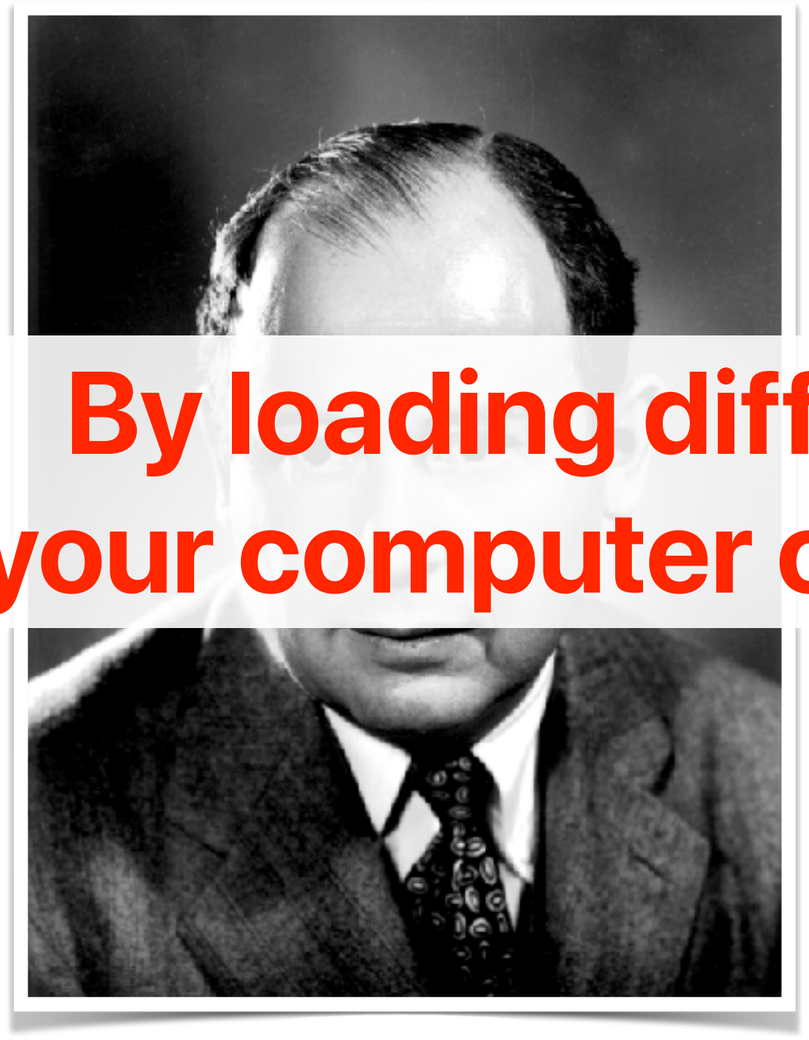
Performance (Preview Version)

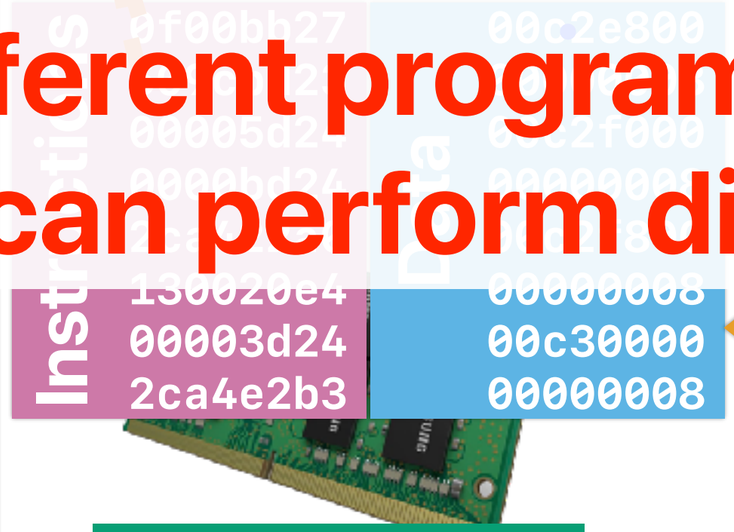
Hung-Wei Tseng

Recap: von Neumman Architecture

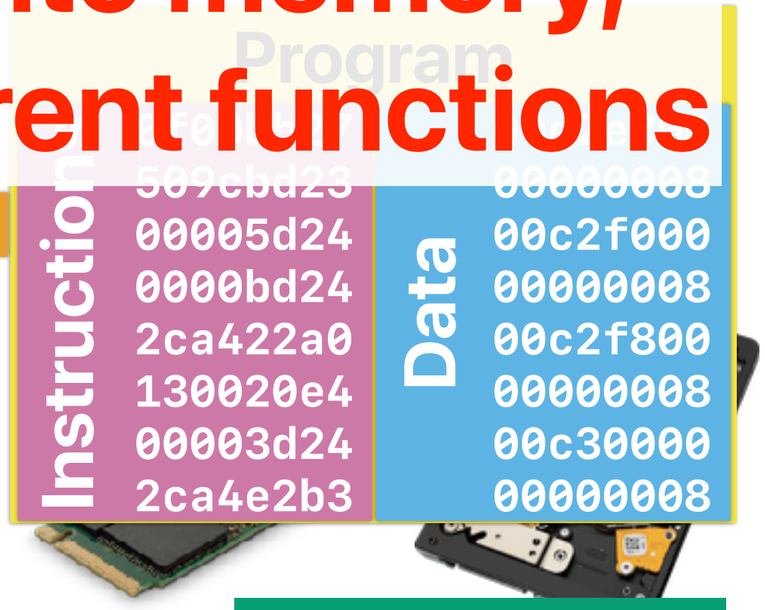


Processor

By loading different programs into memory, your computer can perform different functions



Memory



Storage

Recap: Demo

```
if(option)
    std::sort(data, data + arraySize);

for (unsigned c = 0; c < arraySize*1000; ++c) {
        if (data[c%arraySize] >= INT_MAX/2)
            sum ++;
    }
}
```

$O(nlog_2n)$

$O(n)$

if option is set to 1: $O(nlog_2n)$

otherwise, O(n): $O(n)$

Definition of “Performance”

CANONICAL

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Peer instruction

- Before the lecture — You need to complete the required **reading**
- During the lecture — I'll bring in activities to ENGAGE you in exploring your understanding of the material
  - Popup questions
  - Individual **thinking** — use polls in Zoom to express your opinion
  - Group **discussion**
    - Breakout rooms based on your residential colleges!
    - Use polls in Zoom to express your group's opinion
  - Whole-classroom **discussion** — we would like to hear from you

Read **Think** **Discuss**

Let’s start with “end-to-end latency” — how long it takes to execute a program?

CPU Performance Equation

$$Performance = \frac{1}{Execution\ Time}$$

$$Execution\ Time = \frac{Instructions}{Program} \times \frac{Cycles}{Instruction} \times \frac{Seconds}{Cycle}$$

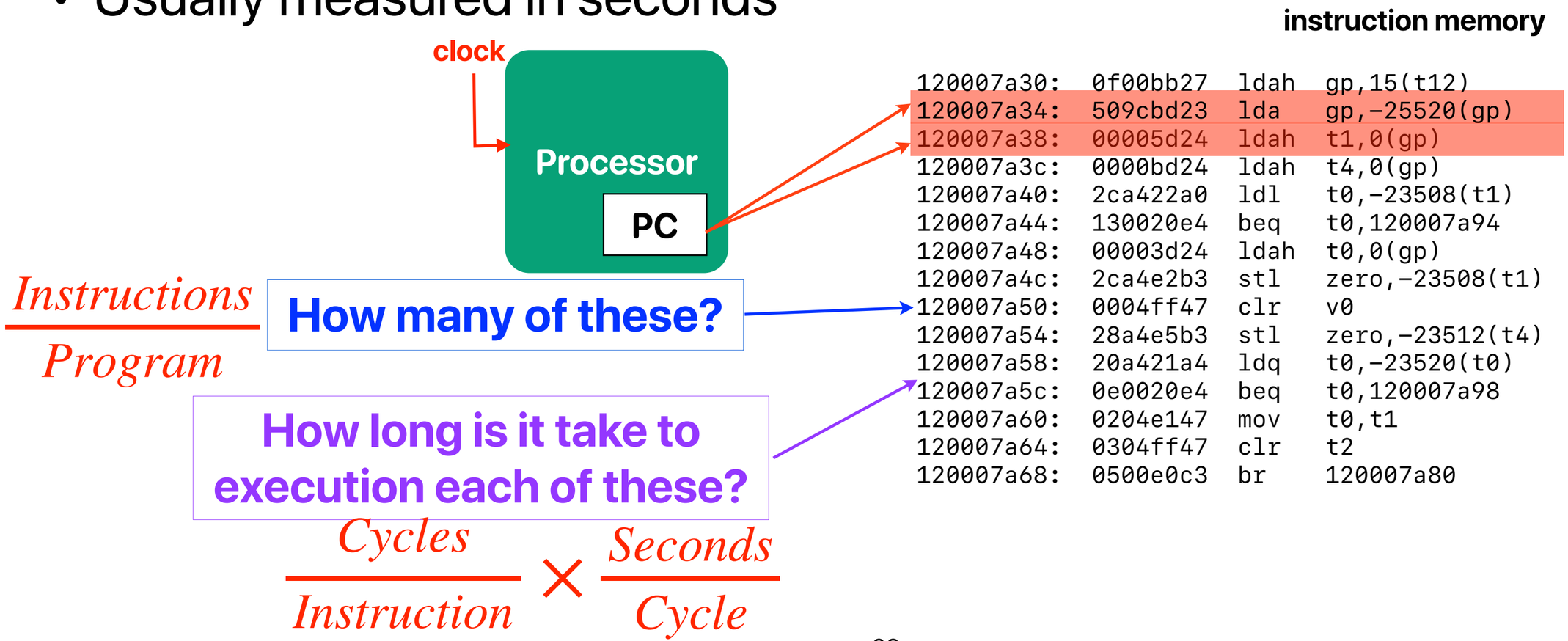
$$ET = IC \times CPI \times CT$$

$$1GHz = 10^9 Hz = \frac{1}{10^9} sec\ per\ cycle = 1\ ns\ per\ cycle$$

$$\frac{1}{Frequency(i.e., clock\ rate)}$$

Execution Time

- The simplest kind of performance
- Shorter execution time means better performance
- Usually measured in seconds



Performance Equation (X)

- Assume that we have an application composed with a total of **5000000000** instructions, in which **20%** of them are "Type-A" instructions with an average **CPI of 8** cycles, **20%** of them are "Type-B" instructions with an average **CPI of 4** cycles and the rest instructions are "Type-C" instructions with average **CPI of 1** cycle. If the processor runs at **3 GHz**, how long is the execution time?

A. 3.67 sec
B. 5 sec
C. 6.67 sec
D. 15 sec
E. 45 sec

$$ET = (5 \times 10^9) \times \underbrace{(20\% \times 8 + 20\% \times 4 + 60\% \times 1)}_{\textbf{average CPI}} \times \frac{1}{3 \times 10^{-9}} sec = 5$$

$$ET = IC \times CPI \times CT$$

Speedup

- The relative performance between two machines, X and Y. Y is n times faster than X

$$n = \frac{Execution\ Time_X}{Execution\ Time_Y}$$

- The speedup of Y over X

$$Speedup = \frac{Execution\ Time_X}{Execution\ Time_Y}$$

Speedup of Y over X

- Consider the same program on the following two machines, X and Y. By how much Y is faster than X?

