

HPC & Parallel Programming

Overview

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Computer Science, Kennesaw State University

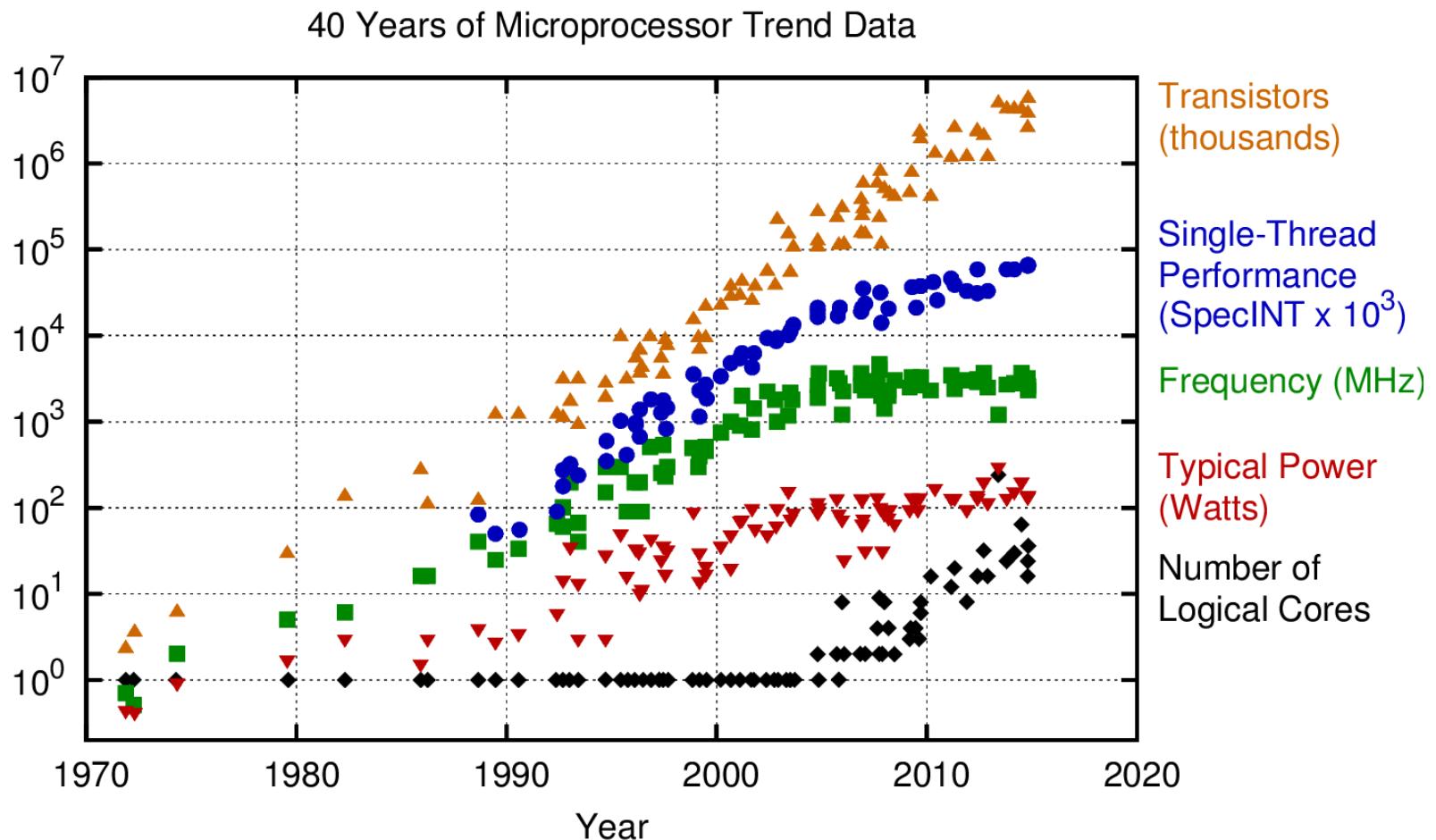
<https://kevinsuo.github.io/>

Changing times

- From 1986 – 2002, microprocessors were speeding like a rocket, increasing in performance an average of 50% per year.
- Since then, it's dropped to about 20% increase per year.



