Measuring the power draw of computers

What you cannot measure, you cannot improve

Mercredi 19 Mai

Power draw of computers

First message

- Most of IT carbon footprint comes from manufacturing
  building computers, smartphone, internet cables, telecom sattelite,...

Still it's worth to monitor our usage,

- Large waste of the computing power in development data centers (K. Khan et al. 2019)
- Our models are over calibrated(Parcollet and Ravanelli 2021)
- We can do just as good with less

This presentation aims at persuading you to measure the energy used by your algorithm

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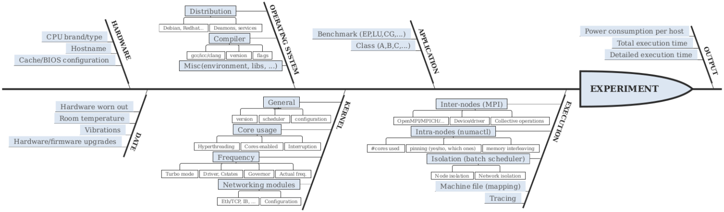
A not so trivial topic

- Difficulty to isolate the energy hungry elements
- Dependent on the built in sensor and constructor support.
- Low level (close to hardware) programming
- Energy depends on the lot of parameters



Picture from Orgerie 2020

What we learn in highschool

- **Joule**: energy transferred to an object when a force of one newton acts on that object in the direction of the force's motion through a distance of one metre (1 newton-metre or Nm)
  - The energy required to lift a medium-sized tomato up 1 metre
- **Watt**: 1 joule per seconds
- **kWh**: ????? Joules

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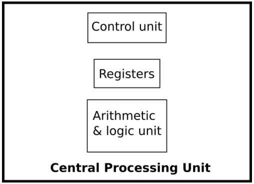
How a computer uses energy?

What we learn at the university

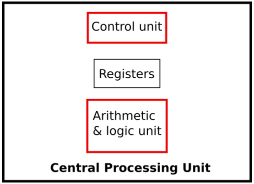
Let's start with the cpu



- From 100Khz in 1971 to some Ghz today
- Composed of millions of transistors (Moore law)
- Cristal of qwartz giving the frequency of the cpu
- Optimization of the frequency to save power (turboboost)

What we learn at the university

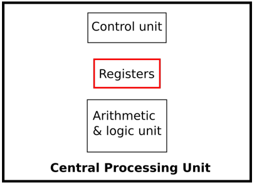
Let's start with the cpu



One cpu Core

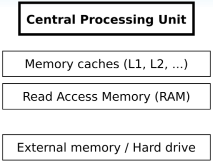
- Instructions set : boolean, floating operations
  - RISC (AMD), CISC (Intel), dedicated FPGA instructions
    `/proc/cpuinfo`
- Conditions the power draw
- Low level programmation with binary networks

Let's start with the cpu



- Registers : fast memory used by the ALU
- 10-100 registers with 8-64 bits

and continue with the memory

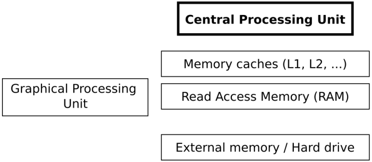


- Memory hierarchy
  - Closer to the cpu → smaller and faster

```
$ lscpu
L1d cache:                        384 KiB
L1i cache:                        256 KiB
L2 cache:                         4 MiB
L3 cache:                         16 MiB
```

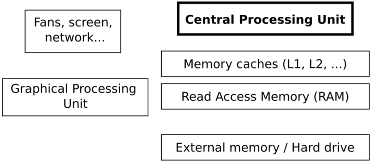
- Moving data up and down the memory hierarchy costs time and power
- Taken into account in optimization code to limit these moves.
  - Eg: Row major or column major storage in matrix multiplication

GPU : major actor in the consumption



- Consumes more than the whole computer (Bridges, Imam, and Mintz 2016)

Other components



- Consumes more than the whole computer (Bridges, Imam, and Mintz 2016)
- Overall a full a diagnostic might be complex
  - lack of available sensors

GPU versus CPU

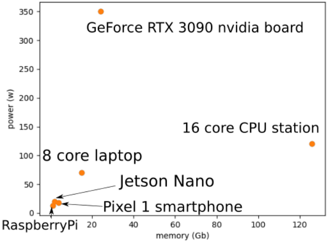
- Invented by nvidia in 1999
- Thousands of cores to enable parallelism
- Lower amount of RAM memory available
- Higher latency : GPU clock speed $<$ CPU clock speed
- Higher memory throughput : GPU operates on larger chunks of data
  - GPU can fetch data from its RAM more quickly
  - CPU bandwidth $<$ GPU bandwidth
- Smaller set of instructions dedicated to graphics and matrix calculus
- More power hungry and requires a CPU

Energy efficient since the computations is faster.