	Clock Rate	Instructions	Percentage of Type-A	CPI of Type-A	Percentage of Type-B	CPI of Type-B	Percentage of Type-C	CPI of Type-C
Machine X	3 GHz	5000000000	20%	8	20%	4	60%	1
Machine Y	5 GHz	5000000000	20%	13	20%	4	60%	1

A. 0.2
B. 0.25
C. 0.8
D. 1.25
E. No changes

$$ET_Y = (5 \times 10^9) \times (20\% \times 13 + 20\% \times 4 + 60\% \times 1) \times \frac{1}{5 \times 10^9} sec = 4$$

$$Speedup = \frac{Execution\ Time_X}{Execution\ Time_Y}$$

$$= \frac{5}{4} = 1.25$$

What Affects Each Factor in Performance Equation

Demo — programmer & performance

A

```
for(i = 0; i < ARRAY_SIZE; i++)
{
  for(j = 0; j < ARRAY_SIZE; j++)
  {
    c[i][j] = a[i][j]+b[i][j];
  }
}
```

B

```
for(j = 0; j < ARRAY_SIZE; j++)
{
  for(i = 0; i < ARRAY_SIZE; i++)
  {
    c[i][j] = a[i][j]+b[i][j];
  }
}
```

$O(n^2)$ **Complexity** $O(n^2)$

Instruction Count?

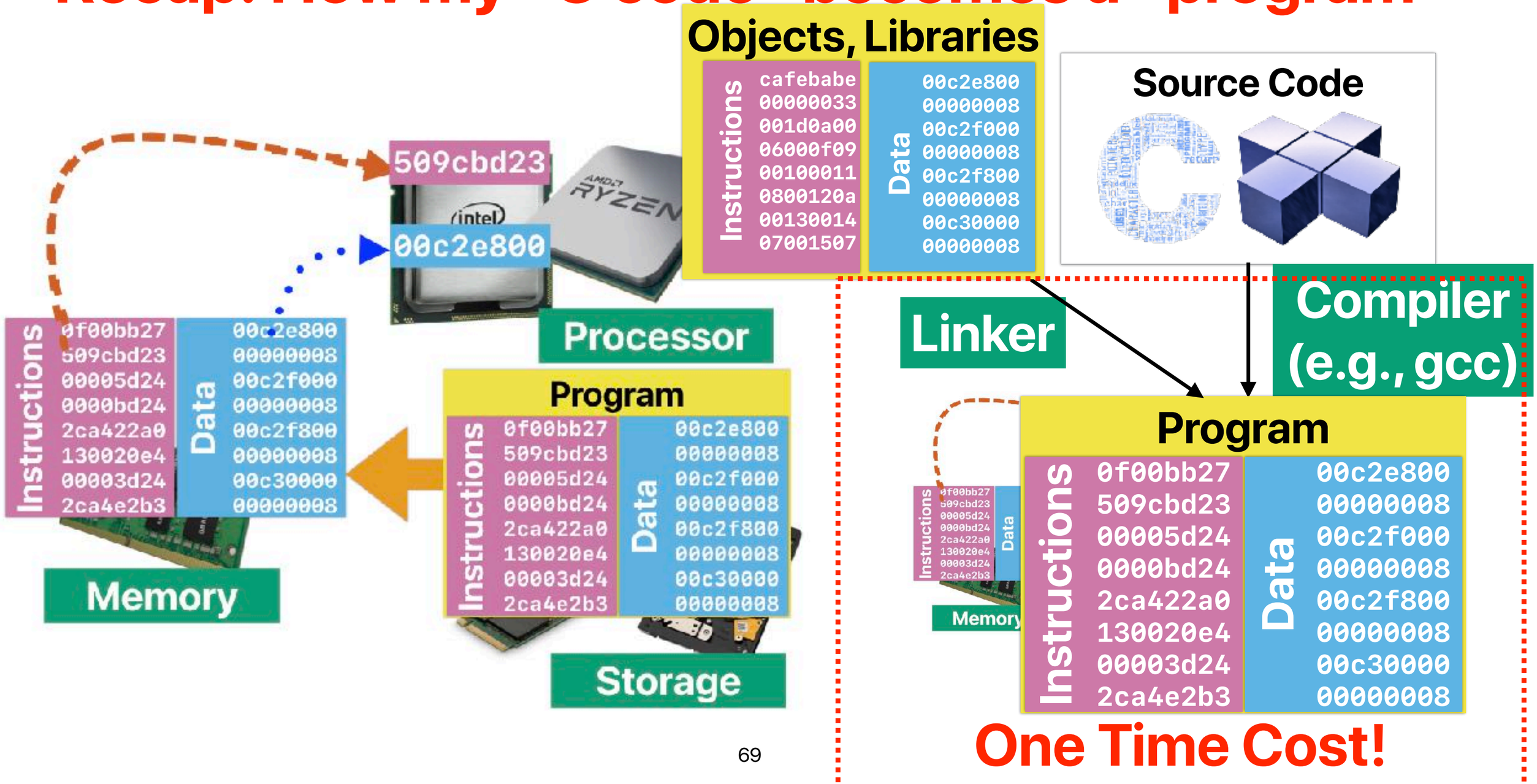
Clock Rate

CPI

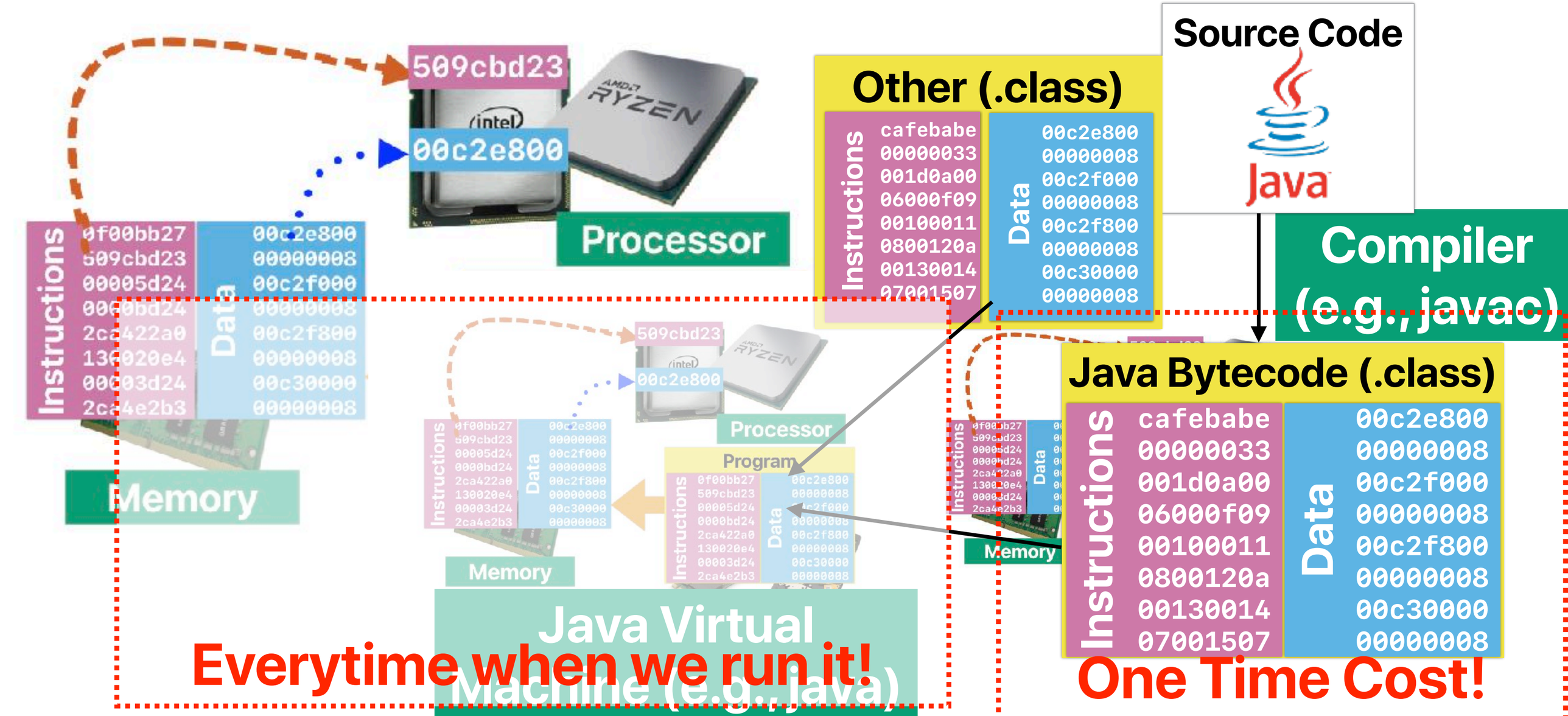
Use “performance counters” to figure out!

- Modern processors provides performance counters
  - instruction counts
  - cache accesses/misses
  - branch instructions/mis-predictions
- How to get their values?
  - You may use “perf stat” in linux
  - You may use Instruments —> Time Profiler on a Mac
  - Intel’s vtune — only works on Windows w/ intel processors
  - You can also create your own functions to obtain counter values

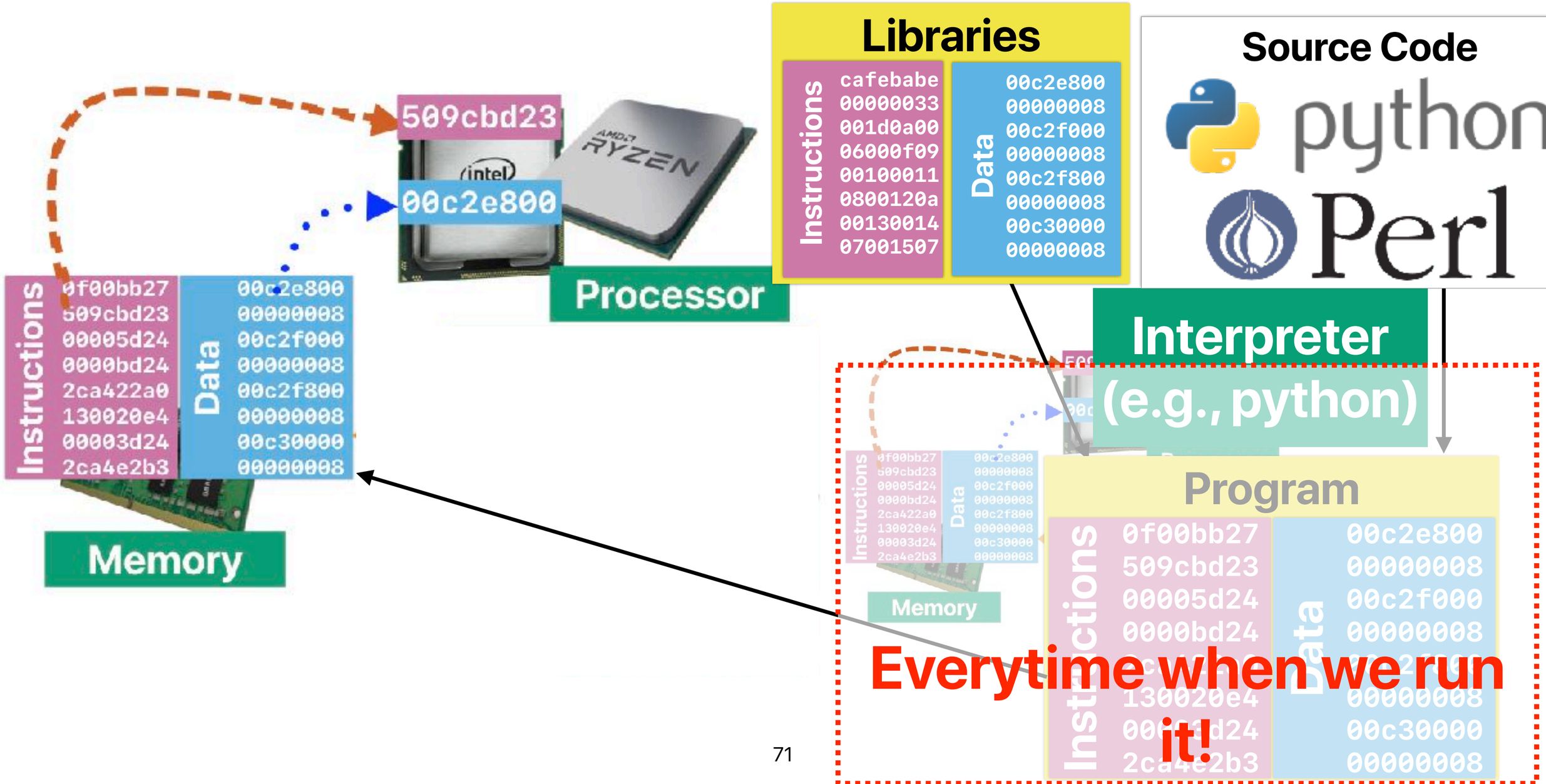
Recap: How my "C code" becomes a "program"



