

CIS 431/531

Intro to Parallel Computing

Lecture 1

Why do we care about parallelism?

What? (Goal)

Learn practical parallel programming (i.e., how to write *fast* code).

Why?

Fast code saves *time* and *energy*.

How?

Parallelism

Data Locality

Specialization

Motivation

Currently, parallelism is driven by
power, memory, and physics.

Performance & Power

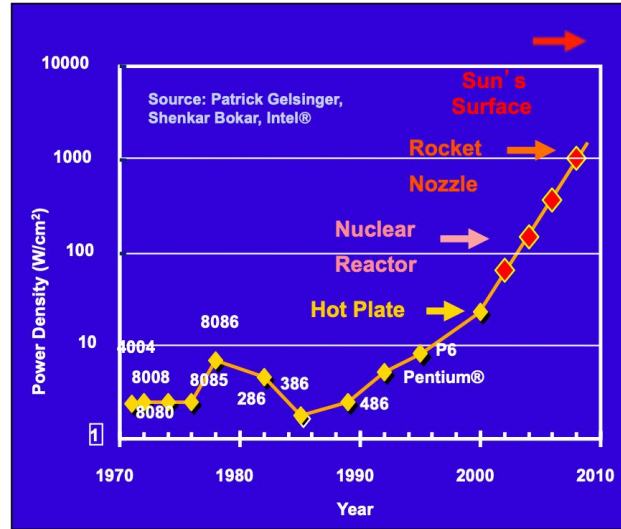
Performance \propto ?

Performance & Power

Performance \propto (cores) \times (freq)

Power \propto ?

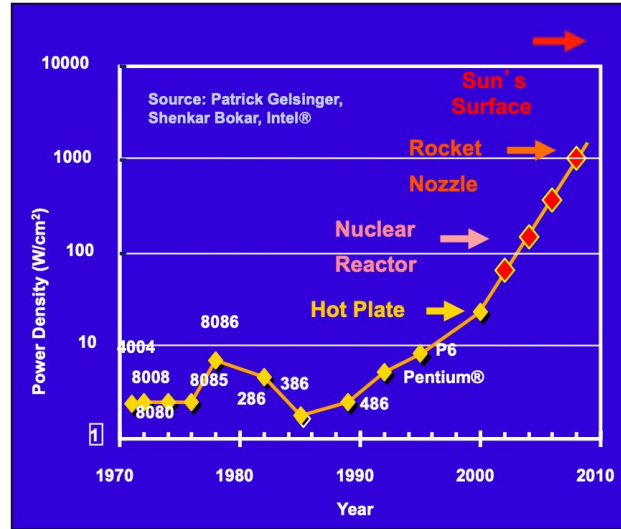
Performance & Power



Performance \propto (cores) \times (freq)

Power \propto (cores) \times (freq^{2.5})

Performance & Power

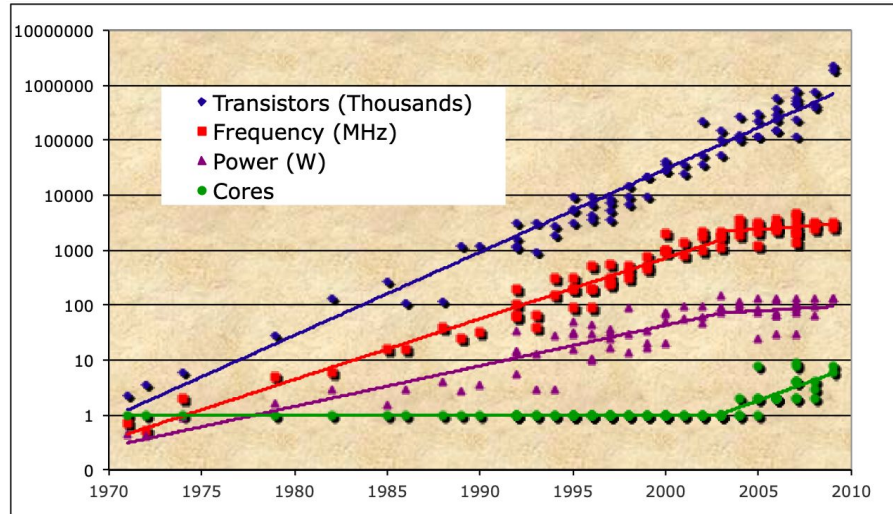


Performance \propto (cores) \times (freq)

Power \propto (cores) \times (freq^{2.5})

*Is it better to increase performance by doubling **frequency** or the number **cores**?*

Parallelism & Power



Notice the transition around **2004**.

