Embedded Software and Hardware for DL

IMT Atlantique
Bretagne-Pays de la Loire
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Course organisation

Sessions

1. Intro Deep Learning,
2. Data Augmentation and Self Supervised Learning,
3. Quantization,
4. Pruning,
5. Factorization,
6. Distillation,
7. Embedded Software and Hardware for DL,
8. Presentations for challenge.

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What are the potential targets ?

- CPU
- GPU
- ASICs
  - IPU (Graphcore)
  - TPU (Google)
  - Edge TPU (Google)
  - Eyeriss (MIT)
  - ...
- FPGA

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Questions

- What are the differences between them ?
- Which use case for each target ?

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- CPU: What are the elements of a CPU ?
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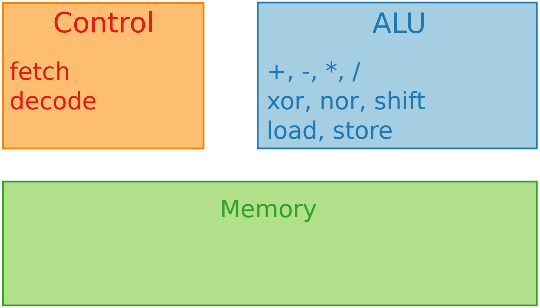
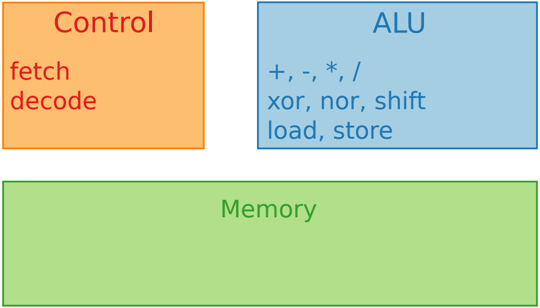
What are the elements of a CPU ?



- Control: Fetches and decodes instructions, controls the ALU,
- ALU: Arithmetical and Logical Unit, performs all computations, exchanges data between memory and register file,
- Memory: Stores data.

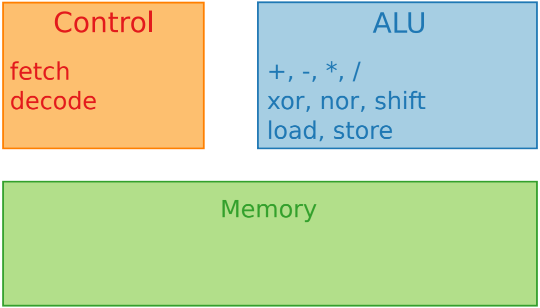
What are the elements of a CPU ?



There are many ways to increase the overall performance of a CPU architecture. The reader may refer to the following book for a broad study of the field.

[1] J. L. Hennessy and D. A. Patterson, *Computer Architecture, Sixth Edition: A Quantitative Approach*, 6th. San Francisco, CA, USA: Morgan Kaufmann Publishers Inc., 2017, ISBN: 0128119055.

What are the elements of a CPU ?



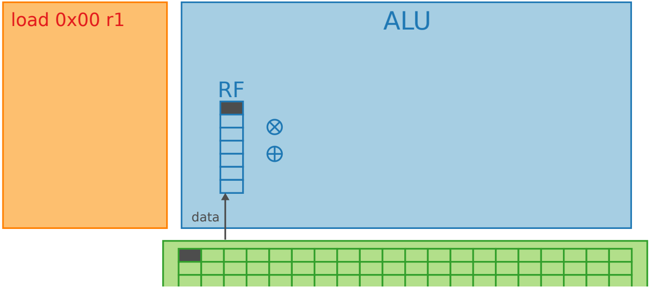
In this course, two key features will be described:

- Increasing the computational parallelism,
- Reducing data accesses time with close and fast memories.