Recap: How my "Java code" becomes a "program"



Recap: How my "Python code" becomes a "program"



Revisited the demo with compiler optimizations!

- gcc has different optimization levels.
  - -O0 — no optimizations
  - -O3 — typically the best-performing optimization

A

```
for(i = 0; i < ARRAY_SIZE; i++)
{
  for(j = 0; j < ARRAY_SIZE; j++)
  {
    c[i][j] = a[i][j]+b[i][j];
  }
}
```

B

```
for(j = 0; j < ARRAY_SIZE; j++)
{
  for(i = 0; i < ARRAY_SIZE; i++)
  {
    c[i][j] = a[i][j]+b[i][j];
  }
}
```

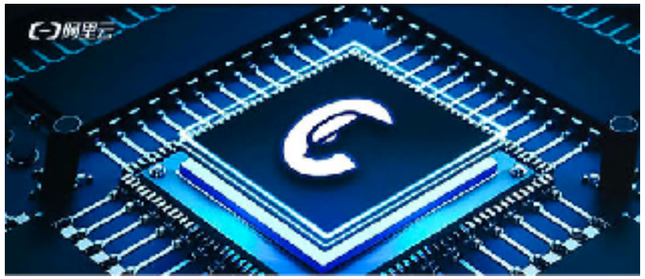
Instruction Set Architecture (ISA) & Performance

Recap: ISA — the interface b/w processor/software

- Operations
  - Arithmetic/Logical, memory access, control-flow (e.g., branch, function calls)
  - Operands
    - Types of operands — register, constant, memory addresses
    - Sizes of operands — byte, 16-bit, 32-bit, 64-bit
- Memory space
  - The size of memory that programs can use
  - The addressing of each memory locations
  - The modes to represent those addresses

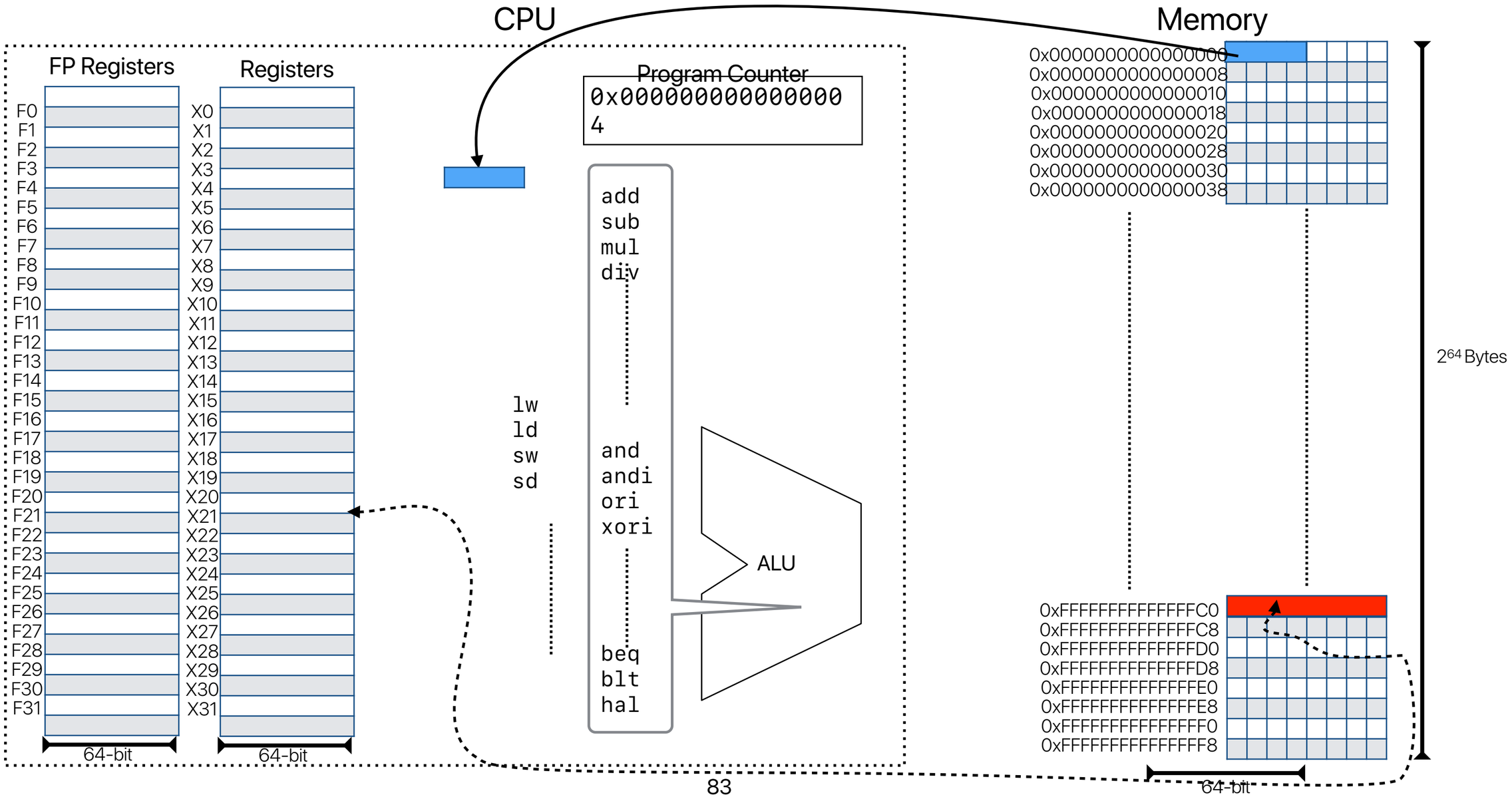
Popular ISAs

arm



RISC-V

The abstracted "RISC-V" machine

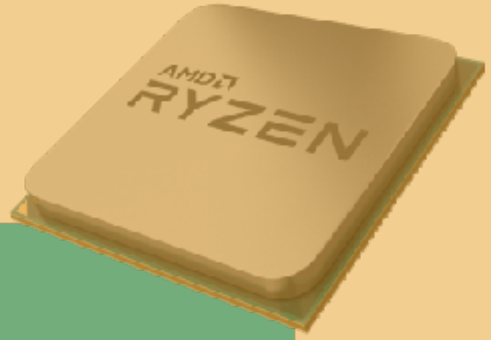


Subset of RISC-V instructions

Category	Instruction	Usage	Meaning
Arithmetic	add	`add  x1, x2, x3`	`x1 = x2 + x3`
	addi	`addi x1,x2, 20`	`x1 = x2 + 20`
	sub	`sub  x1, x2, x3`	`x1 = x2 – x3`
Logical	and	`and  x1, x2, x3`	`x1 = x2 & x3`
	or	`or   x1, x2, x3`	`x1 = x2 | x3`
	andi	`andi x1, x2, 20`	`x1 = x2 & 20`
	sll	`sll  x1, x2, 10`	`x1 = x2 * 2^10`
	srl	`srl  x1, x2, 10`	`x1 = x2 / 2^10`
Data Transfer	ld	`ld   x1, 8(x2)`	`x1 = mem[x2+8]`
	sd	`sd   x1, 8(x2)`	`mem[x2+8] = x1`
Branch	beq	`beq  x1, x2, 25`	`if(x1 == x2), PC = PC + 100`
	bne	`bne  x1, x2, 25`	`if(x1 != x2), PC = PC + 100`
Jump	jal	`jal  25`	`$ra = PC + 4, PC = 100`
	jr	`jr   $ra`	`PC = $ra`

The only type of instructions can access memory

Popular ISAs

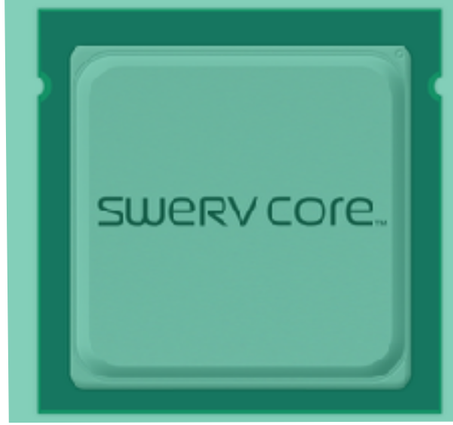


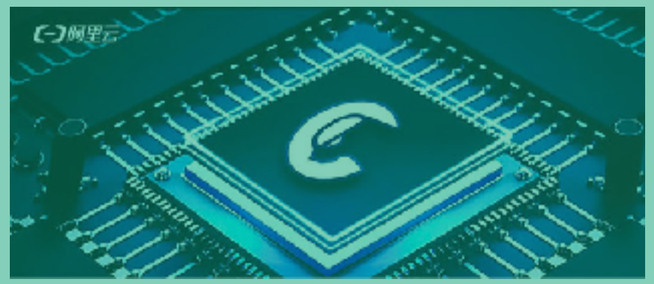
x86

Complex Instruction Set Computers (CISC)

arm

Reduced Instruction Set Computers (RISC)