Changing times

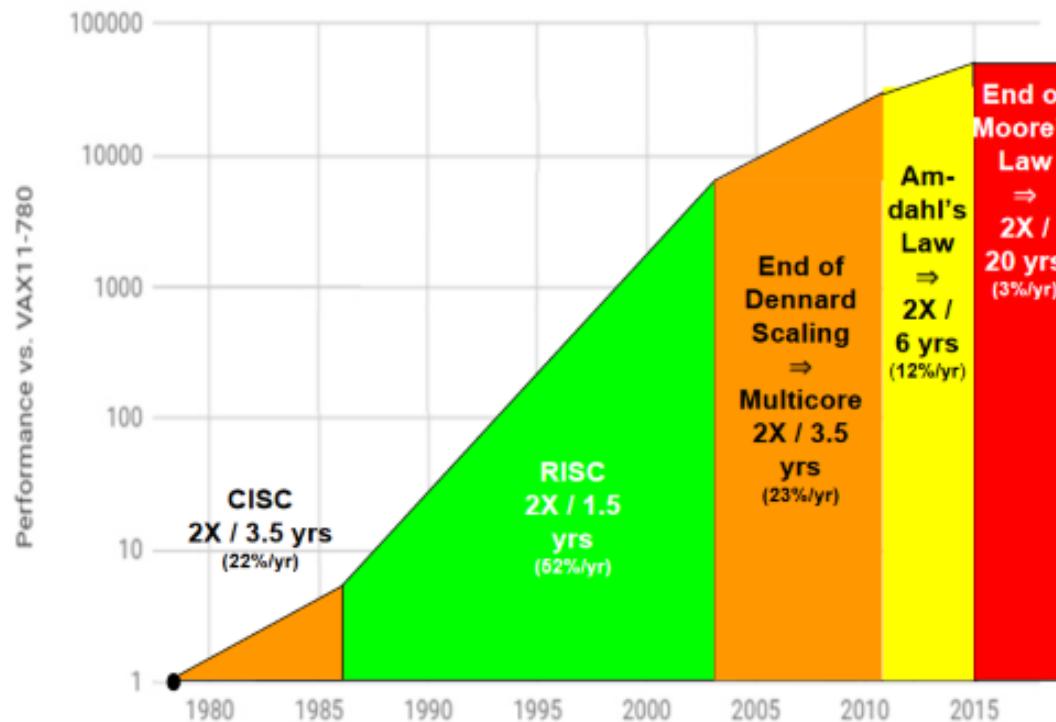


Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten
New plot and data collected for 2010-2015 by K. Rupp