Other hardwares

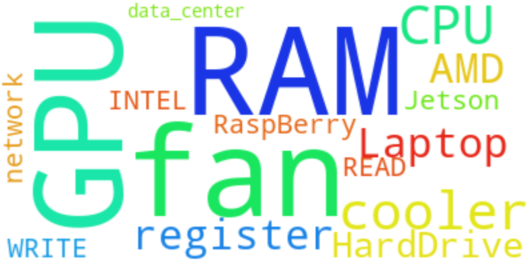
- AMD CPU: RISC instruction set lower energy than Intel processors
- Programmable circuits with custom instruction set
  - Field-programmable gate array
  - Application-specific integrated circuit (ASIC):
    Implements the Tensor Processing Unit.
- Small devices
  - Rasberrypi
  - Jetson Cards
- Neuromorphic sensors (Guillaume Bellec presentation this morning)

Some perspective numbers



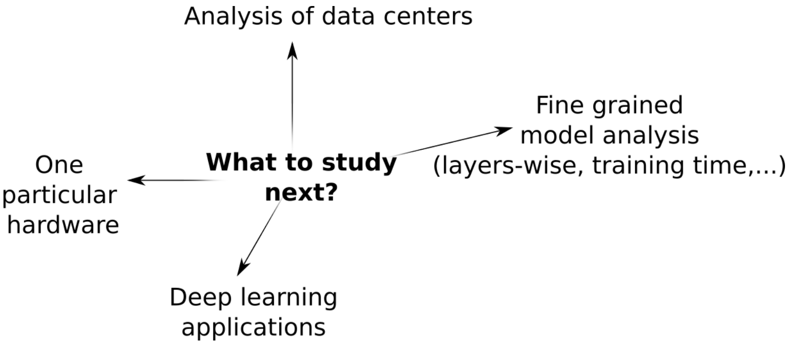
Power usage versus memory capacity

- How to rank machines by efficiency ?
- Compromise between, power, memory, computing capacity



How to measure all of it?

Different angles to tackle



Related work on consumption measurements

- Opensource libraries for machine learning carbon footprint (Henderson et al. 2020; Anthony, Kanding, and Selvan 2020)
  - based on RAPL and nvidia-smi
- Fine grained studies on a specific Jetson hardware (Rodrigues, Riley, and Luján 2018; Holly, Wendt, and Lechner 2020; Arafa et al. 2020)
- Generic libraries from the data center community : Papi, Likwid
- Machine learning based prediction models (Cai et al. 2017, Jia et al. 2015)
- French Startup : https://github.com/hubblo-org

Hard to get recover exactly what you measure on your power meter.
Developping from scratch requires complex low level programming skills

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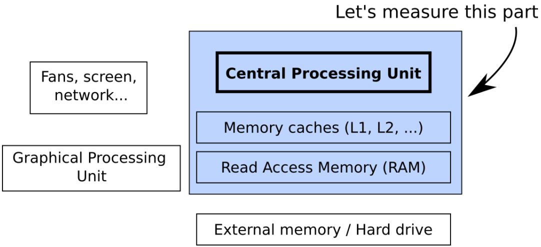
RAPL to measure Intel CPUs



RAPL to measure Intel CPUs

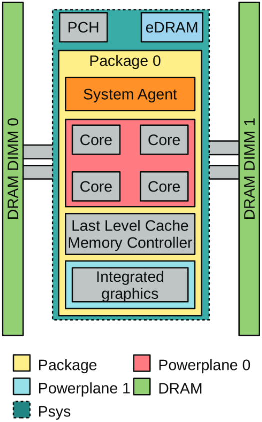
Running Average Power Limit

- Present since the Sandy bridge architecture in 2011
- Now supported by integrated voltage regulators in addition to power models
- Reports the accumulated energy consumption
- Recording at 1000Hz
- Requires administrator privilege

RAPL Organisation

Different counters for physically meaningfull domains:

- Power Plane 0 : CPU
- Power Plane 1 : Processor graphics on the socket.
- DRAM : energy consumption of the RAM
- Psys : System on Chip energy consumption



K. N. Khan et al. 2018

Access to RAPL measurements

- Model specific registers

  `/dev/cpu/core_id/msr`

  - Read MSR register bit by bit (not trivial)
  - See intel documentation (not trivial)
  - And activate the kernel module

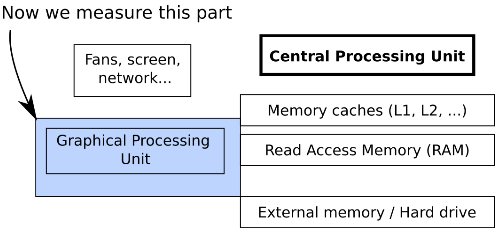
    ```
    sudo modprobe msr
    ```

- **Linux**: Exposition of a sysfs tree with powercap

  Accumulation of energy consumption in Joules

  ```
  sudo chmod -R 755 /sys/class/powercap/intel-rapl/
  ```

nvidia-smi to measure Nvidia GPUs



nvidia-smi

NVIDIA System Management Interface, based on top of the NVIDIA Management Library (NVML, cuda v4.1, 2011)