Increasing Parallelism : SIMD

- SIMD: Single Instruction Multiple Data
- Hardware feature in ALU
- Available in Intel CPUs (SSE, AVX)
- Available in ARM CPUs (Neon)

Increasing Parallelism : SIMD



- "Normal" Single Instruction Single Data (SISD) example
- Load data from memory to register file
- Execute multiplication
- Execute addition

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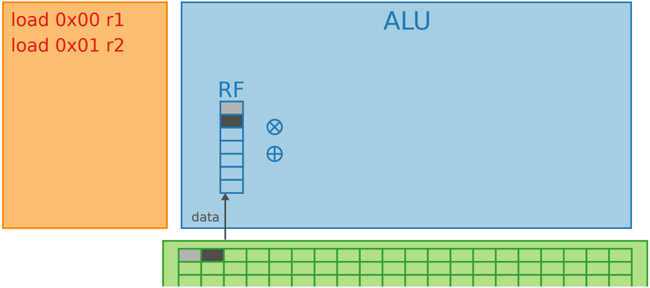

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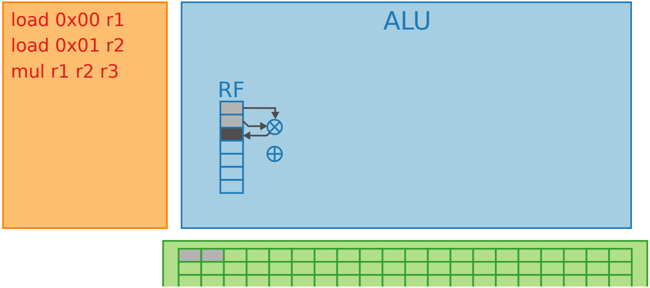

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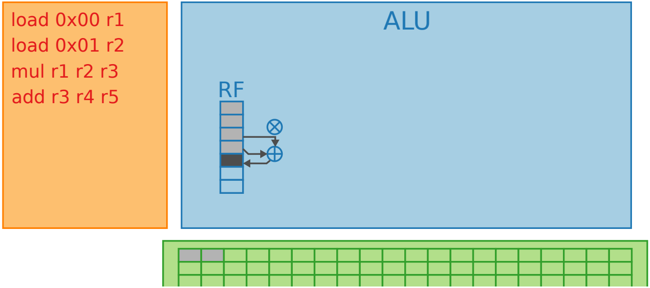

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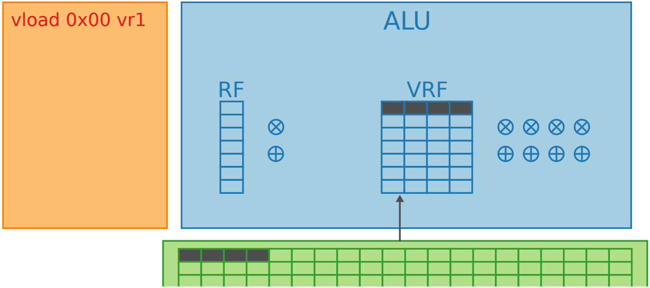

- Single Instruction Multiple Data
- Additional hardware
- Parallel load
- Parallel arithmetic
- Increase number of computations per instruction

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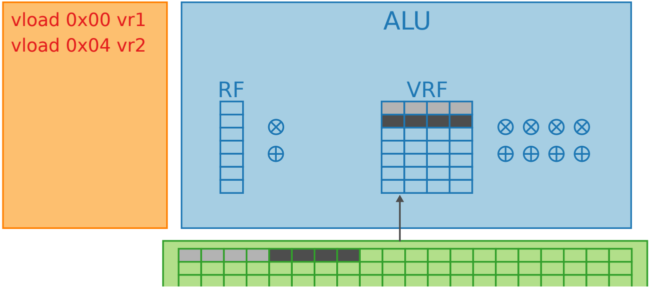

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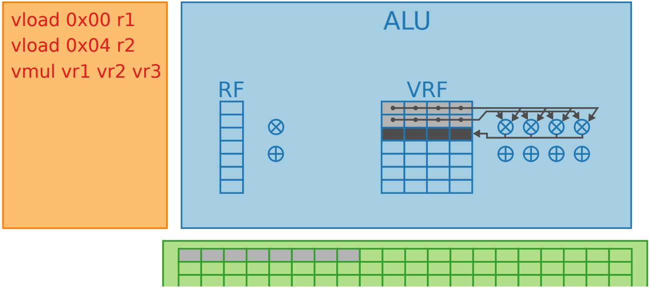