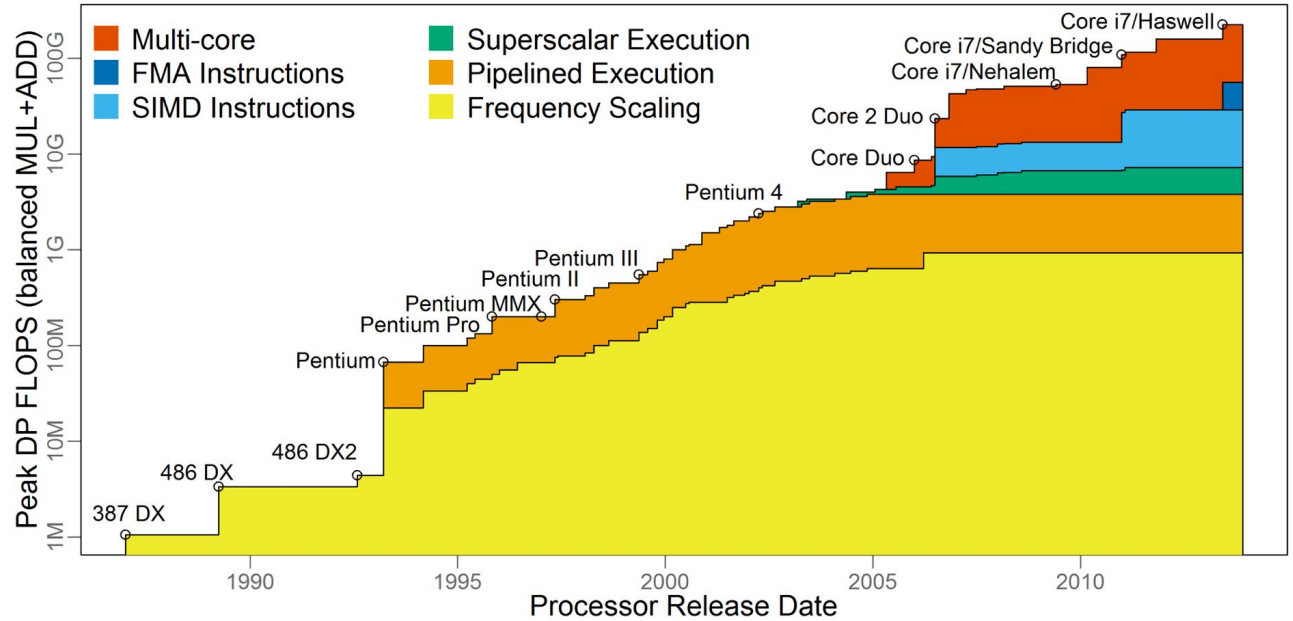
End of *Dennard Scaling*.

Parallelism & Power

Conclusion

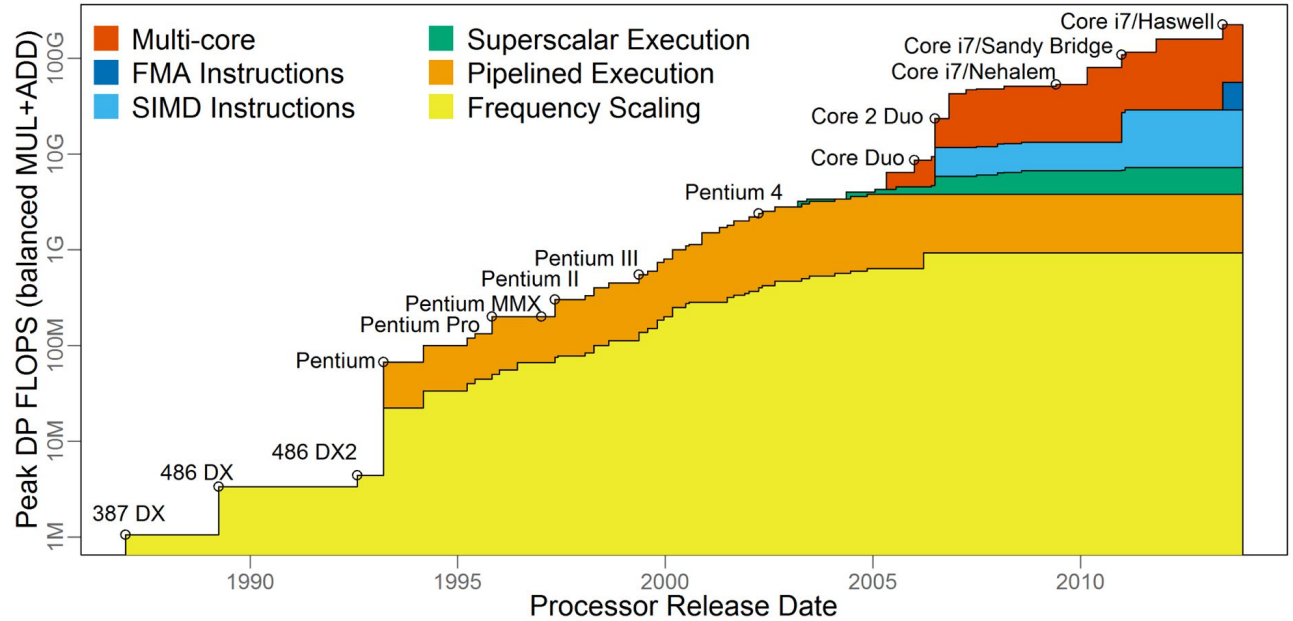
- We **HAVE** to rely on increasing the number of cores to increase the performance of a processor
- This means that **programmers** have to write code that can take advantage of parallelism to better utilize processors

Performance Factors



What else has been done to increase performance?

