# Introduction to Computation Technologies in Deep Learning

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- Dense Numerical Computation
  - CPU Computation
  - Other Computation Devices
  - Computation & Memory Gap

**CPU Computation** 

# Instruction: The Hardware/Software Interface What is a program?

# Modern CPU Technologies

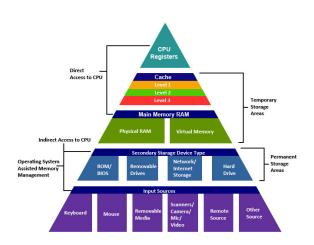
Instr. No.	Pipeline Stage								
1	IF	ID	EX	MEM	WB				
2		IF	ID	EX	МЕМ	WB			
3			IF	ID	EX	МЕМ	WB		
4				IF	ID	EX	мем		
5					IF	ID	EX		
Clock Cvcle	1	2	3	4	5	6	7		

Pipeline <sup>1</sup>

**CPU Computation** 

- Superpipelining increases stage number and simplifies each stage
- Superscalar dispatches multiple instructions to implement instruction-level parallelism
- Out-of-order execution executes according to availability of input data rather than original program order

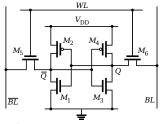
# Memory Hierarchy



**CPU Computation** 

## RAM Implementation

Static Random-Access Memory (SRAM)



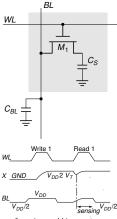
Advantages:

- Fast
- 2 Low power consumption
- No refresh circuit

Image from https://en.wikipedia.org/wiki/Static\_random-access\_memory

# RAM Implementation

Dynamic Random-Access Memory (DRAM)



Advantages:

- High density
- 2 Cheap

**Refresh**: periodically read blocks and write back.

Image from http://docencia.ac.upc.edu/master/MIRI/NCD/docs/04-Memory%20Structures-2.pdf

# Cache Hierarchy

A hierarchical design for better trade-off between memory capacity and latency.

#### **eDRAM Based Cache**

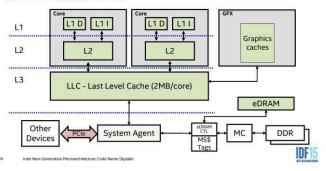


Image from

https://www.anandtech.com/show/9582/intel-skylake-mobile-desktop-launch-architecture-analysis/5

**CPU Computation** 

## Cache Hierarchy

A hierarchical design for better trade-off between memory capacity and latency.

#### Core i7 Xeon 5500 Series

L1 hit	$\sim$ 4 cycles
L2 hit	$\sim 10$ cycles
L3 hit line unshared	$\sim$ 40 cycles
L3 hit, shared line in another core	$\sim$ 65 cycles
L3 hit, modified in another core	$\sim$ 75 cycles
Remote L3	$\sim 100-300 \text{ cycles}$
Local DRAM	$\sim 60~\text{ns}$
Remote DRAM	$\sim 100~\mathrm{ns}$

#### source:

https://software.intel.com/sites/products/collateral/hpc/vtune/performance\_analysis\_guide.pdf

Cache line

**CPU Computation** 

```
tag data block flag bits (valid, dirty)
```

Indexing

```
tag (40bit) index (6bit) block offset (6bit)
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Cache line

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Associativity
 Number of different tags to be kept under the same index

Cache line

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Indexing

tag (40bit) index (6bit) block offset (6bit)

- Associativity
   Number of different tags to be kept under the same index
- VIPT Addressing Virtually indexed, physically tagged (VIPT)
  - Solve aliasing problem
  - Simultaneous cache and TLB lookup

Interesting reading: http://igoro.com/archive/
gallery-of-processor-cache-effects/

#### Example

```
$ grep -m1 name /proc/cpuinfo
model name : Intel(R) Core(TM) i5-6200U CPU @ 2.30GHz
$ cat /sys/devices/system/cpu/cpu0/cache/index0/{size,ways_of_associativity,coherency_line_size}}
32K
8
64
```

- block offset: log<sub>2</sub> 64 = 6bit
- index:  $\log_2(32 \text{KiB}/64 \text{B}/8) = 6 \text{bit}$
- tag: 52 6 6 = 40bit (48-bit virtual memory and 52-bit physical memory)

Note that *block offset* and *index* together take 12 bits, which is equal to page size (4KiB), so VIPT can be easily implemented.

CPU Computation

#### **SIMD**

Single instruction, multiple data

Store multiple data items in one register and process them in a single instruction.

#### Calculation of theoretical FLOPS<sup>2</sup>

$$FLOPS = f \cdot w \cdot IPC$$

*f* : frequency

w : SIMD width (number of floats per register)

IPC: SIMD instructions per cycle



<sup>&</sup>lt;sup>2</sup>floating point operations per second

#### **SIMD**

Single instruction, multiple data

#### Example

Intel® CPUs usually have IPC = 2. However if FMA is supported, IPC should be counted as 4 since 2 FMA instructions is essentially 4 floating point operations.

Intel® Xeon® Platinum 8180M²
# of Cores 28
Processor Base Frequency 2.50 GHz
Max Turbo Frequency 3.80 GHz
# of AVX-512 FMA Units 2

$$FLOPS = 3.8 Gcyc/s \times 4 instr/cyc \times 16 float/instr$$
  
= 243.2 GFLOPS  
 $FLOPS \quad TOT = FLOPS \times 28 = 6.8 TFLOPS$ 

<sup>&</sup>lt;sup>2</sup>data available at

## A MatMul Example

**CPU Computation** 