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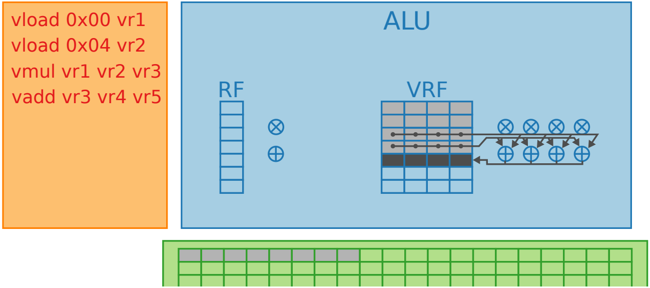

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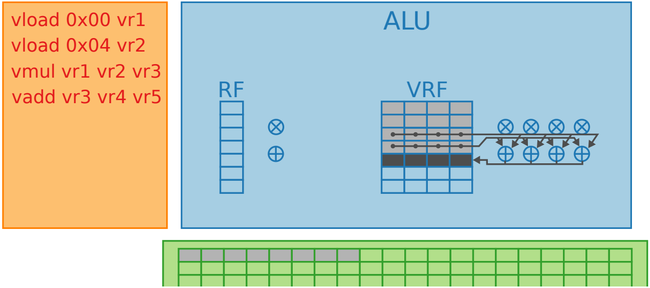
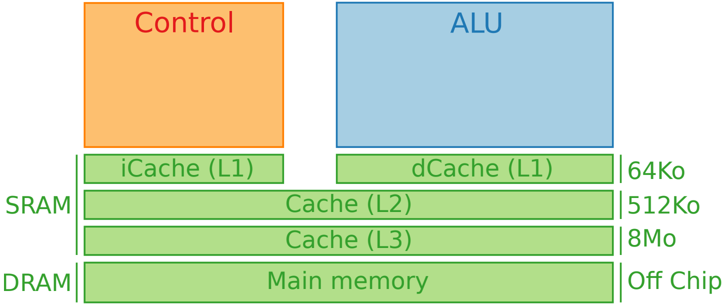


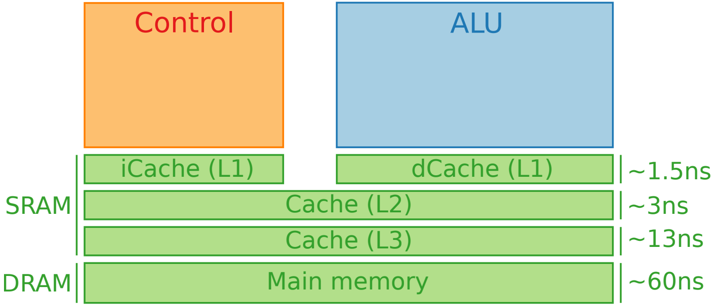
- Increased parallelism
- Multiple quantization formats handled (8-, 16-, 32-, 64-bit)
- The more quantized, the more parallel
- Need aligned data in memory

Cache hierarchy



- Hiérarchie de la cache
- SRAM vs DRAM
- Premier accès
- Cache Hit
- Cache Miss

Cache hierarchy



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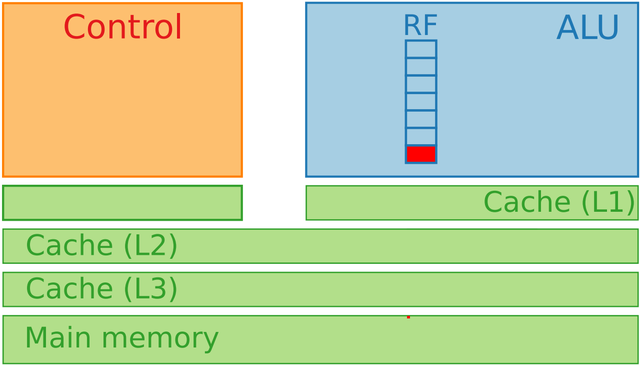