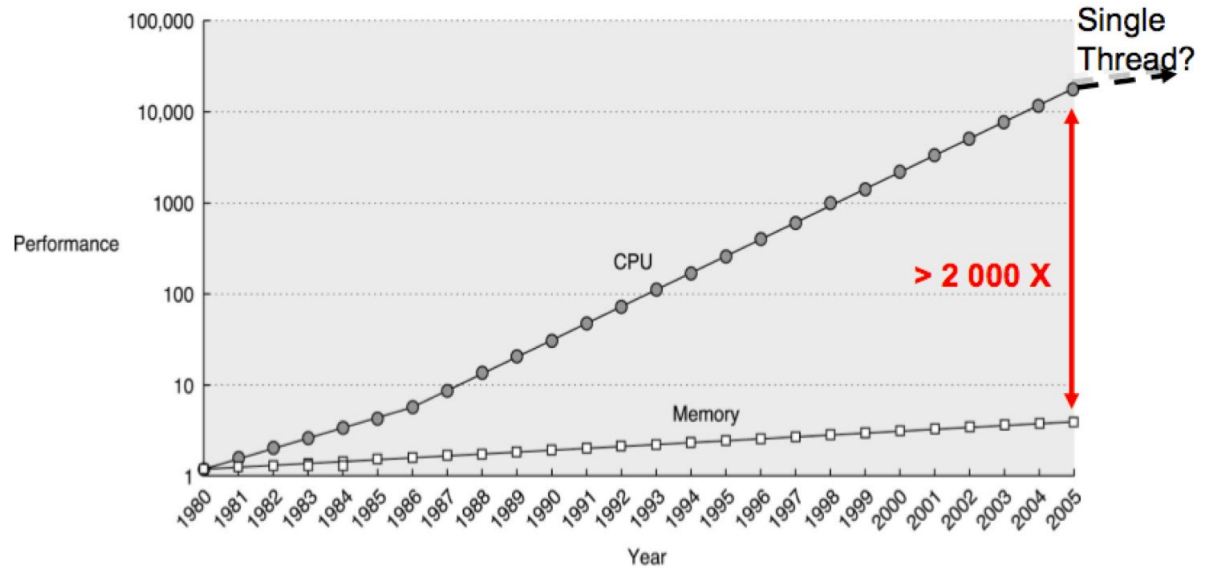
Performance Factors



What else has been done to increase performance?

Low-precision operations, tensor cores, neural engines, etc.

Memory



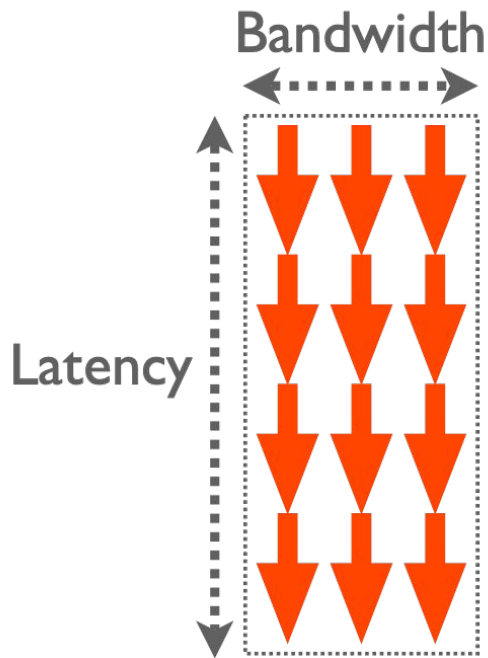
Memory performance has scaled much more slowly than instruction performance (i.e., FLOPS)

Historically, memory

latency halves every ~9 years

bandwidth doubles every ~3 years

Memory



Little's Law (queuing theory)

$$L = \lambda W$$

Equivalently,

$$\text{Concurrency} = \text{Latency} \times \text{Bandwidth}$$

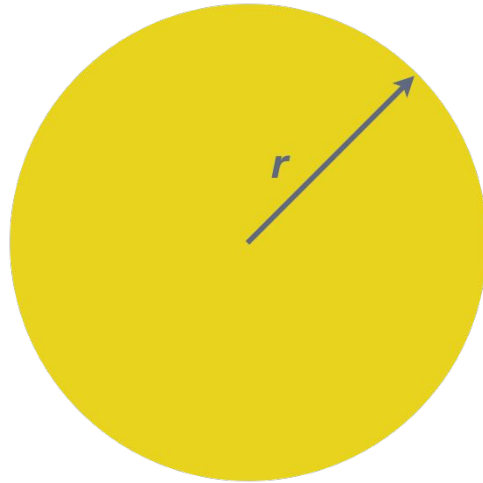
That is, larger the latency and bandwidth, more concurrency (i.e., threads) is required to fully utilize the memory bandwidth.

Memory

Conclusion

- To keep the increased number of processing units busy, we must deliver data at a higher rate (i.e., higher bandwidth).
- However, higher bandwidth requires having more memory requests in-flight, which can only happen if you can find more independent threads of execution (i.e., increased parallelism).

Physical Limits



Size of a modern processor -
40mm x 40mm -> $r = 20\text{mm}$

Speed of light = $3 \times 10^8 \text{ m/s}$

Time to go from one end of a chip
to the other $t = (40 \times 10^{-3} \text{ m}) / (3 \times 10^8 \text{ m/s}) = 1.33 \times 10^{-10} \text{ seconds}$

One operation CANNOT take
more than $1.33 \times 10^{-10} \text{ seconds}$.

Equivalently, clock frequency
cannot exceed $1 / (1.33 \times 10^{-10}) = 7.5 \text{ GHz}$

Latest Intel I9-11900K runs at 5.3
GHz

Physical Limits

1. Quantum mechanics (e.g., quantum tunneling effect)
2. EUV (extreme ultraviolet) lithography

Conclusion

As a result of these trends, **parallelism** has become **ubiquitous**.
No matter what system scale you care about, parallelism affects you.



Apple A17 Pro System-on-chip (SoC)

3nm process

19 Billion transistors

2x performance cores (up to 3.78 GHz)

4x power-efficiency cores (up to 2.11 GHz)

6x GPU cores (up to 1.4 GHz)

16x Neural Engine cores

~8 Watts



Intel Core i9-13900KS

10nm process

8x performance cores (up to 5.4 GHz)

16x power-efficiency cores (up to 4.3 GHz)

6 GHz single core boost frequency

32x GPU cores (up to 1.65 GHz)

Gaussian & Neural accelerator

~125 Watts



Frontier Supercomputer (Department of Energy)
1.102 exaFLOPs (quintillion or 10^{18})
9,472x AMD Epyc 7453 CPUs
606,208 cores @ 2GHz
37,888x AMD Radeon Instinct MI250x GPUs
8,335,360 cores @ up to 1.7 GHz
21 MWatts

Beyond Parallelism

To achieve extreme performance, more is needed - **data locality** and **specialization**.