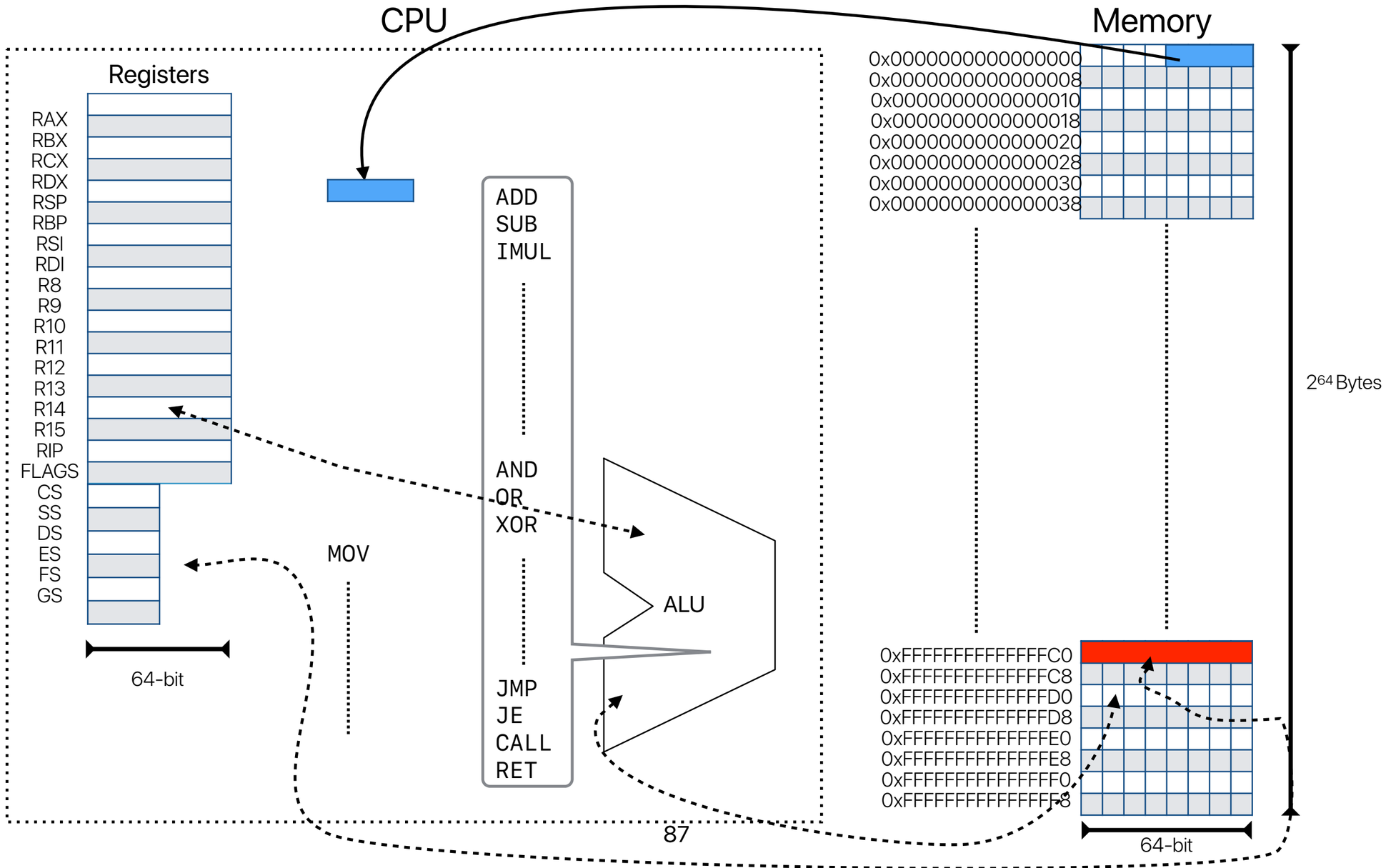


RISC-V

How many operations: CISC v.s. RISC

- CISC (Complex Instruction Set Computing)
  - Examples: x86, Motorola 68K
  - Provide **many powerful/complex** instructions
    - Many: more than 1503 instructions since 2016
    - Powerful/complex: an instruction can perform both ALU and memory operations
    - Each instruction takes more cycles to execute
- RISC (Reduced Instruction Set Computer)
  - Examples: ARMv8, RISC-V, MIPS (the first RISC instruction, invented by the authors of our textbook)
  - Each instruction only performs simple tasks
  - Easy to decode
  - Each instruction takes less cycles to execute

The abstracted x86 machine



RISC-V v.s. x86

	RISC-V	x86
ISA type	Reduced Instruction Set Computers (RISC)	Complex Instruction Set Computers (CISC)
instruction width	32 bits	1 ~ 17 bytes
code size	larger	smaller
registers	32	16
addressing modes	reg+offset	base+offset base+index scaled+index scaled+index+offset
hardware	simple	complex

How about complexity?

How about “computational complexity”

- Algorithm complexity provides a good estimate on the performance if —
  - Every instruction takes exactly the same amount of time
  - Every operation takes exactly the same amount of instructions

These are unlikely to be true

Summary of CPU Performance Equation

$$Performance = \frac{1}{Execution\ Time}$$

$$Execution\ Time = \frac{Instructions}{Program} \times \frac{Cycles}{Instruction} \times \frac{Seconds}{Cycle}$$

$$ET = IC \times CPI \times CT$$

- IC (Instruction Count)
  - ISA, Compiler, algorithm, programming language, **programmer**
- CPI (Cycles Per Instruction)
  - Machine Implementation, microarchitecture, compiler, application, algorithm, programming language, **programmer**
- Cycle Time (Seconds Per Cycle)
  - Process Technology, microarchitecture, **programmer**

Amdahl's Law — and It's Implication in the Multicore Era

H&P Chapter 1.9

M. D. Hill and M. R. Marty. Amdahl's Law in the Multicore Era. In Computer, vol. 41, no. 7, pp. 33-38, July 2008.

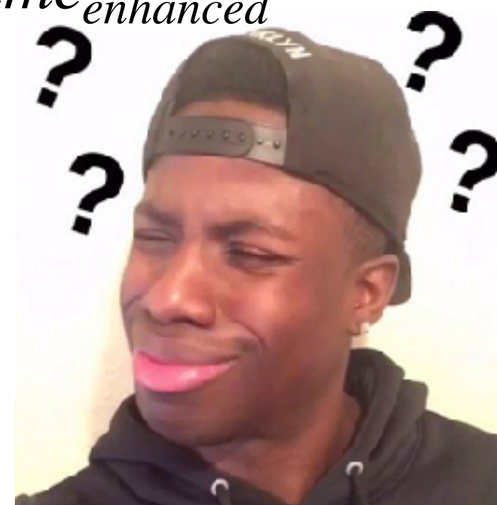
Amdahl's Law

$$Speedup_{enhanced}(f, s) = \frac{1}{(1 - f) + \frac{f}{s}}$$

f — The fraction of time in the original program

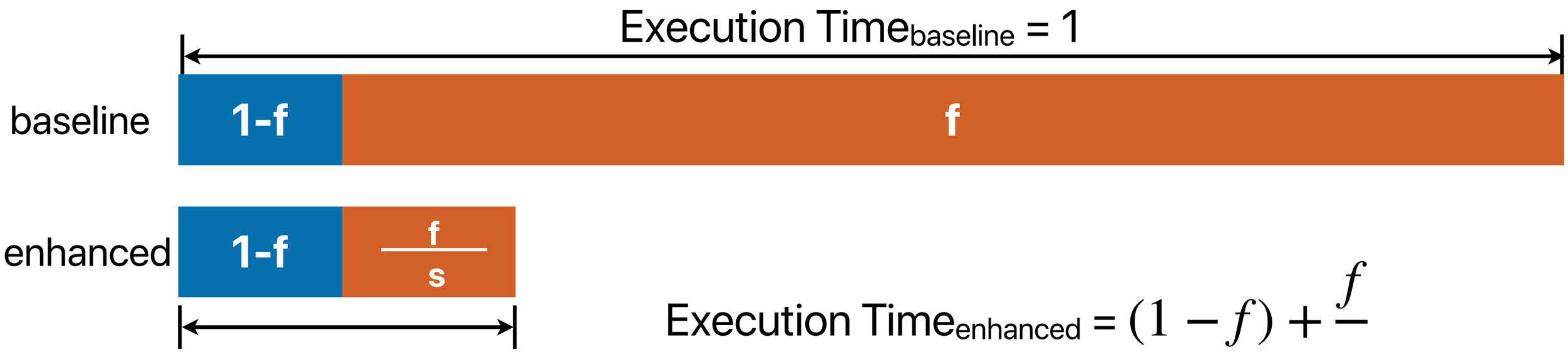
s — The speedup we can achieve on f

$$Speedup_{enhanced} = \frac{Execution\ Time_{baseline}}{Execution\ Time_{enhanced}}$$



Amdahl's Law

$$Speedup_{enhanced}(f, s) = \frac{1}{(1 - f) + \frac{f}{s}}$$



Execution Time$_{enhanced}$ = $(1 - f) + \frac{f}{s}$

$$Speedup_{enhanced} = \frac{Execution\ Time_{baseline}}{Execution\ Time_{enhanced}} = \frac{1}{(1 - f) + \frac{f}{s}}$$

Amdahl's Law on Multiple Optimizations

- We can apply Amdahl's law for multiple optimizations
- These optimizations must be dis-joint!
  - If optimization #1 and optimization #2 are dis-joint:

$$Speedup_{enhanced}(f_{Opt1}, f_{Opt2}, s_{Opt1}, s_{Opt2}) = \frac{1}{(1 - f_{Opt1} - f_{Opt2}) + \frac{f\_Opt1}{s\_Opt1} + \frac{f\_Opt2}{s\_Opt2}}$$

  - If optimization #1 and optimization #2 are not dis-joint:

$$Speedup_{enhanced}(f_{OnlyOpt1}, f_{OnlyOpt2}, f_{BothOpt1Opt2}, s_{OnlyOpt1}, s_{OnlyOpt2}, s_{BothOpt1Opt2}) = \frac{1}{(1 - f_{OnlyOpt1} - f_{OnlyOpt2} - f_{BothOpt1Opt2}) + + \frac{f\_BothOpt1Opt2}{s\_BothOpt1Opt2} + \frac{f\_OnlyOpt1}{s\_OnlyOpt1} + \frac{f\_OnlyOpt2}{s\_OnlyOpt2}}$$

Corollary #1 on Multiple Optimizations

- If we can pick just one thing to work on/optimize

$$Speedup_{max}(f_1, \infty) = \frac{1}{(1 - f_1)}$$
$$Speedup_{max}(f_2, \infty) = \frac{1}{(1 - f_2)}$$
$$Speedup_{max}(f_3, \infty) = \frac{1}{(1 - f_3)}$$
$$Speedup_{max}(f_4, \infty) = \frac{1}{(1 - f_4)}$$

The biggest f_x would lead to the largest $Speedup_{max}$!

Corollary #2 — make the common case fast!

- When f is small, optimizations will have little effect.
- Common == **most time consuming** not necessarily the most frequent
- The uncommon case doesn’t make much difference
- The common case can change based on inputs, compiler options, optimizations you’ve applied, etc.