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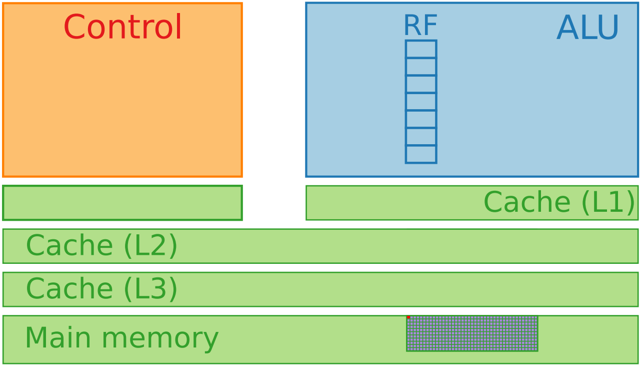

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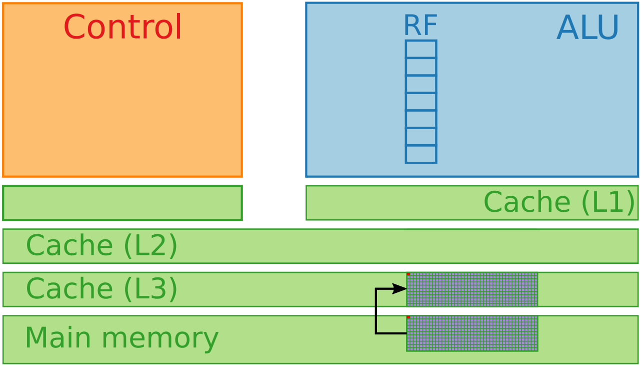

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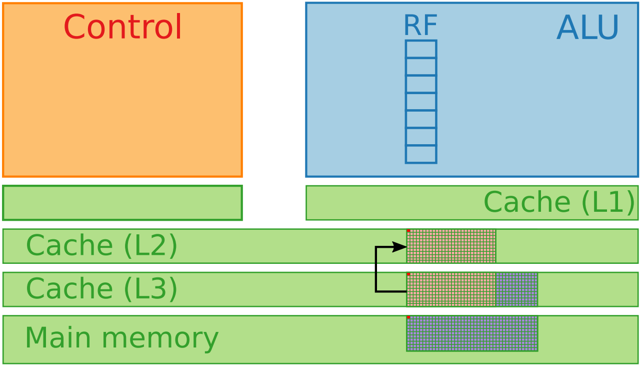

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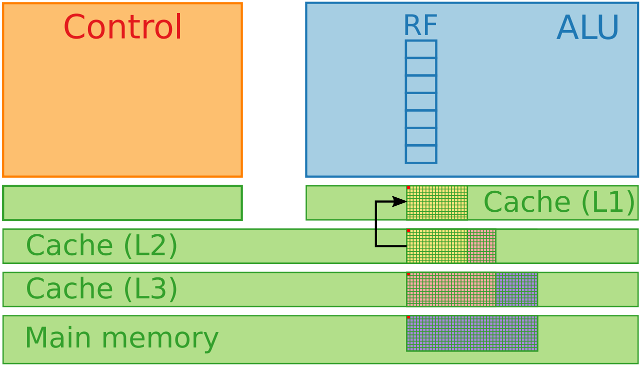

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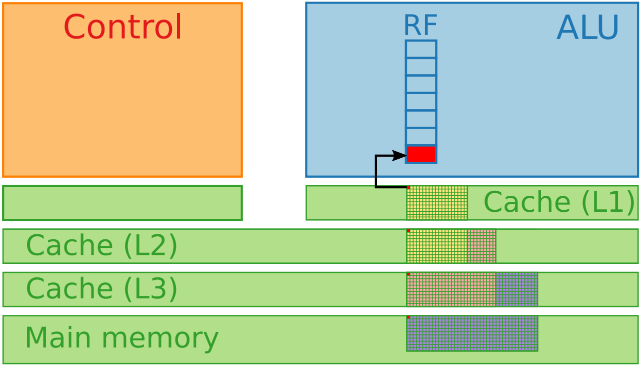

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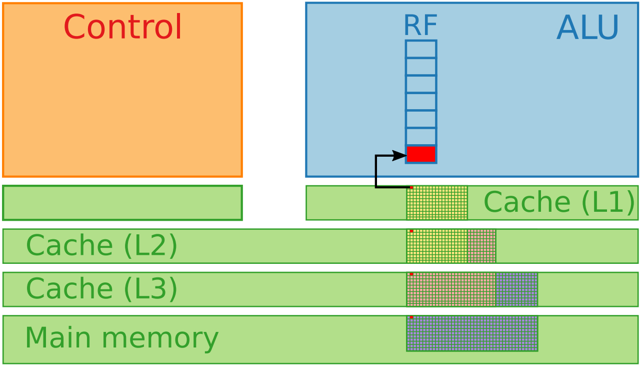