- Data locality is necessary since bandwidth is much slower than processor performance
- What about specialization?

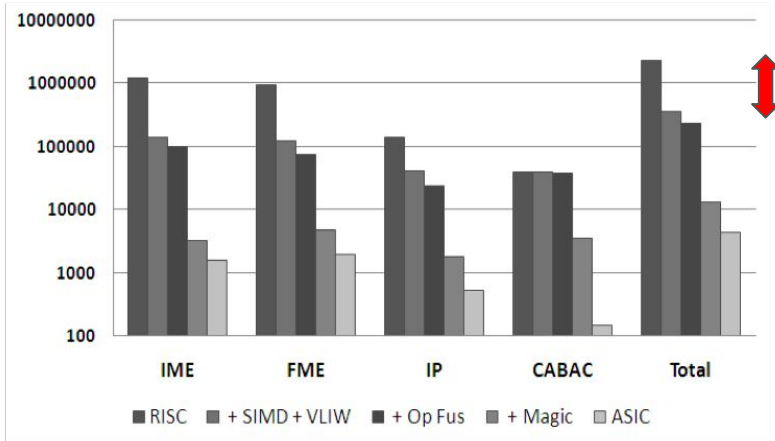


Figure 2. Each set of bar graphs represents energy consumption (μJ) at each stage of optimization for IME, FME, IP and CABAC respectively. Each optimization builds on the ones in the previous stage with the first bar in each set representing RISC energy dissipation followed by generic optimizations such as SIMD and VLIW, operation fusion and ending with “magic” instructions

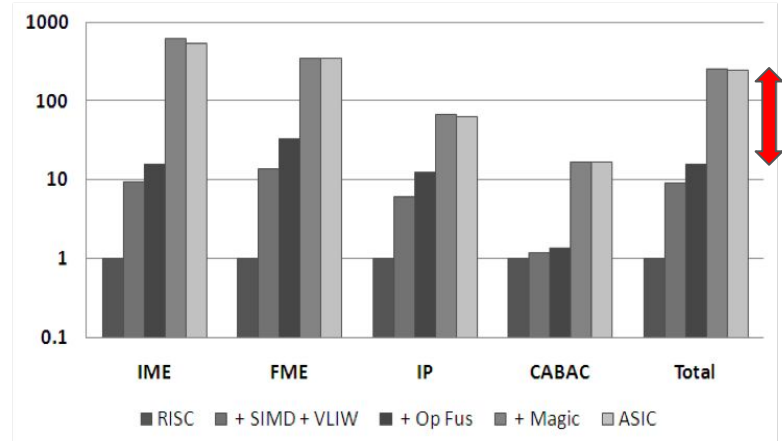


Figure 3. Each set of bar graphs represents speedup at each stage of optimization. Each optimization builds on those of the previous stage with the first bar in each set representing RISC speedup, followed by generic optimizations such as SIMD and VLIW, then operation fusion and finally “magic” instructions

~ 10x in energy (left) and time (right) from generic optimizations

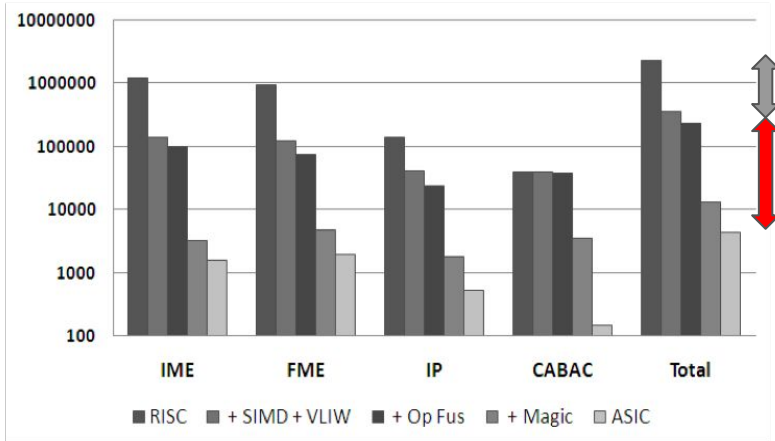


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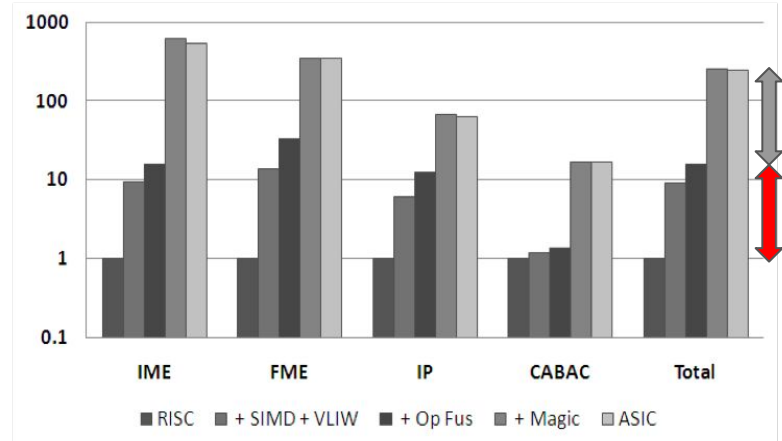