Identify the most time consuming part

- Compile your program with -pg flag
- Run the program
  - It will generate a gmon.out
  - gprof your_program gmon.out > your_program.prof
- It will give you the profiled result in your_program.prof

Corollary #2.1 Don't hurt non-common part too mach

- If the program spend 90% in A, 10% in B. Assume that an optimization can accelerate A by 9x, by hurts B by 10x…
- Assume the original execution time is T. The new execution time

$$ET_{new} = \frac{ET_{old} \times 90\,\%}{9} + ET_{old} \times 10\% \times 10$$

$$ET_{new} = 1.1 \times ET_{old}$$

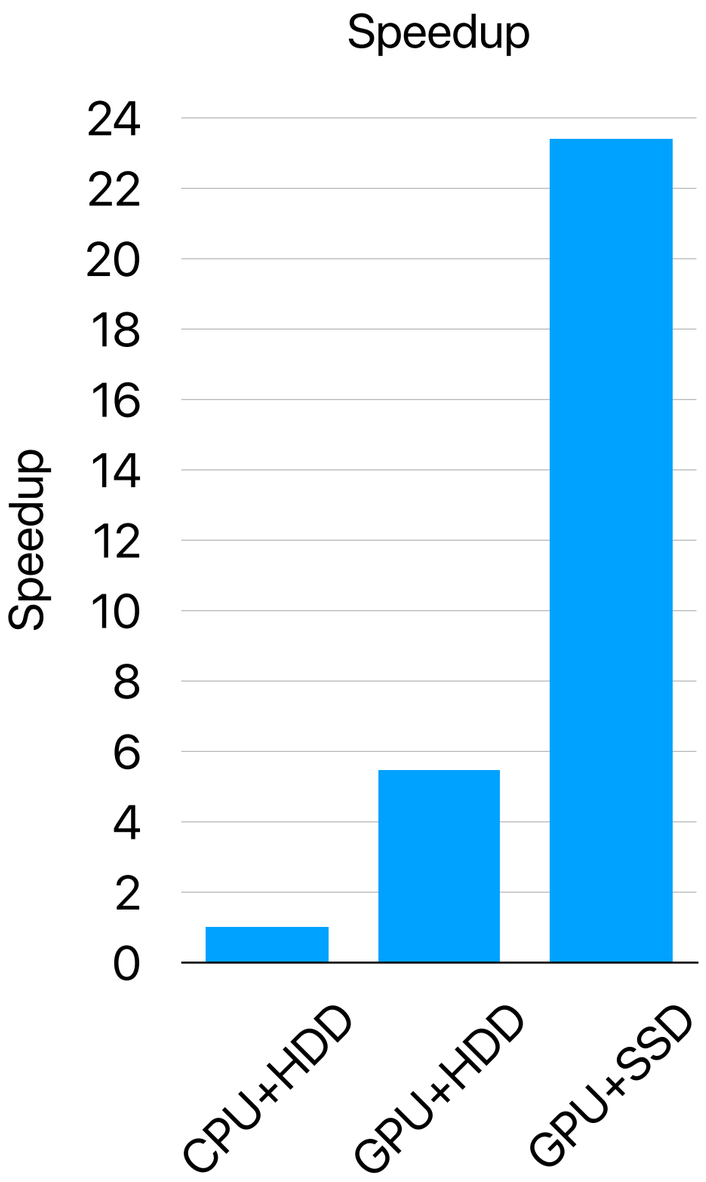
$$Speedup = \frac{ET_{old}}{ET_{new}} = \frac{ET_{old}}{1.1 \times ET_{old}} = 0.91 \times$$ ……slowdown!

You may not use Amdahl's Law for this case as Amdahl's Law does NOT
(1) consider overhead
(2) bound to slowdown

Corollary #3 — optimization has a moving target

- With optimization, the common becomes uncommon.
- An uncommon case will (hopefully) become the new common case.
- Now you have a new target for optimization — You have to revisit "Amdahl's Law" every time you applied some optimization

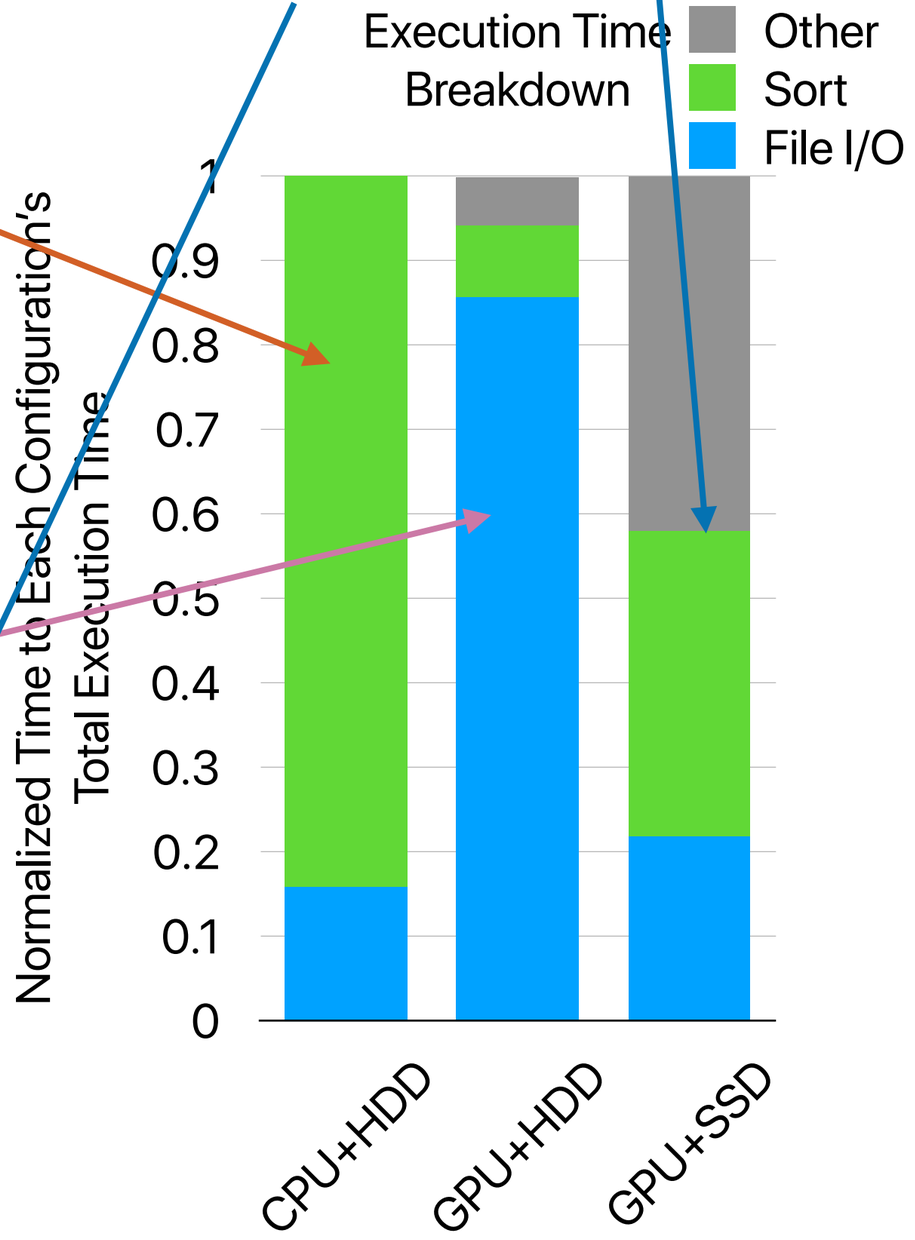
Demo — sort



Sort was the most significant

File I/O is now more critical to performance

Something else (e.g., data movement) matters more



Amdahl's Law on Multicore Architectures

- Symmetric multicore processor with n cores (if we assume the processor performance scales perfectly)

$$Speedup_{parallel}(f_{parallelizable}, n) = \frac{1}{(1 - f_{parallelizable}) + \frac{f\_parallelizable}{n}}$$