```
void matmul(float *a, float *b, float *c, int n) {
    for (int i = 0; i < n; ++ i) {
        for (int j = 0; j < n; ++ j) {
            float sum = 0;
            for (int k = 0; k < n; ++ k) {
                sum += a[i * n + k] * b[k * n + j];
            }
            c[i * n + j] = sum;
```

# A MatMul Example

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Swap the loops on j and k

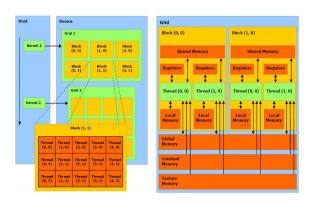
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Dense Numerical Computation
Other Computation Devices

## **NVIDIA GPU**

A single instruction, multiple thread architecture



#### Image from<sup>3</sup>

<sup>&</sup>lt;sup>3</sup>Marco Nobile et al. "cuTauLeaping: A GPU-Powered Tau-Leaping Stochastic Simulator for Massive Parallel Analyses of Biological Systems". In: 9 (Mar. 2014), e91963.

## **NVIDIA GPU**

A single instruction, multiple thread architecture

```
__global__ void add(float *a, float *b, float *c, int n) {
   int id = blockIdx.x*blockDim.x+threadIdx.x;
   if (id < n)
        c[id] = a[id] + b[id];
}</pre>
```

- Memory Coalescing
   Adjacent threads access adjacent memories simultaneously
- Parallelism
   Divide the total work among many tiny threads

### **NVIDIA GPU**

A single instruction, multiple thread architecture





#### Tesla V100 for NVLink

- 15.7*TFLOPS* for single-precision
- 125 TFLOPS for half-precision

Image from https://arstechnica.com/gadgets/2017/05/nvidia-tesla-v100-gpu-details/

#### The Trend

- On cloud: high density computation
   e.g. Google TPU 3.0 pods are claimed to achieve 100PFLOPS
- On edge: low precision
   e.g. int8 in cDSP supported by Qualcomm's SNPE
- Automatic kernel tuning & generation
   An active research area. Typical projects include Halide<sup>3</sup>,
   TVM<sup>4</sup> and TensorComprehension<sup>5</sup>

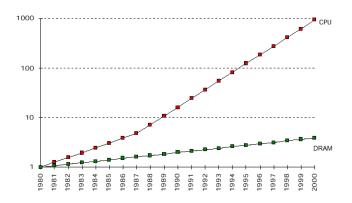
<sup>5</sup>https://facebookresearch.github.io/TensorComprehensions/



<sup>3</sup>http://halide-lang.org/

<sup>4</sup>http://tvmlang.org/

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Graph from<sup>6</sup>

<sup>&</sup>lt;sup>6</sup>Carlos Carvalho. "The gap between processor and memory speeds". In:

# Challenges from NN Architecture Computation-sparse structure seems to be beneficial.

Architecture	Computation	Memory
Small kernel	$\frac{k2^2}{k1^2}$	Param $\frac{k1^2}{k2^2}$
Large stride	$\frac{1}{s^2}$	Output $\frac{1}{s^2}$
Group/depthwise conv	$\frac{1}{g^2}$	Param $\frac{1}{g}$
Shuffle/concat	0	1

#### Roofline Model

A visualization method to characterize computation/memory

Performance P (FLOPS) is approximately a function of arithmetic intensity I (FLOP/byte) for a particular architecture<sup>7</sup>.

#### Naïve Roofline

$$P = \min \left\{ \begin{array}{l} \pi \\ \beta \times I \end{array} \right.$$

where  $\pi$  is the peak computing performance and  $\beta$  is the peak bandwidth.

#### Roofline Model

A visualization method to characterize computation/memory

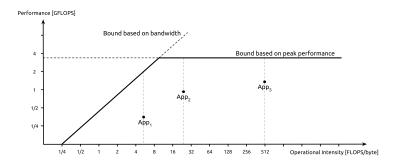


Image from https://en.wikipedia.org/wiki/Roofline\_model

# Thanks!

Questions and feedback are welcome:)