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~ 10x in energy (left) and time (right) from generic optimizations (hardware & software)

~ 10x+ in energy (left) and time (right) from application-specific customization

Specialization

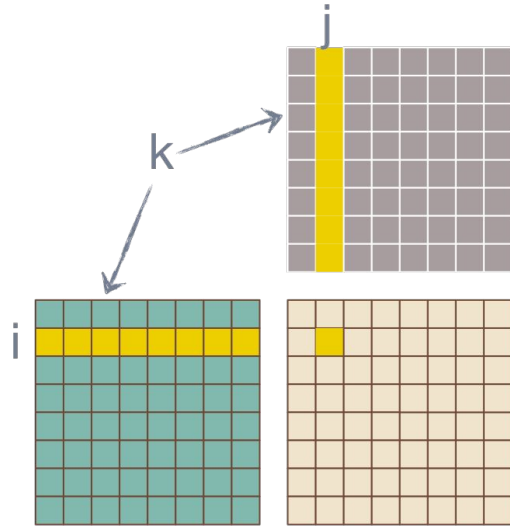
1. Application-specific integrated circuit (ASIC) is **500x** more energy efficient than general-purpose chip multi-processors (CMP)
2. Over **90%** of energy is “**overhead**” (e.g., instruction fetch/decode, etc.) because the cost of actual FLOP is very cheap.

Conclusion

These observations imply we need to pay attention to **data movement** and exploit **custom units** (e.g., GPUs) to improve energy efficiency and performance (in addition to parallelization)

Theory vs. Practice

Example: **Matrix multiply** (non-Strassen)



$$C \leftarrow C + A * B$$

```
for i = 1 to n do
  for j = 1 to n do
    for k = 1 to n do
       $C[i,j] \leftarrow C[i,j] + A[i,k] \cdot B[k,j]$ 
```

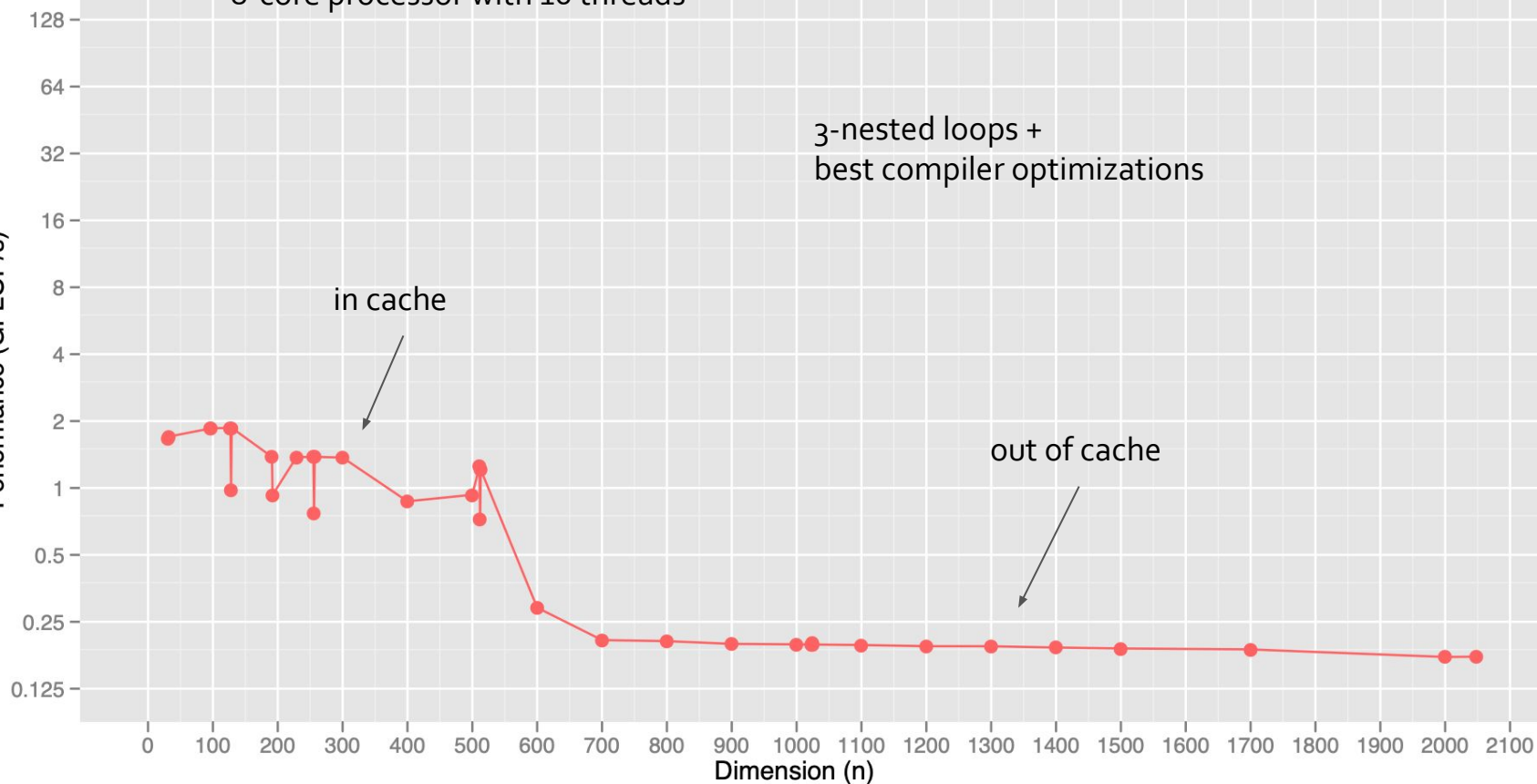
8-core processor with 16 threads

3-nested loops +
best compiler optimizations

Performance (GFLOP/s)

