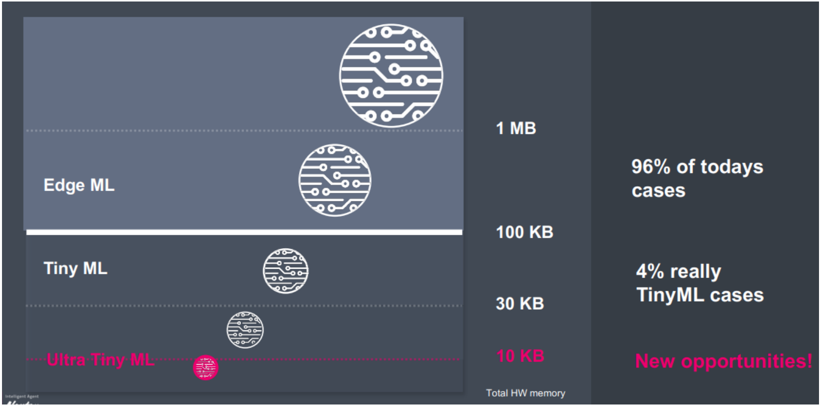


Figure 13: Benchmark of the tiny ML field [NEUTON.AI, 2022]

What is Tiny ML?

- What is tinyML ?
  TinyML: When a neural network model can be run at an energy cost of below 1 mW

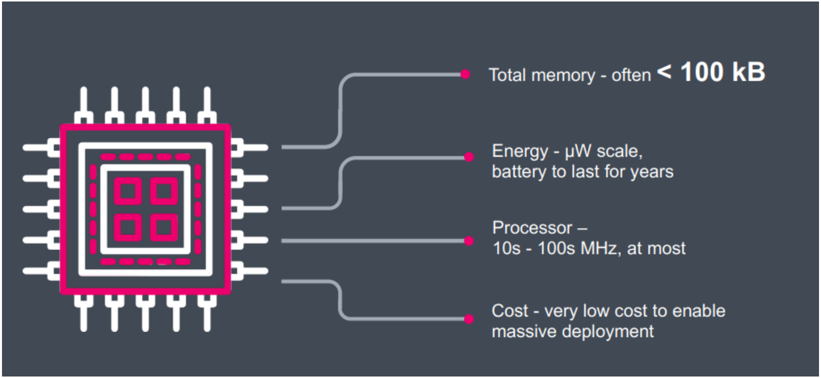


Figure 14: Definition of TinyML by Pete Warden[NEUTON.AI, 2022]

Tiny ML ?

- This presentation is highly inspired by the book *TinyML: Machine Learning with TensorFlow Lite on Arduino and Ultra-Low-Power Microcontrollers by Warden and Situnayake [Pete Warden, 2019].*

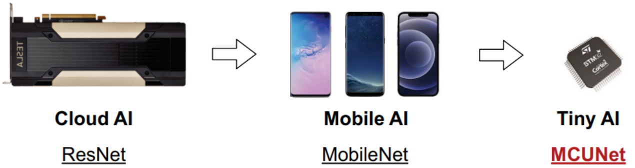


Figure 15: Different models for different capacities [Han, 2021]

It is also inspired by many presentations yielded at the TinyML Summit every year (March 2022)

Why ?

- Function – wanting a smart device to act quickly and locally (independent of the Internet).
- Cost – accomplishing this with simple, lower cost hardware.
- Privacy – not wanting to share all sensor data externally.
- Efficiency – smaller device form-factor, energy-harvesting or longer battery life.

Limitations in terms of hardware

- Decrease in energy consumption → limitations in sRAM memory, flash memory, microprocessor capacities

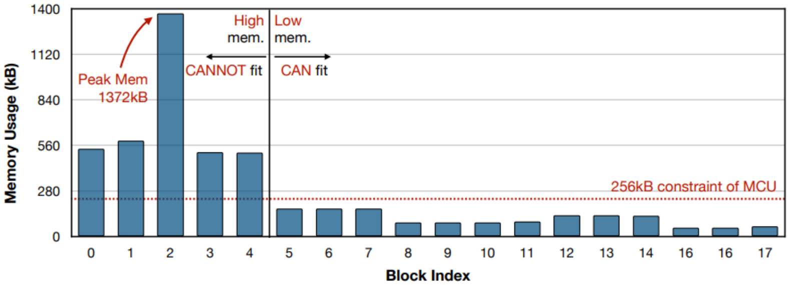


Figure 16: Per-block memory usage of MobileNetV2 [Ji Lin, 2021]

→ What is important is the **Peak memory** !