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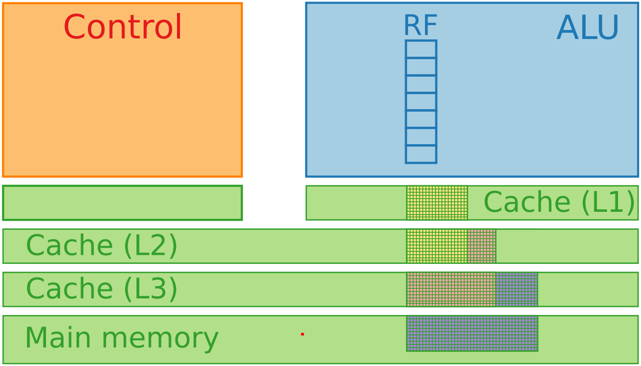

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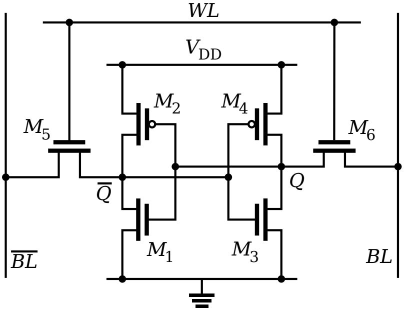
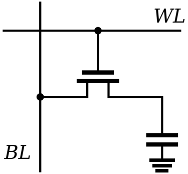


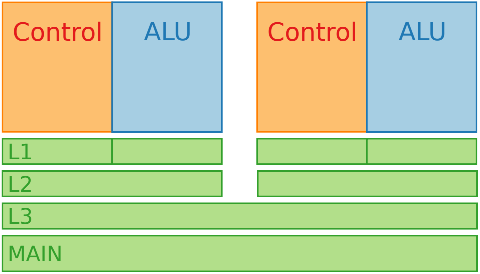
SRAM



DRAM

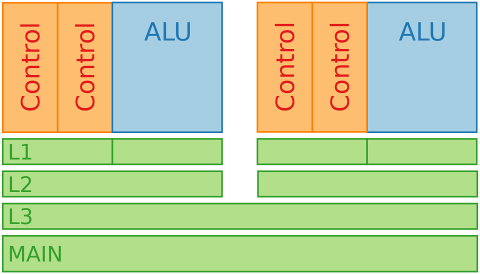
- SRAM 6T (typically) vs DRAM 1T
- SRAM is more expensive
- DRAM is denser
- DRAM needs refreshment
- SRAM is faster

Multicore



- Add CPU cores on the same chip
- Last Level Cache (LLC) is shared between cores
- Linear increasing of computing capacity

Simultaneous Multi Threading (SMT)



- Known as "Hyperthreading" which is Intel's own SMT implementation
- Multiple instruction threads (here 2) are processed on each core
- Sublinear increasing of computing capacity, resources are shared

GPU

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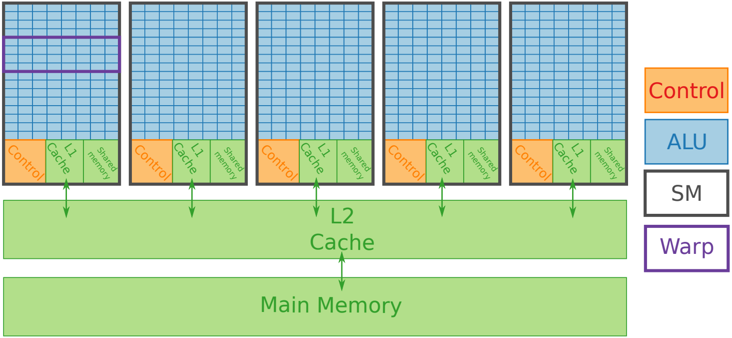

- GPUs have a huge computation power
- Simpler control
- Each core execute warps of 32 threads (Nvidia)
- Same instructions in each thread, but different execution contexts
- Yields higher throughput, but also higher latency