Moore's Law

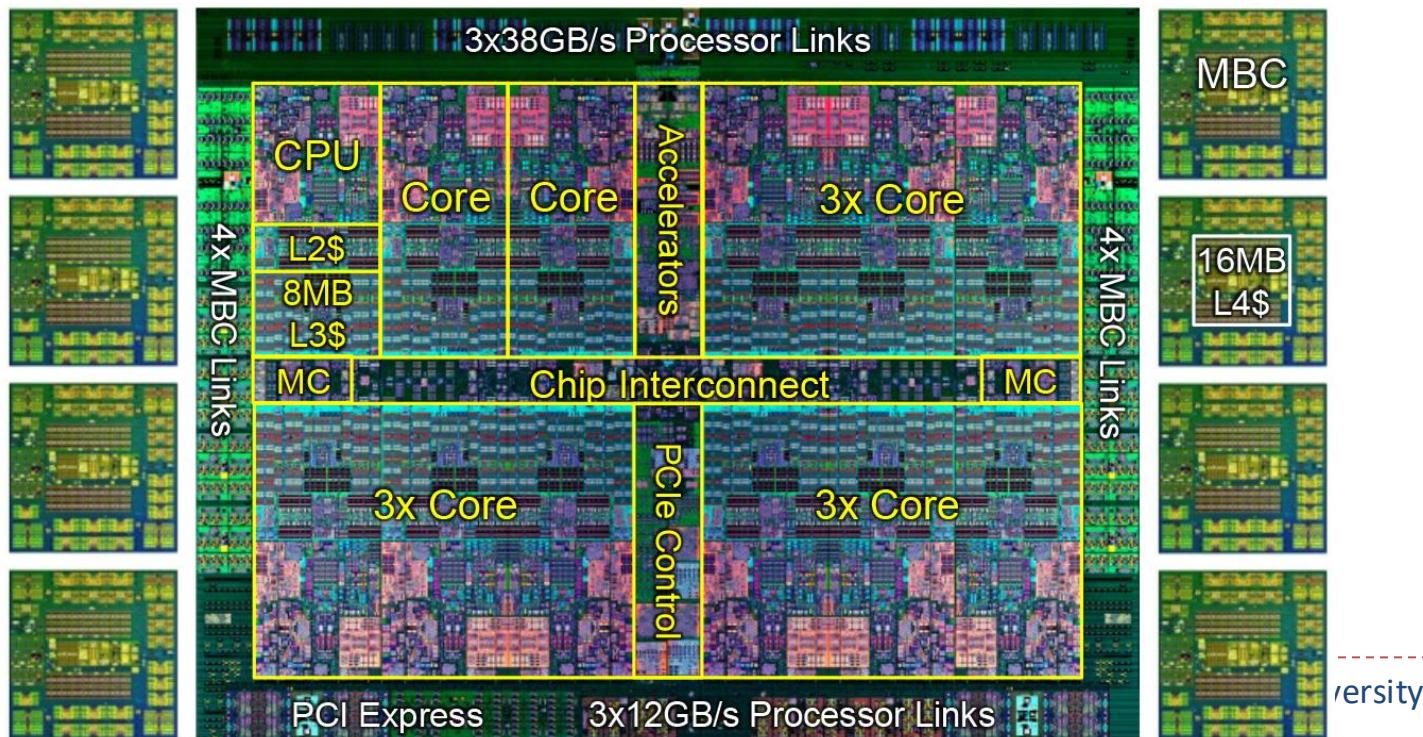
- The observation that the number of transistors in a dense integrated circuit doubles about every two years



An intelligent solution

[https://www.techradar.com/news/ amd-ryzen-threadripper-3990x-is-a-ridiculous-64-core-cpu-and-its-coming-soon](https://www.techradar.com/news/amd-ryzen-threadripper-3990x-is-a-ridiculous-64-core-cpu-and-its-coming-soon)

- Instead of designing and building faster microprocessors, put multiple processors on a single integrated circuit.



Now it's up to the programmers

- Adding more processors doesn't help much if programmers aren't aware of them...
- ... or don't know how to use them.
- Serial programs don't benefit from this approach (in most cases).