Demo — merge sort v.s. bitonic sort on GPUs

Merge Sort

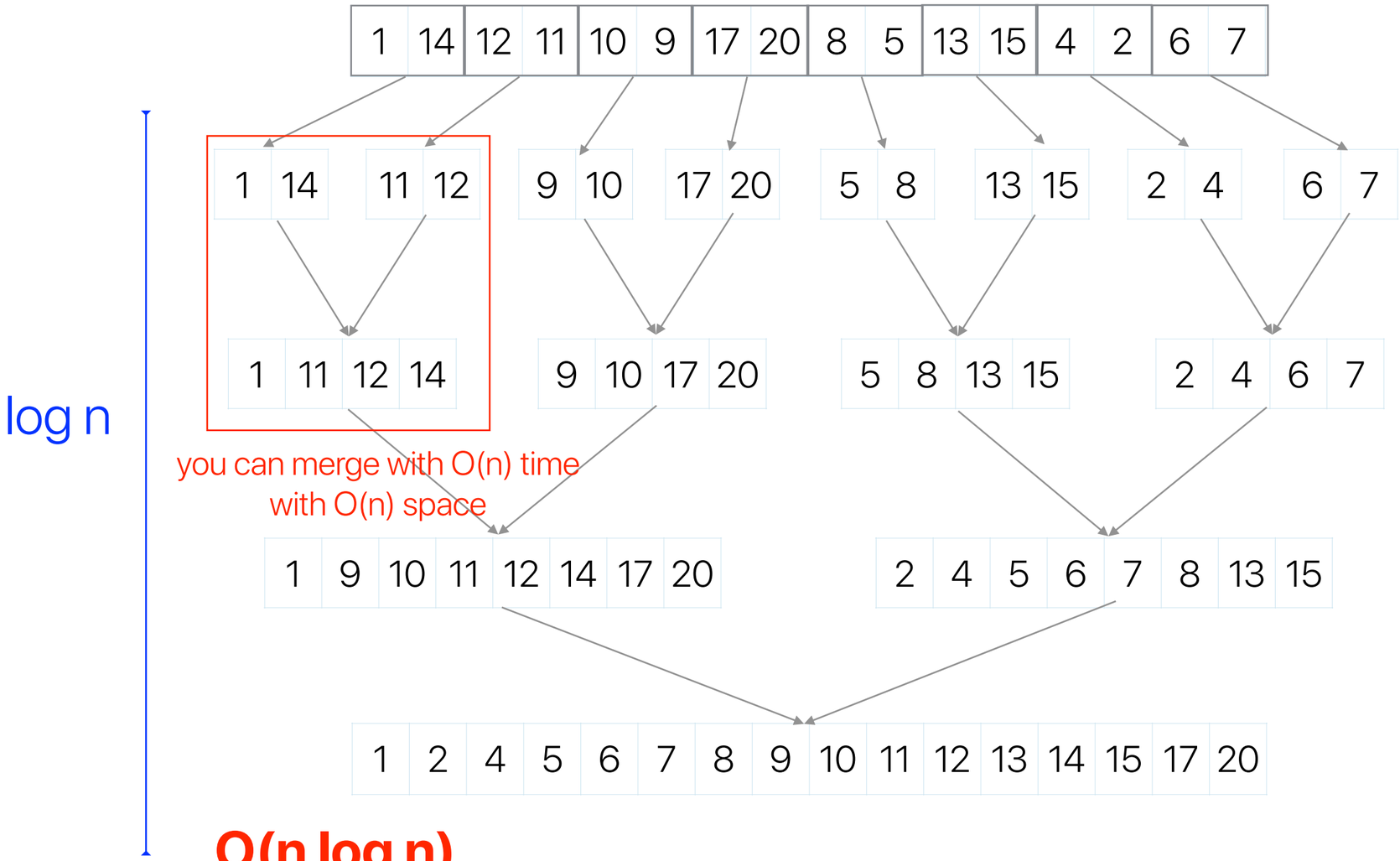
$O(nlog_2n)$

Bitonic Sort

$O(nlog_2^2n)$

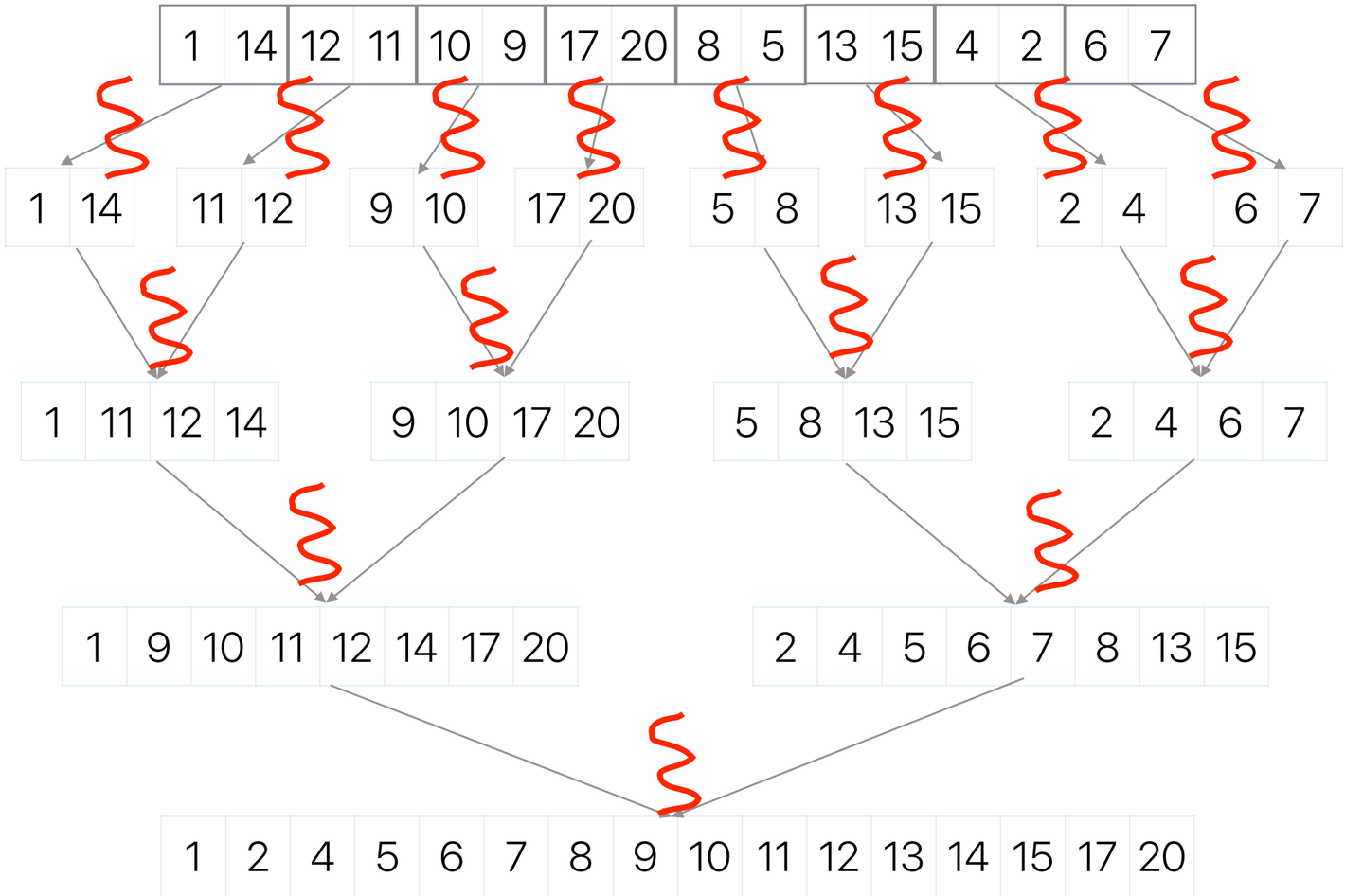
```
void BitonicSort() {

    int i,j,k;

    for (k=2; k<=N; k=2*k) {
        for (j=k>>1; j>0; j=j>>1) {
            for (i=0; i<N; i++) {
                int ij=i^j;
                if ((ij)>i) {
                    if ((i&k)==0 && a[i] > a[ij])
                        exchange(i,ij);
                    if ((i&k)!=0 && a[i] < a[ij])
                        exchange(i,ij);
                }
            }
        }
    }
}
```

Merge sort

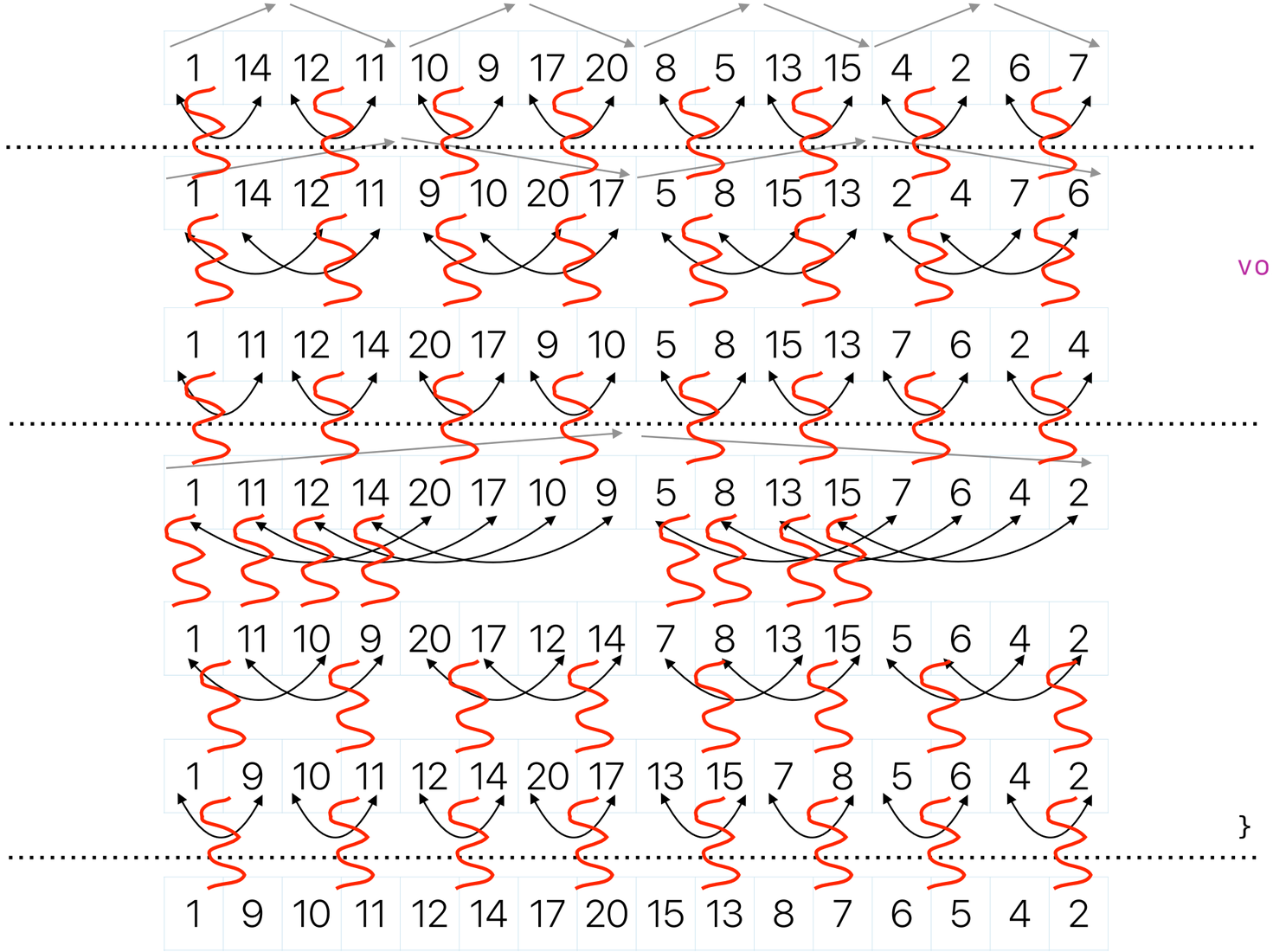


O(n log n)

Parallel merge sort

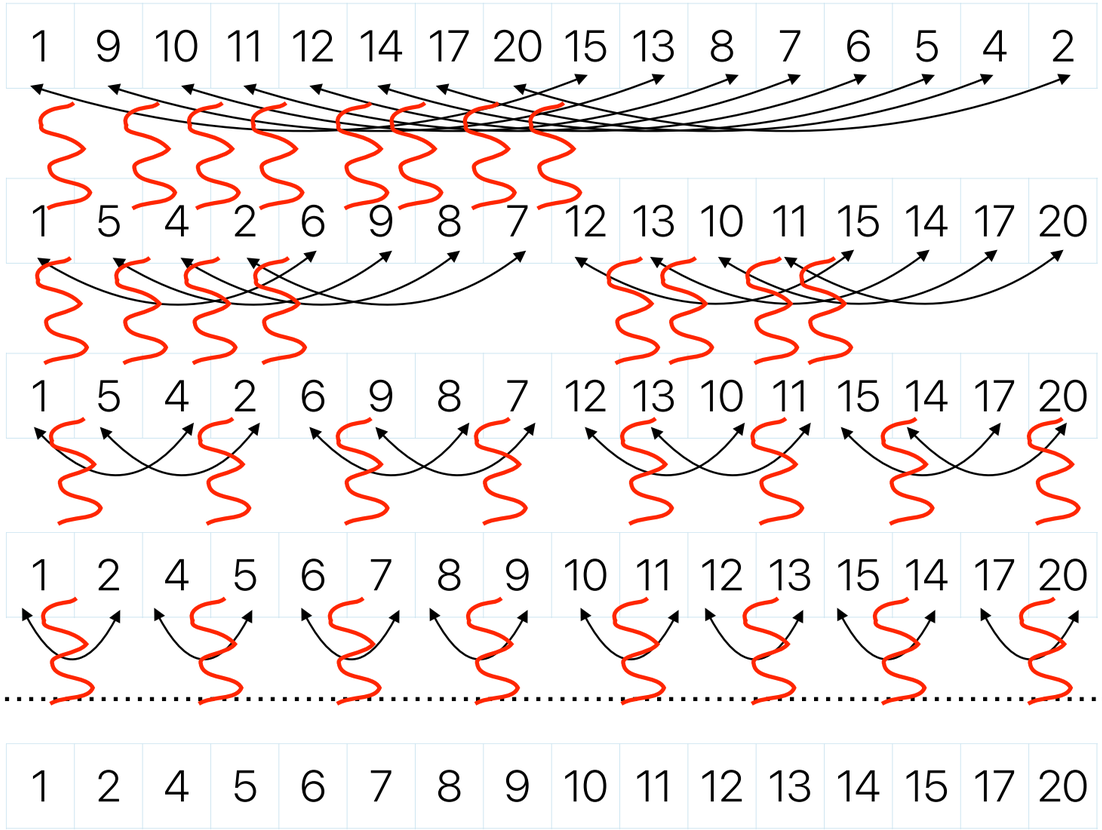


Bitonic sort




```
void BitonicSort() {

    int i,j,k;

    for (k=2; k<=N; k=2*k) {
        for (j=k>>1; j>0; j=j>>1) {
            for (i=0; i<N; i++) {
                int ij=i^j;
                if ((ij)>i) {
                    if ((i&k)==0 && a[i] > a[ij])
                        exchange(i,ij);
                    if ((i&k)!=0 && a[i] < a[ij])
                        exchange(i,ij);
                }
            }
        }
    }
}
```

Bitonic sort (cont.)




```
void BitonicSort() {

    int i,j,k;

    for (k=2; k<=N; k=2*k) {
        for (j=k>>1; j>0; j=j>>1) {
            for (i=0; i<N; i++) {
                int ij=i^j;
                if ((ij)>i) {
                    if ((i&k)==0 && a[i] > a[ij])
                        exchange(i,ij);
                    if ((i&k)!=0 && a[i] < a[ij])
                        exchange(i,ij);
                }
            }
        }
    }
}
```

benefits — in-place merge (no additional space is necessary), very stable comparison patterns

$O(n \log^2 n)$ — hard to beat $n(\log n)$ if you can't parallelize this a lot!