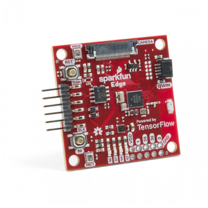
Micro-controllers

- A typical microcontroller system consists of a processor core, an on-chip SRAM block and an on-chip embedded flash
- Constraints
  - Peak memory usage of the model computations $<$ memory usage.
  - Number of parameters in the model $<$ flash memory storage
  - Model size and the peak memory $<$ 250 KB each;
  - CNN computation $<$ 60 million multiply-adds per inference at high accuracy

Comparison between hardwares

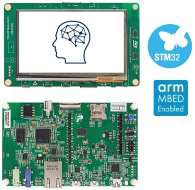
Micro-controller	Price	Memory	Specificities
Arduino Nano 33 BLE Sense	29,70€	256 kB	
SparkFun Edge	$16.50	384kB	
ST Microelectronics STM32F746G Discovery kit	$54.0	340 kB	Screen / included camera

Table 1: Main micro-controllers on the market for tinyML



(a) SparkFun Edge

(b) Arduino Nano



(c) ST

Arduino Nano 33 BLE Sense: Components

Sensor	Power
IMU	$1mW$
Weather (humidity, and temperature)	$5\mu W$
barometric sensor	10 μW
microphone	$300\mu W$
Gesture, proximity, light	?
Bluetooth® Low Energy connectivity	40 mW

Table 2: Components integrated

Possibility to connect many sensors such as cameras for recognition (1 mW at 30 FPS for 320 $\times$ 320-pixel monochrome image sensor).

Applications of tinyML

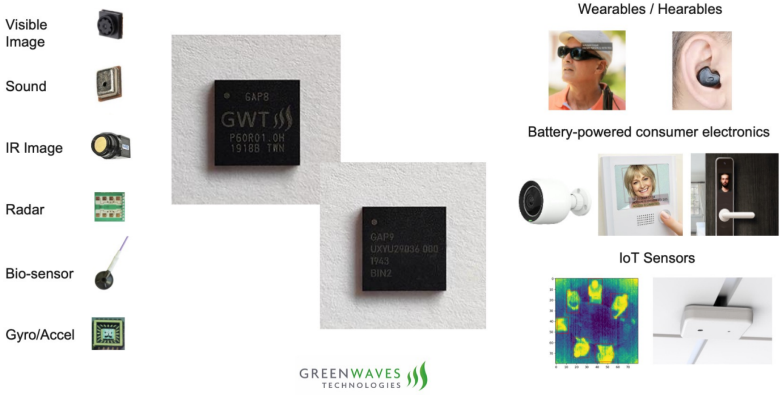


Figure 18: Different possible applications of tinyML [Fournarakis, 2021b]

More precision: Patch-Based Learning

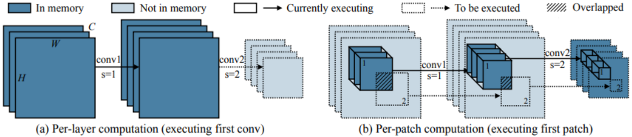


Figure 19: Apply filters on patch only: Patch-Based Learning [Ji Lin, 2021]

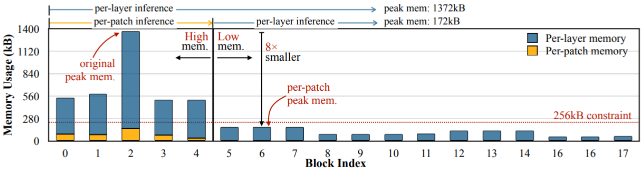


Figure 20: Reduce the peak memory ! Tradeoff between overall computation time and performances

Conclusion

- Using actual pipelines needs tricks and engineering,
- Using more maths can lead to new more sustainable optimizers,
- Model parallelism and hardware is very important -> Jordy et Matthieu

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