in cache

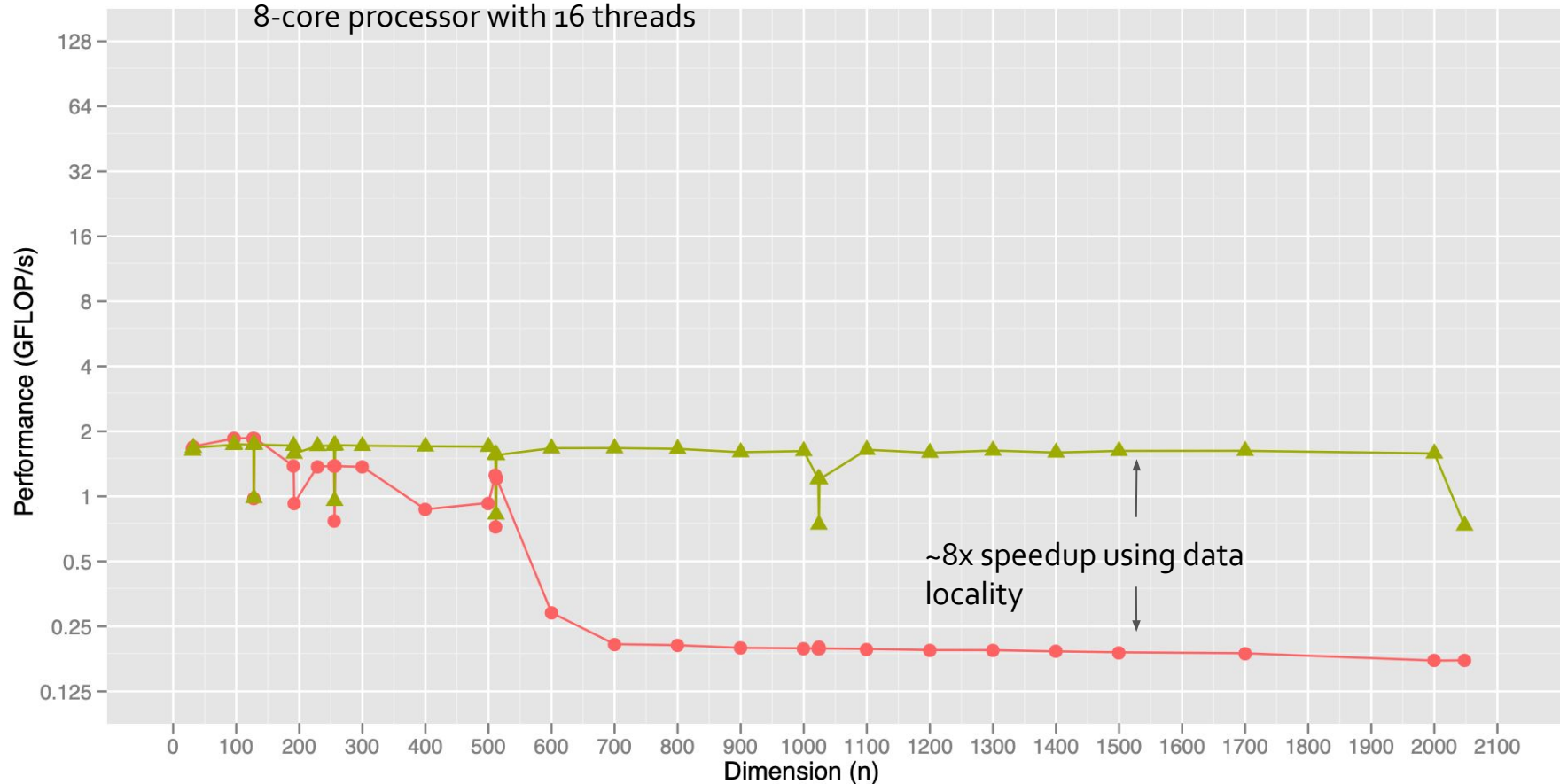
out of cache



Code

● Baseline ▲ Blocked ■ Cilk++ (rec): p=16 + Intel MKL ⊠ Intel MKL: p=16

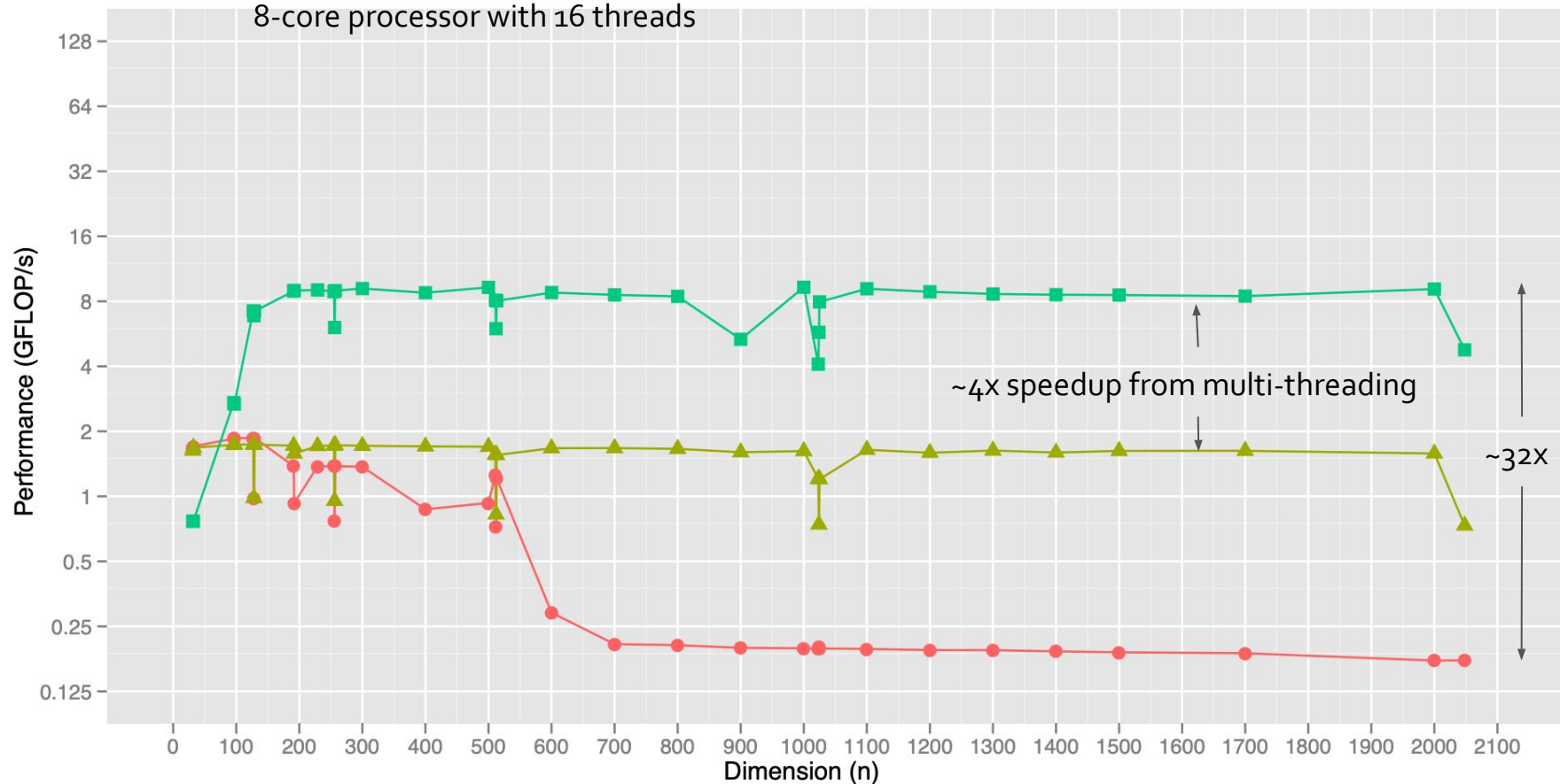