Corollary #4

$$Speedup_{parallel}(f_{parallelizable}, \infty) = \frac{1}{(1 - f_{parallelizable}) + \frac{f\_parallelizable}{\infty}}$$

$$Speedup_{parallel}(f_{parallelizable}, \infty) = \frac{1}{(1 - f_{parallelizable})}$$

- If we can build a processor with unlimited parallelism
  - The complexity doesn't matter as long as the algorithm can utilize all parallelism
  - That's why bitonic sort or MapReduce works!
- **The future trend of software/application design is seeking for more parallelism rather than lower the computational complexity**

Is it the end of computational complexity?

Corollary #5

$$Speedup_{parallel}(f_{parallelizable}, \infty) = \frac{1}{(1 - f_{parallelizable}) + \frac{f\_parallelizable}{\infty}}$$

$$Speedup_{parallel}(f_{parallelizable}, \infty) = \frac{1}{(1 - f_{parallelizable})}$$

- Single-core performance still matters
  - It will eventually dominate the performance
  - If we cannot improve single-core performance further, finding more "parallelizable" parts is more important
  - Algorithm complexity still gives some "insights" regarding the growth of execution time in the same algorithm, though still not accurate

However, parallelism is not "tax-free"

- Synchronization
- Preparing data
- Addition function calls
- Data exchange if the parallel hardware has its own memory hierarchy

$$\text{Execution Time}_{\text{enhanced}} = \frac{(1-f)}{perf(r)} + \frac{f}{n}$$

Lessons learned from Amdahl's Law

$$Speedup_{enhanced}(f, s) = \frac{1}{(1 - f) + \frac{f}{s}}$$

- Corollary #1: Maximum speedup
- Corollary #2: Make the common case fast
  - Common case changes all the time
- Corollary #3: Optimization is a moving target
- Corollary #4: Exploiting more parallelism from a program is the key to performance gain in modern architectures
- Corollary #5: Single-core performance still matters

$$Speedup_{max}(f, \infty) = \frac{1}{(1 - f)}$$

$$Speedup_{max}(f_1, \infty) = \frac{1}{(1 - f_1)}$$

$$Speedup_{max}(f_2, \infty) = \frac{1}{(1 - f_2)}$$

$$Speedup_{max}(f_3, \infty) = \frac{1}{(1 - f_3)}$$

$$Speedup_{max}(f_4, \infty) = \frac{1}{(1 - f_4)}$$

$$Speedup_{parallel}(f_{parallelizable}, \infty) = \frac{1}{(1 - f_{parallelizable})}$$

$$Speedup_{parallel}(f_{parallelizable}, \infty) = \frac{1}{(1 - f_{parallelizable})}$$

Choose the right metric — Latency v.s. Throughput/Bandwidth

Latency v.s. Bandwidth/Throughput

- Latency — the amount of time to finish an operation
  - End-to-end execution time of “something”
  - Access time
  - Response time
- Throughput — the amount of work can be done within a given period of time (typically “something” per “timeframe” or the other way around)
  - Bandwidth (MB/Sec, GB/Sec, Mbps, Gbps)
  - IOPs (I/O operations per second)
  - FLOPs (Floating-point operations per second)
  - IPS (Inferences per second)

RAID — Improving throughput

MORE SPECS

Model Code (Capaci

Gener

DIMENSION (WxHxD)
100 X 69.85 X 6.8 (mm)

TRIM SUPPORT
Yes

ENCRYPTION SUPPORT
AES 256-bit Encryption (Class 0) TCG/Opal
IEEE1667 (Encrypted drive)

Performance[2]

SEQUENTIAL READ
Up to 550 MB/s

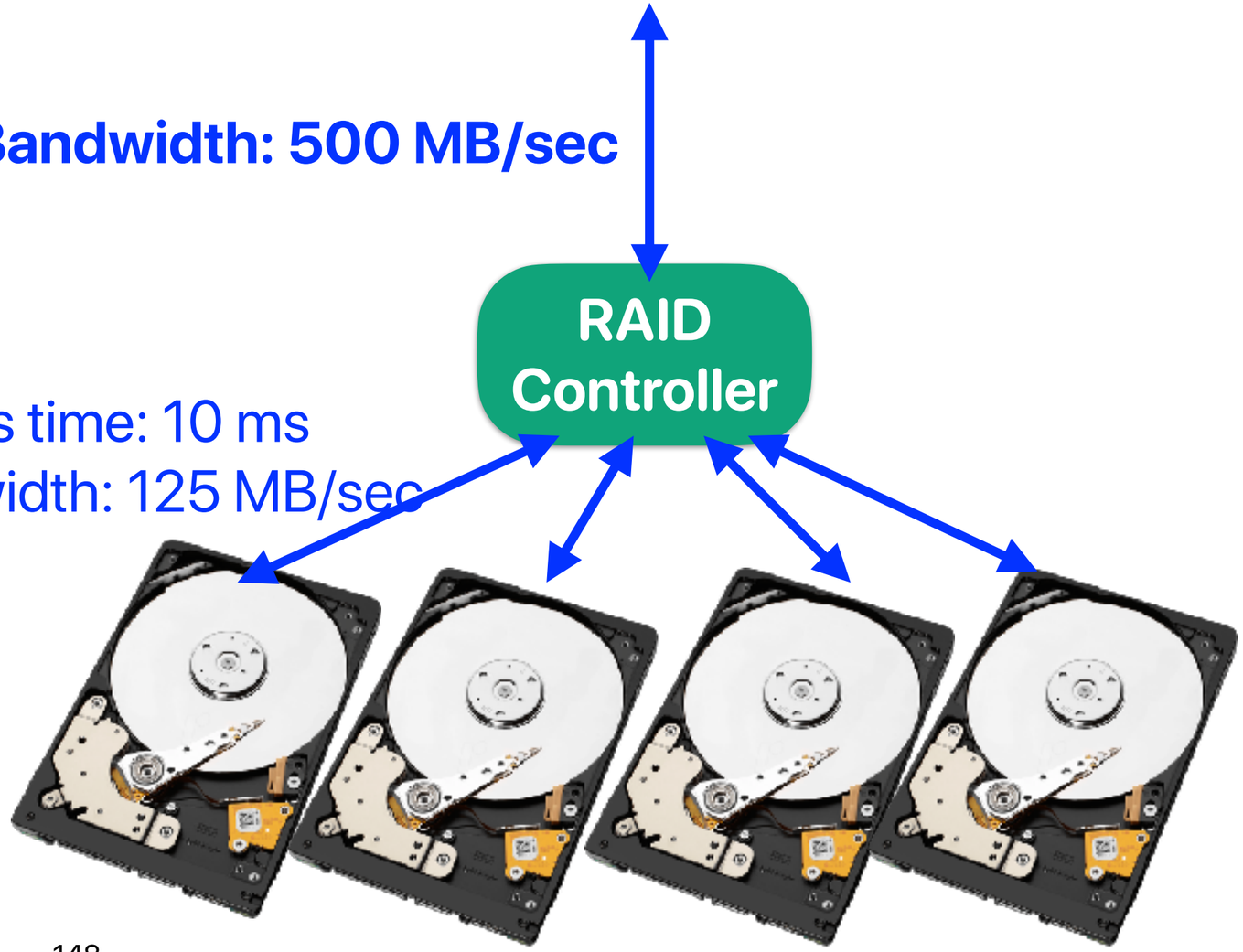
RANDOM WRITE (4KB, QD32)
Up to 89,000 IOPS

Environment

AVERAGE POWER CONSUMPTION (SYSTEM LEVEL)[3]
1,000 GB: Average 2.2 W Maximum 4.0 W
2,000 GB: Average 3.1 W Maximum 4.2 W
4,000 GB: Average 3.1 W Maximum 5.4 W
(Burst mode)

Aggregated Bandwidth: 500 MB/sec

Access time: 10 ms
Bandwidth: 125 MB/sec



What have we learned?

- Bandwidth does not necessary reflect the performance
- GPUs have better “throughput”, but end2end latency is worse than CPUs if your samples are small

Latency/Delay v.s. Throughput

	Toyota Prius	100 Gb Network
	•100 miles (161 km) from UCSD •75 MPH on highway! •Max load: 374 kg = 2,770 hard drives (2TB per drive)	•100 miles (161 km) from UCSD •Lightspeed! — $3*10^8$m/sec •Max load:4 lanes operating at 25GHz
bandwidth	290GB/sec	100 Gb/s or 12.5GB/sec
total latency	3.5 hours	2 Peta-byte over 167772 seconds = 1.94 Days
latency in getting the first moivie	You see nothing in the first 3.5 hours	100GB/100Gb = 8 secs! You can start watching the first movie in 8 secs!

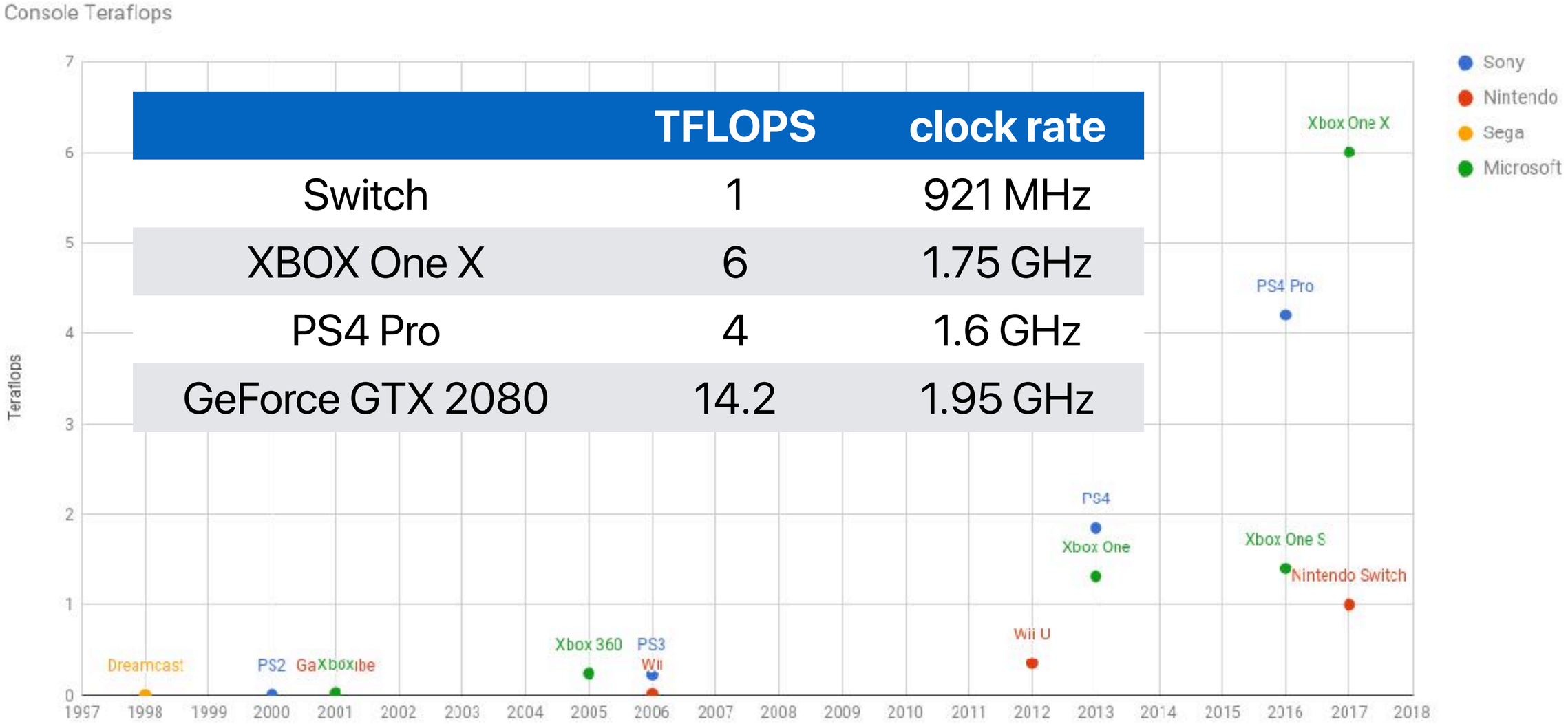
"Fair" Comparisons

Andrew Davison. Twelve Ways to Fool the Masses When Giving Performance Results on Parallel Computers. In Humour the Computer, MITP, 1995

V. Sze, Y. -H. Chen, T. -J. Yang and J. S. Emer. How to Evaluate Deep Neural Network Processors: TOPS/W (Alone) Considered Harmful. In IEEE Solid-State Circuits Magazine, vol. 12, no. 3, pp. 28-41, Summer 2020.