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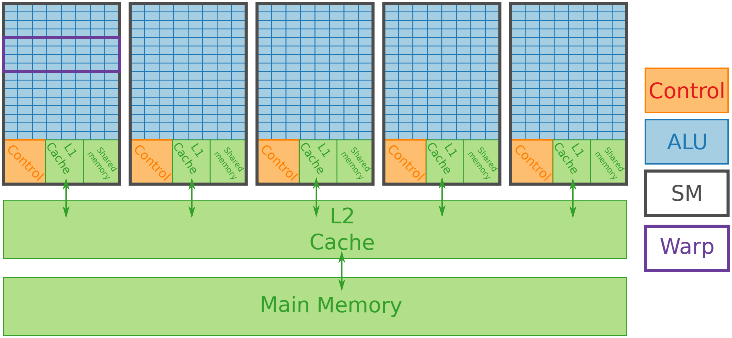

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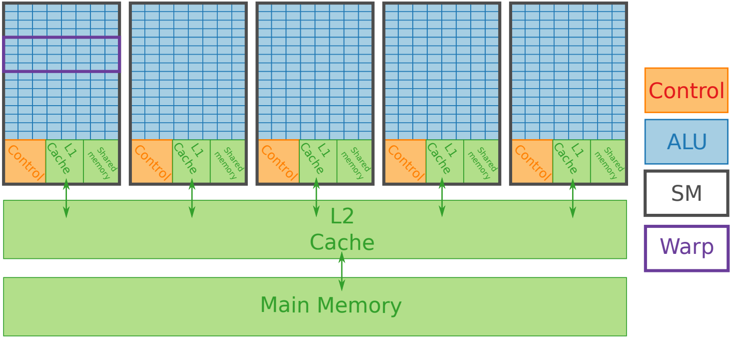

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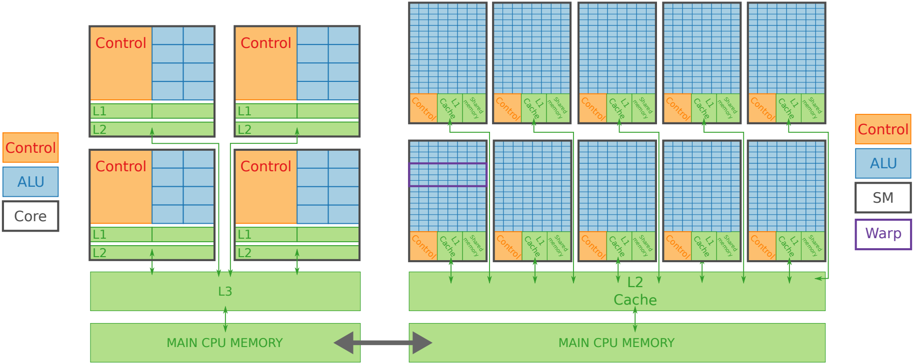
CPU vs GPU



- Sequential vs Parallel

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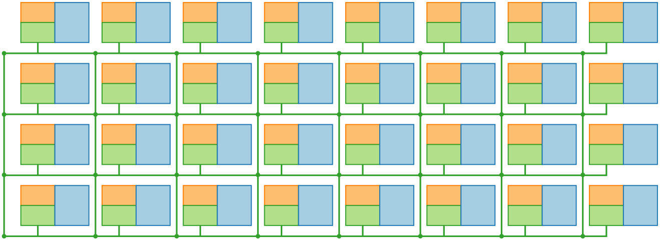
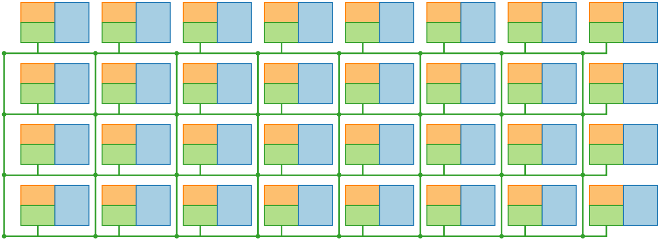
ASICs : Example of Graphcore's IPU