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Code

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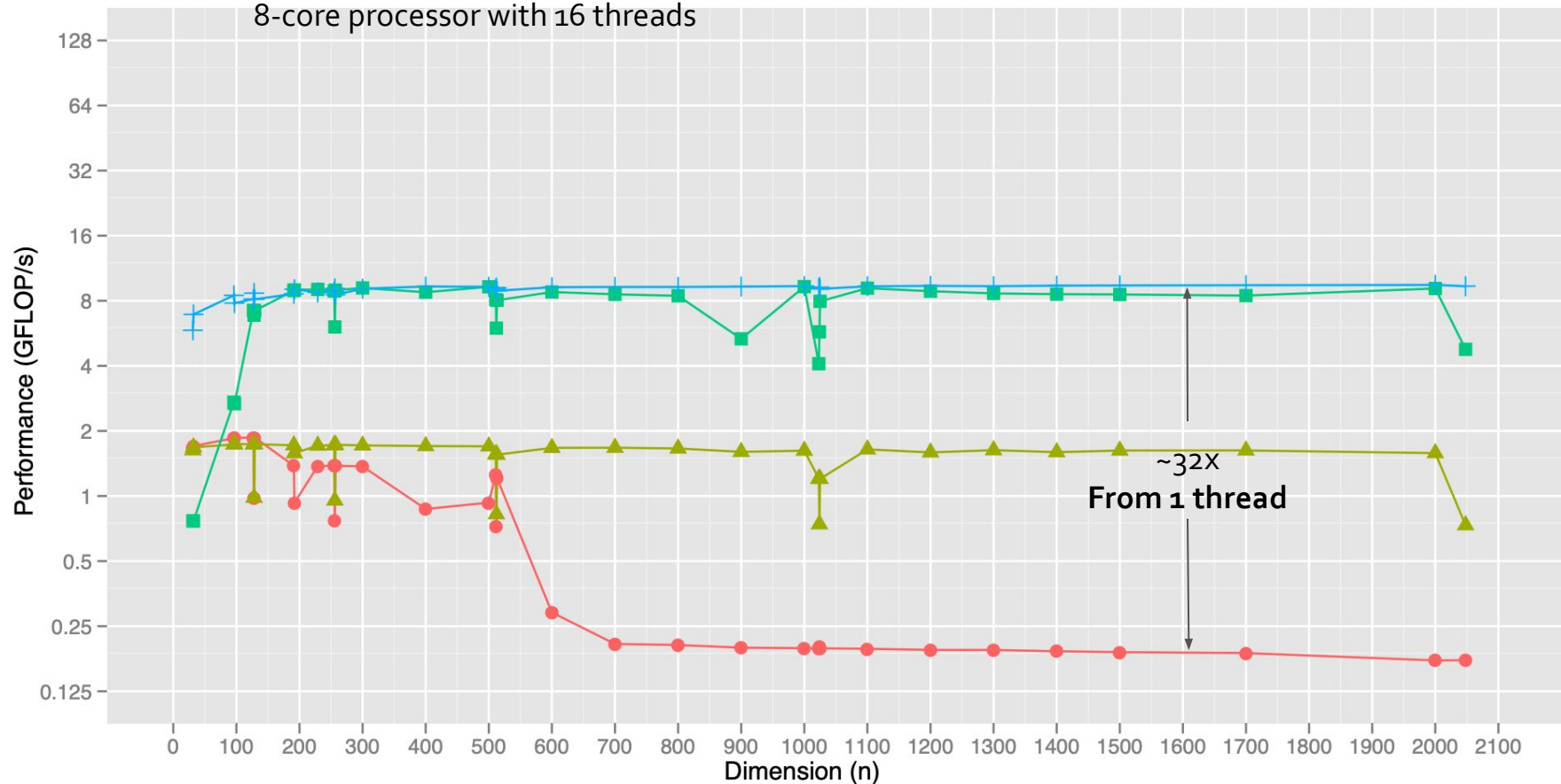
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Code