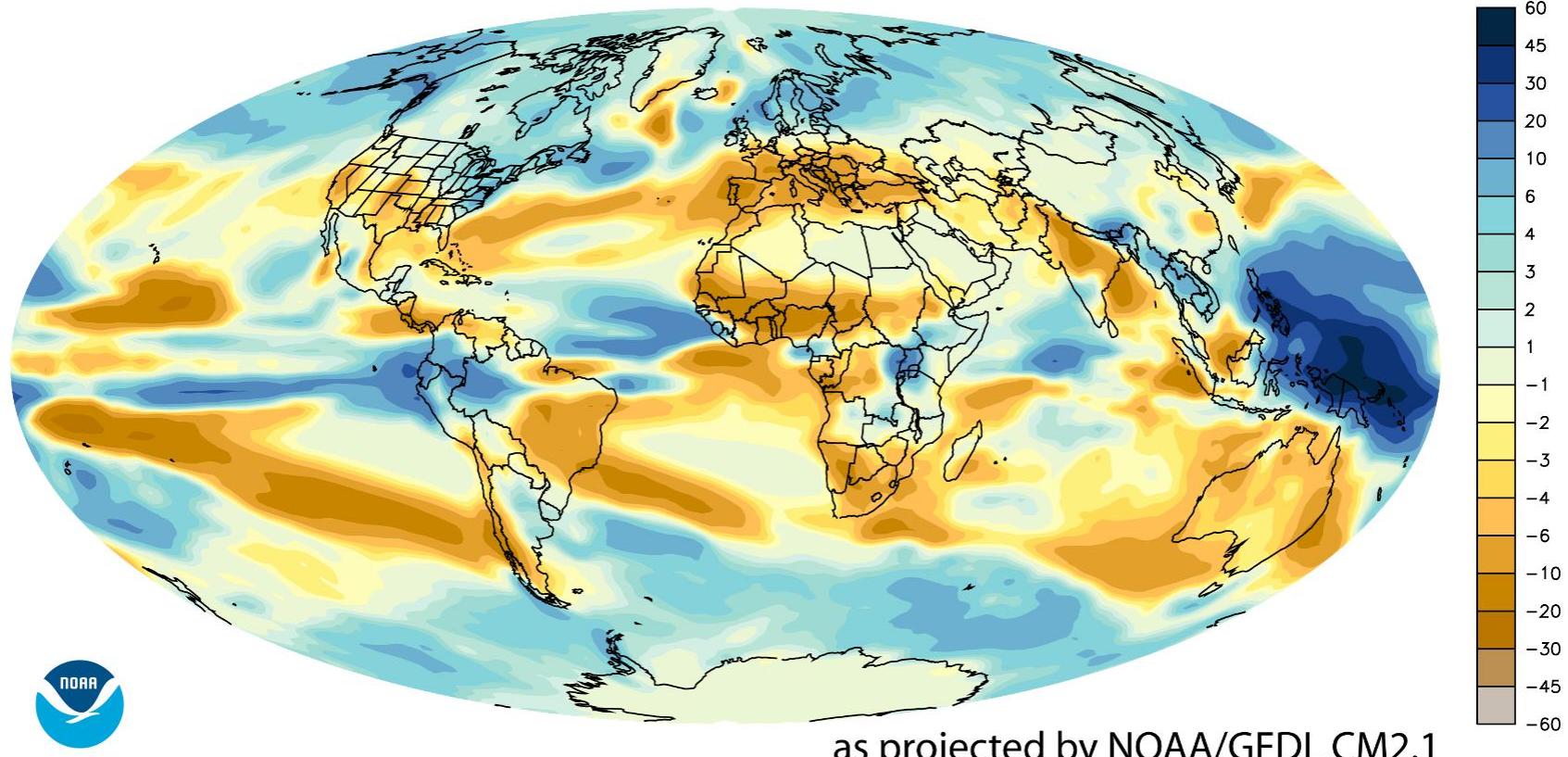
Why we need ever-increasing performance

- Computational power is increasing, but so are our computation problems and needs.
- Problems we never dreamed of have been solved because of past increases, such as decoding the human genome.
- More complex problems are still waiting to be solved.