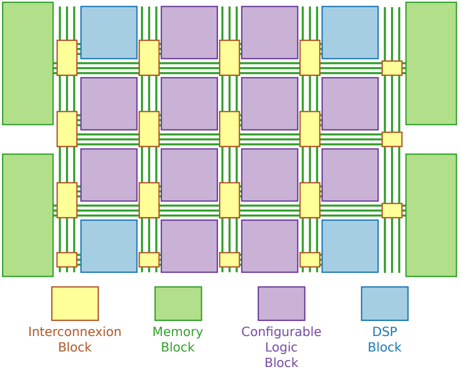
- Manycore approach :
- Each core handles 6 independent threads
- Fully distributed cache memory
- 256Ko / core

ASICs : Example of Graphcore's IPU



- Claims better efficiency ($/Gops, kWh/Gops)
- Claims faster inference
- Cautious: lack of independent benchmarks

FPGAs : (Re)Configurable Integrated Circuits



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- No "Non Recurring Engineering" compared to custom ASIC
- Prototyping
- Small markets

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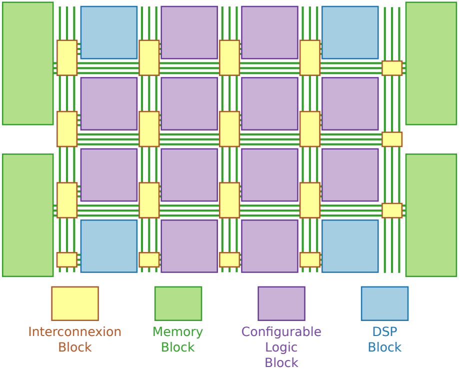

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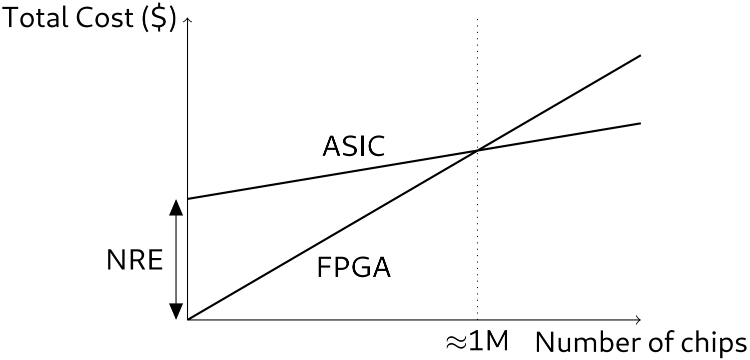

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Remote vs Local use cases

Use case

Remote

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Key features

- Throughput
- Cost ($/Gops)
- Scaling

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Use case

Local

Key features

- Availability
- Power consumption
- Cost ($/unit)
- Latency
- Data privacy

Remote vs Local use cases

Use case
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Use case
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Targets
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- Edge TPU
- Embedded GPU (Tegra)
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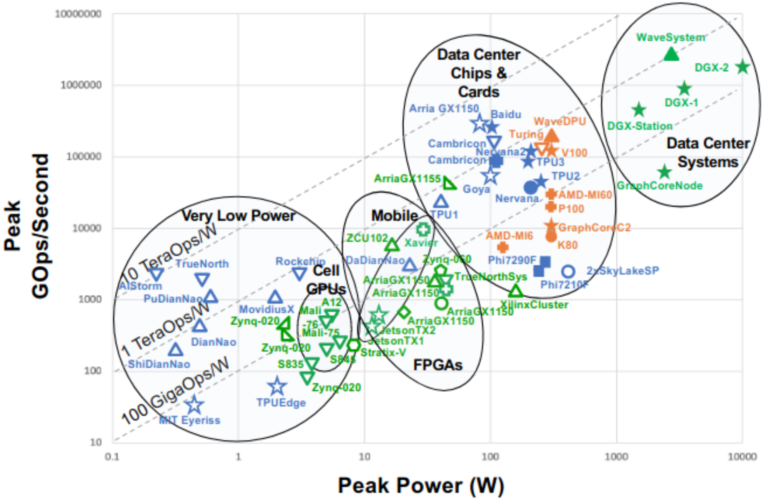

A. Reuther, P. Michaleas, M. Jones, V. Gadepally, S. Samsi and J. Kepner, "Survey and Benchmarking of Machine Learning Accelerators," 2019 IEEE High Performance Extreme Computing Conference (HPEC), 2019, pp. 1-9, doi: 10.1109/HPEC.2019.8916327.