- Baseline
- ▲ Blocked
- Cilk++ (rec): p=16
- + Intel MKL
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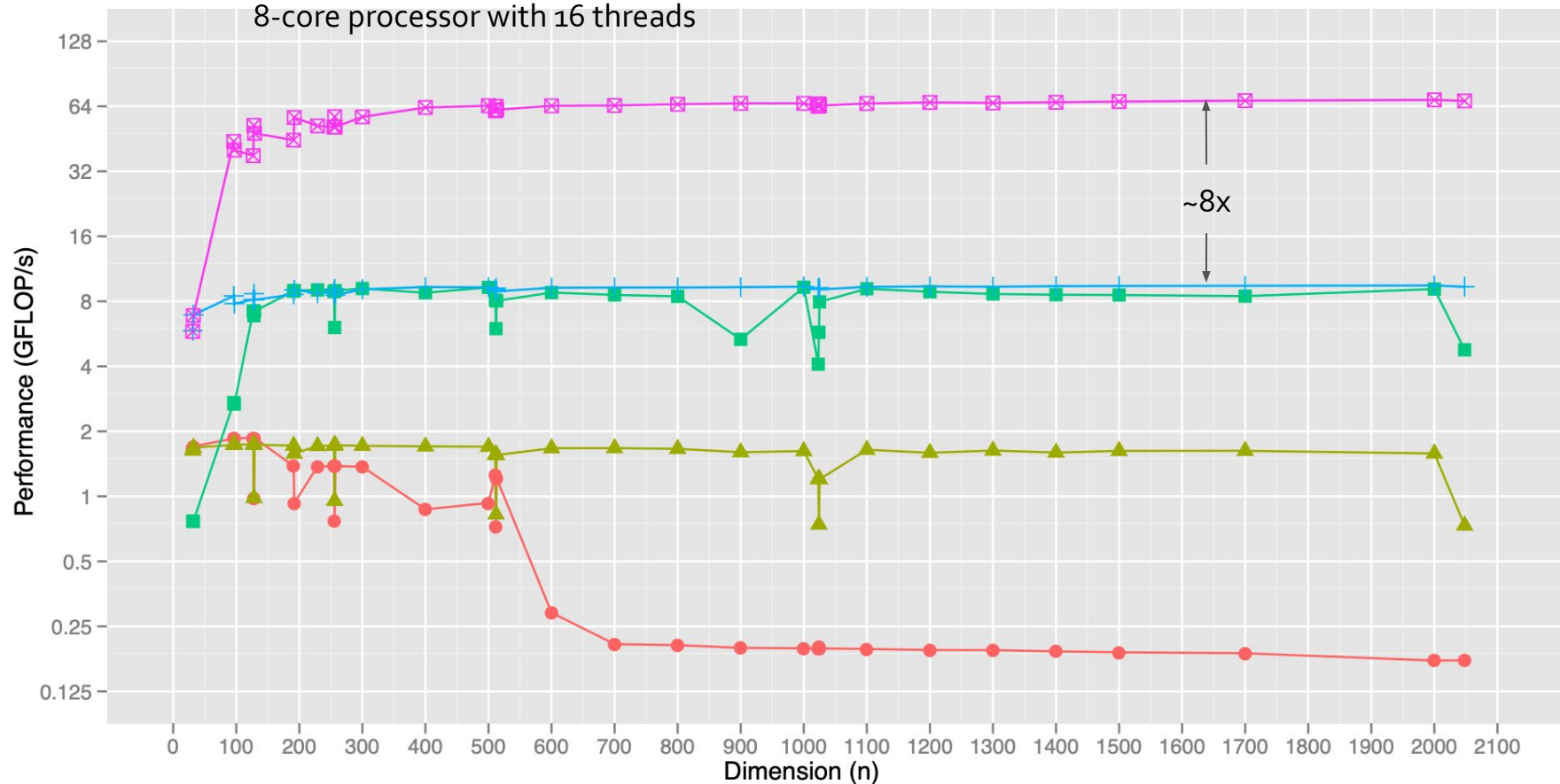
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Code

- Baseline
- Blocked
- Cilk++ (rec): p=16
- Intel MKL
- Intel MKL: p=16

8-core processor with 16 threads



Can Compilers Do This?

Proebsting's Law

Compilers double code performance every **18 years**.

vs. **2 years** for transistors (Moore's Law) and **3 years** for memory

Questions

Misc.

- All coding **must be** version controlled using **git** on **BitBucket**.
 - **Commit your code frequently!**
- All reports must be written using **Latex**.

Syllabus