- Gpu global statisics and memory usage per process

  ```
  $ nvidia-smi -q -x
  ```

  - The power consumption is given for the entire board
  - +/- 5% accuracy of current power draw.
  - Memory usage per gpu and per process
  - Percentage of usage of each gpu

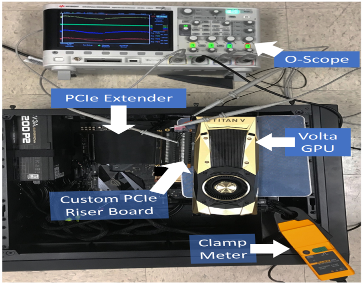
nvidia-smi

NVIDIA System Management Interface, based on top of the NVIDIA Management Library (NVML, cuda v4.1, 2011)

- Per process Average utilization values for streaming multiprocessors (SM)

```
$ nvidia-smi pmon # up  to  4  devices
# gpu        pid  type   sm   mem   enc   dec   command
# Idx          #   C/G    %     %     %     %   name
    0       1114     G    -     -     -     -   Xorg
    0       1289     G    -     -     -     -   gnome-shell
    0    1135553     C   76     0     -     -   python
```

Fine grained measurement



Arafa et al. 2020

- Fine grained measurement at instruction level
- Verification with powermeters.

Let's dive into practice!

Deep Learning Power Measure @UPPA

Clone AIPowerMeter from github!

We are developing (yet another) python module for :

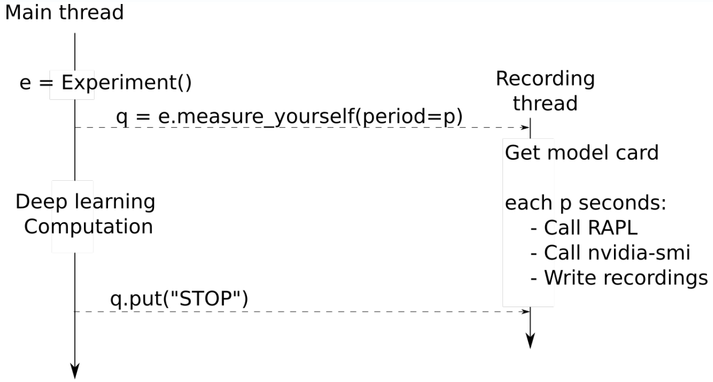
- Recording the power of a specific process
- Focus on accessibility and analysis for data scientist
- Model card, number of parameters and macs

```
process, queue = exp.measure_yourself(period=2)

 ###################
#  place here the code that you want to profile
################

q.put(experiment.STOP_MESSAGE)
```

Multi threading under the hood



- Energy recording only for the main thread
- Queue to communicate between the threads

Get power draw by process

- RAPL and nvidia-smi provides the global power consumption
- Using memory and processor usage from psutil to obtain the consumption by program
- However some of the components are shared from all programs.

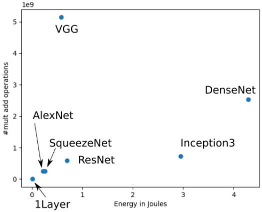
Divide in equal parts? ignore these parts?

Experiment

Let's test classics network on a random synthetic image

- Energy consumed by 200K forward passes
- input image is $(3 \times 128 \times 128)$
- AlexNet, VGG, Resnet, SqueezeNet, DenseNet, Inception
- 1 convolutional layer with a (3×3) kernel

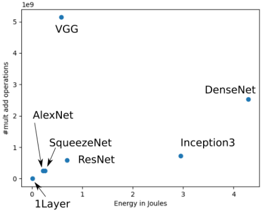
RAPL Organisation

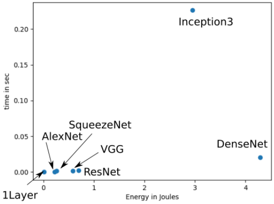


\# mult add *versus* power

- How good or bad are proxy measures ?

RAPL Organisation



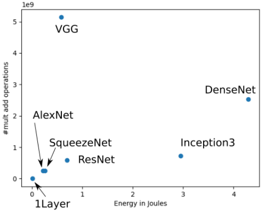


\# mult add *versus* power

- can you be slow and low power ?

time *versus* power

RAPL Organisation



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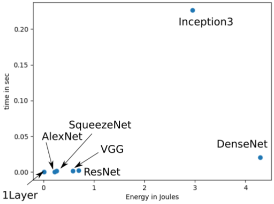

time *versus* power

- Two factors here : Duration and usage !

A lot to discover for deep learning!

Join the community

- SustaiNLP 2020: Workshop on Simple and Efficient Natural Language Processing
- Low-Power Computer Vision Challenge since 2015

Or just be better at optimizing (understanding) your program:

```
torch.backends.cudnn.benchmark = True
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References I

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