And what about software ?

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- Broadly used
- Programmed and optimized to be used on CPU and GPU
- Not systematically ported on each target
- Supporting these frameworks becomes critical for chips makers

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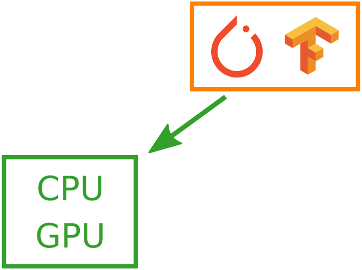

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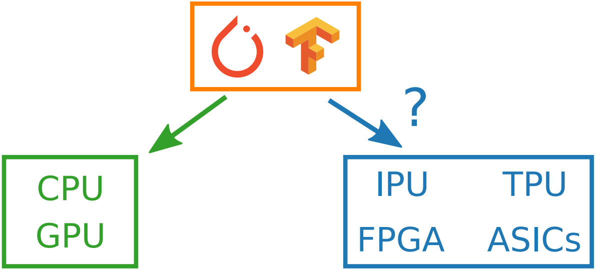

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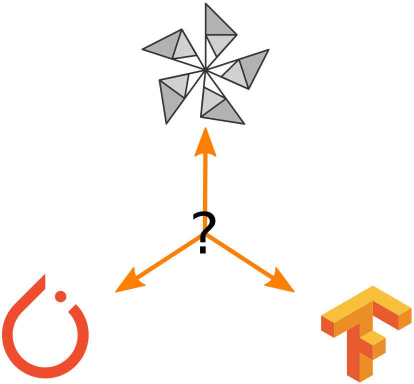

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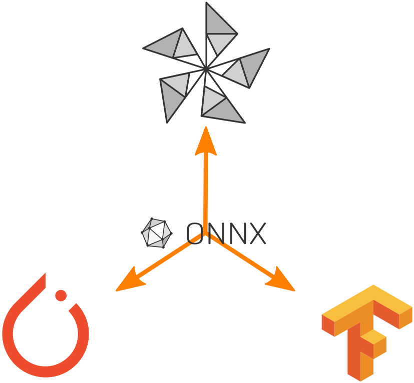
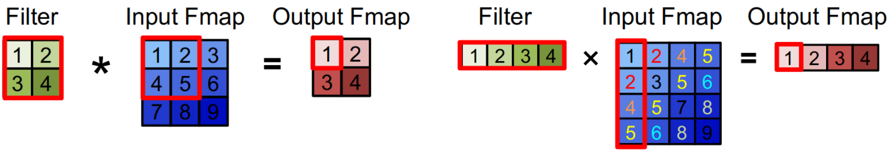


Software for CPU & GPU: matrix multiplication



Convolution

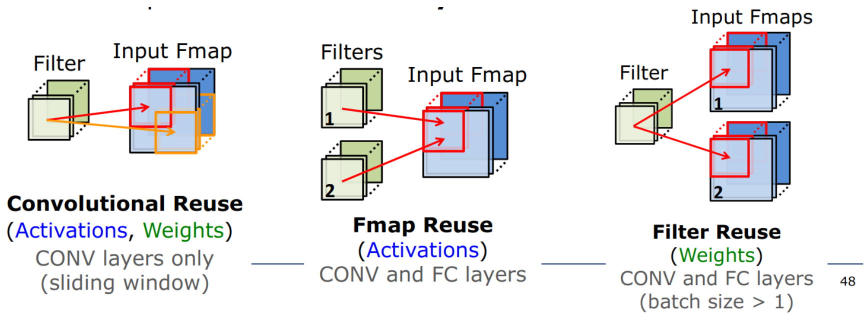
Matrix Multiply (by Toeplitz Matrix)

Data is repeated

- Use existing optimized libraries
- Repeating Data

From: `http://eyeriss.mit.edu/2019_neurips_tutorial.pdf`

Software for CPU & GPU: data reuse



- Keep data in caches
- Activations and / or weights

From: `http://eyeriss.mit.edu/2019_neurips_tutorial.pdf`