TFLOPS (Tera FLoating-point Operations Per Second)

	TFLOPS	clock rate
Switch	1	921 MHz
XBOX One X	6	1.75 GHz
PS4 Pro	4	1.6 GHz
GeForce GTX 2080	14.2	1.95 GHz



Is TFLOPS (Tera FLoating-point Operations Per Second) a good metric?

$$TFLOPS = \frac{\#\ of\ floating\ point\ instructions \times 10^{-12}}{Exection\ Time}$$

$$= \frac{IC \times \%\ of\ floating\ point\ instructions \times 10^{-12}}{IC \times CPI \times CT}$$

$$= \frac{\%\ of\ floating\ point\ instructions \times 10^{-12}}{CPI \times CT}$$

IC is gone!

- Cannot compare different ISA/compiler
  - What if the compiler can generate code with fewer instructions?
  - What if new architecture has more IC but also lower CPI?
- Does not make sense if the application is not floating point intensive

TFLOPS (Tera FLoating-point Operations Per Second)

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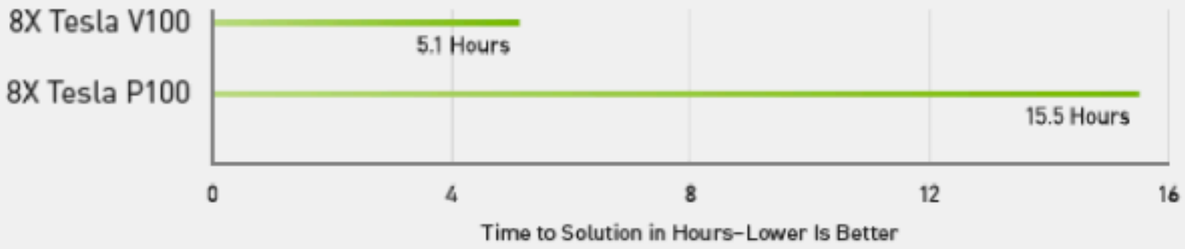
Deep Learning Training in Less Than a Workday



Server Config: Dual Xeon E5-2699 v4 2.6 GHz | 8X NVIDIA® Tesla® P100 or V100 | ResNet-50 Training on MXNet for 90 Epochs with 1.28M ImageNet Dataset.

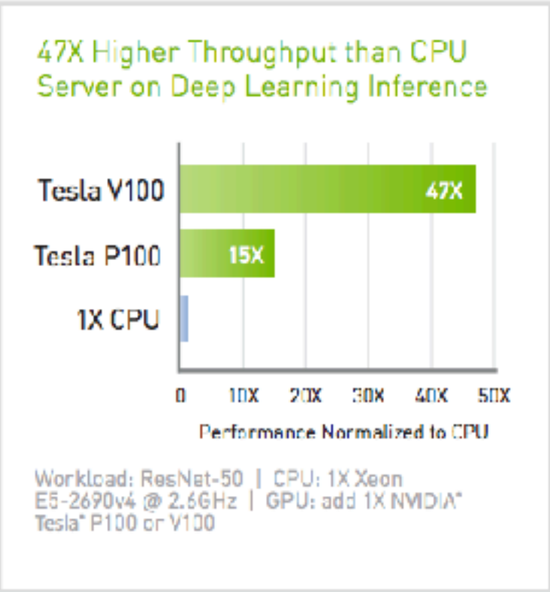
AI TRAINING

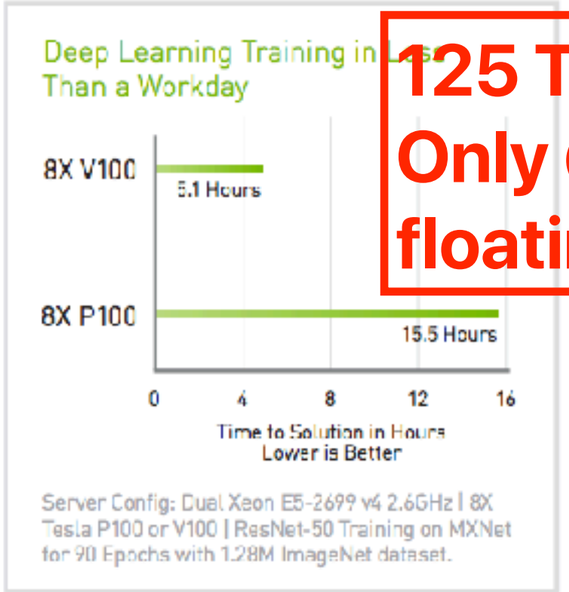
From recognizing speech to training virtual personal assistants and teaching autonomous cars to drive, data scientists are taking on increasingly complex challenges with AI. Solving these kinds of problems requires training deep learning models that are exponentially growing in complexity, in a practical amount of time.

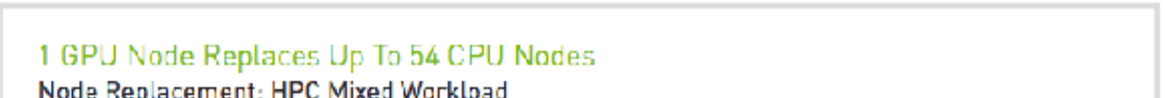
With 640 Tensor Cores, Tesla V100 is the world's first GPU to break the 100 teraFLOPS (TFLOPS) barrier of deep learning performance. The next generation of NVIDIA NVLink™ connects multiple V100 GPUs at up to 300 GB/s to create the world's most powerful computing servers. AI models that would consume weeks of computing resources on previous systems can now be trained in a few days. With this dramatic reduction in training time, a whole new world of problems will now be solvable with AI.

The Most Advanced Data Center GPU Ever Built.

NVIDIA® Tesla® V100 is the world's most advanced data center GPU ever built to accelerate AI, HPC, and graphics. Powered by NVIDIA Volta, the latest GPU architecture, Tesla V100 offers the performance of up to 100 CPUs in a single GPU—enabling data scientists, researchers, and engineers to tackle challenges that were once thought impossible.

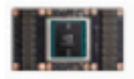






125 TFLOPS Only @ 16-bit floating point

SPECIFICATIONS



	Tesla V100 PCIe	Tesla V100 SXM2
GPU Architecture	NVIDIA Volta	
NVIDIA Tensor Cores	640	
NVIDIA CUDA® Cores	5,120	
Double-Precision Performance	7 TFLOPS	7.8 TFLOPS
Single-Precision Performance	14 TFLOPS	15.7 TFLOPS
Tensor Performance	112 TFLOPS	125 TFLOPS
GPU Memory	32GB /16GB HBM2	
Memory Bandwidth	900GB/sec	
ECC	Yes	
Interconnect Bandwidth	32GB/sec	300GB/sec
System Interface	PCIe Gen3	NVIDIA NVLink
Form Factor	PCIe Full Height/Length	SXM2
Max Power		

They try to tell it's the better AI hardware

https://blogs.nvidia.com/blog/2017/04/10/ai-drives-rise-accelerated-computing-datacenter/

	K80 2012	TPU 2015	P40 2016
Inferences/Sec <10ms latency	$^1/_{13}$X	1X	2X
Training TOPS	6 FP32	NA	12 FP32
Inference TOPS	6 FP32	90 INT8	48 INT8
On-chip Memory	16 MB	24 MB	11 MB
Power	300W	75W	250W
Bandwidth	320 GB/S	34 GB/S	350 GB/S

Inference per second

$$\frac{Inferences}{Second} = \frac{Inferences}{Operation} \times \frac{Operations}{Second}$$

$$= \frac{Inferences}{Operation} \times [\frac{operations}{cycle} \times \frac{cycles}{second} \times \#\_of\_PEs \times Utilization\_of\_PEs]$$

	Hardware	Model	Input Data
Operations per inference		v	
Operations per cycle	v		
Cycles per second	v		
Number of PEs	v		
Utilization of PEs	v	v	
Effectual operations out of (total) operations		v	v
Effectual operations plus unexploited ineffectual operations per cycle	v		

What's wrong with inferences per second?

- There is no standard on how they inference — but these affect!
  - What model?
  - What dataset?
  - Quality?
- That's why Facebook is trying to promote an AI benchmark — MLPerf

- *Pitfall: For NN hardware, Inferences Per Second (IPS) is an inaccurate summary performance metric.*

Our results show that IPS is a poor overall performance summary for NN hardware, as it's simply the inverse of the complexity of the typical inference in the application (e.g., the number, size, and type of NN layers). For example, the TPU runs the 4-layer MLP1 at 360,000 IPS but the 89-layer CNN1 at only 4,700 IPS, so TPU IPS vary by 75X! Thus, using IPS as the single-speed summary is *even more misleading* for NN accelerators than MIPS or FLOPS are for regular processors [23], so IPS should be even more disparaged. To compare NN machines better, we need a benchmark suite written at a high-level to port it to the wide variety of NN architectures. Fathom is a promising new attempt at such a benchmark suite [3].

Extreme Multitasking Performance

- Dual 4K external monitors
- 1080p device display
- 7 applications

What's missing in this video clip?

- The ISA of the "competitor"
- Clock rate, CPU architecture, cache size, how many cores
- How big the RAM?
- How fast the disk?

12 ways to Fool the Masses When Giving Performance Results on Parallel Computers

- Quote only 32-bit performance results, not 64-bit results.
- Present performance figures for an inner kernel, and then represent these figures as the performance of the entire application.
- Quietly employ assembly code and other low-level language constructs.
- Scale up the problem size with the number of processors, but omit any mention of this fact.
- Quote performance results projected to a full system.
- Compare your results against scalar, unoptimized code on Crays.
- When direct run time comparisons are required, compare with an old code on an obsolete system.
- If MFLOPS rates must be quoted, base the operation count on the parallel implementation, not on the best sequential implementation.
- Quote performance in terms of processor utilization, parallel speedups or MFLOPS per dollar.
- Mutilate the algorithm used in the parallel implementation to match the architecture.
- Measure parallel run times on a dedicated system, but measure conventional run times in a busy environment.
- If all else fails, show pretty pictures and animated videos, and don't talk about performance.