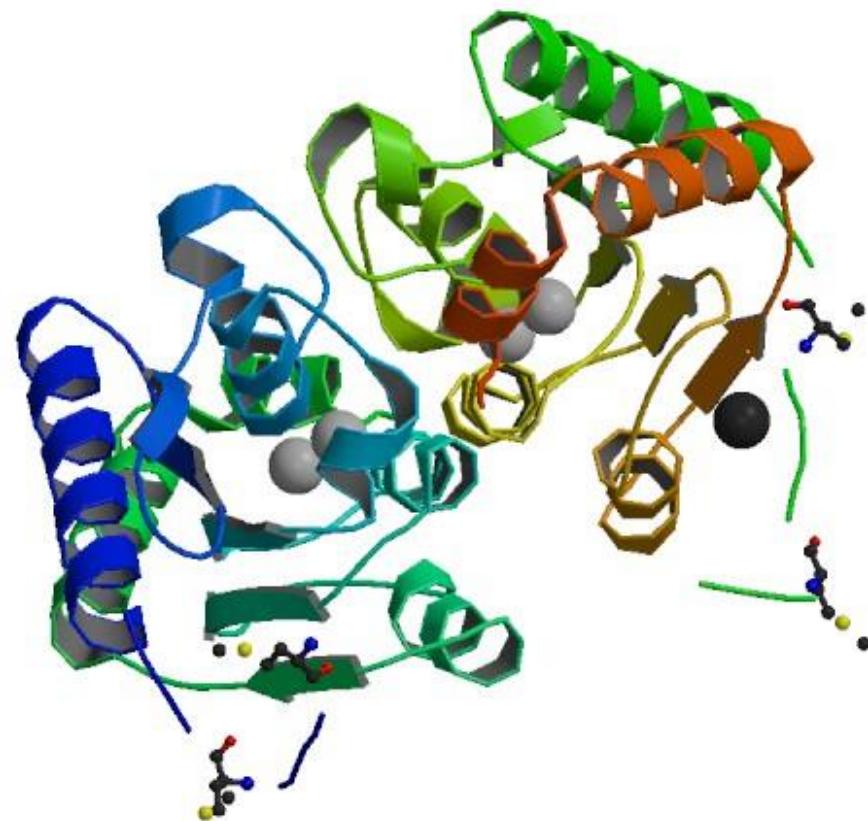
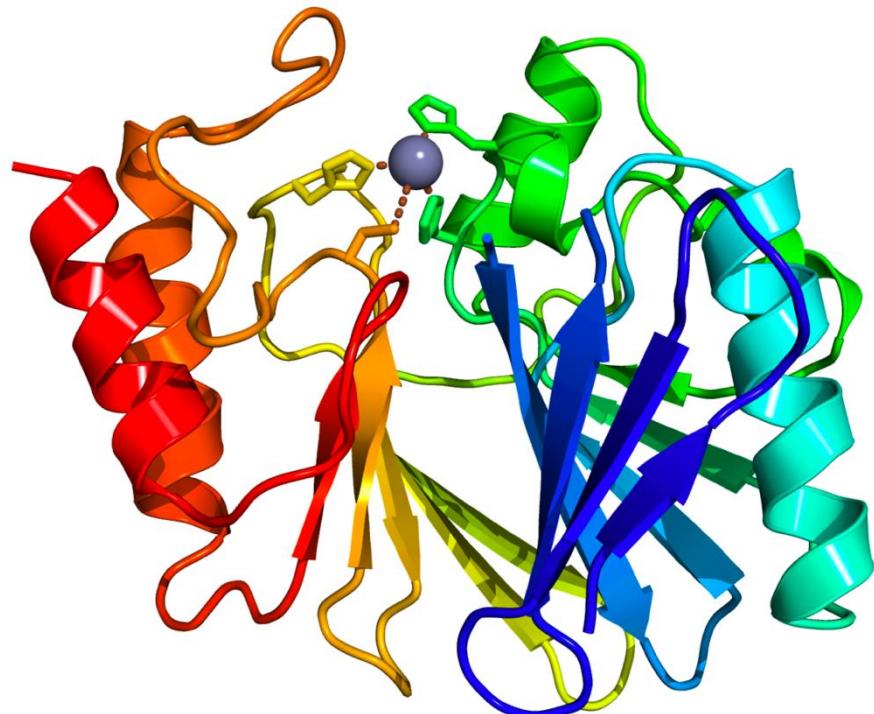


Climate modeling

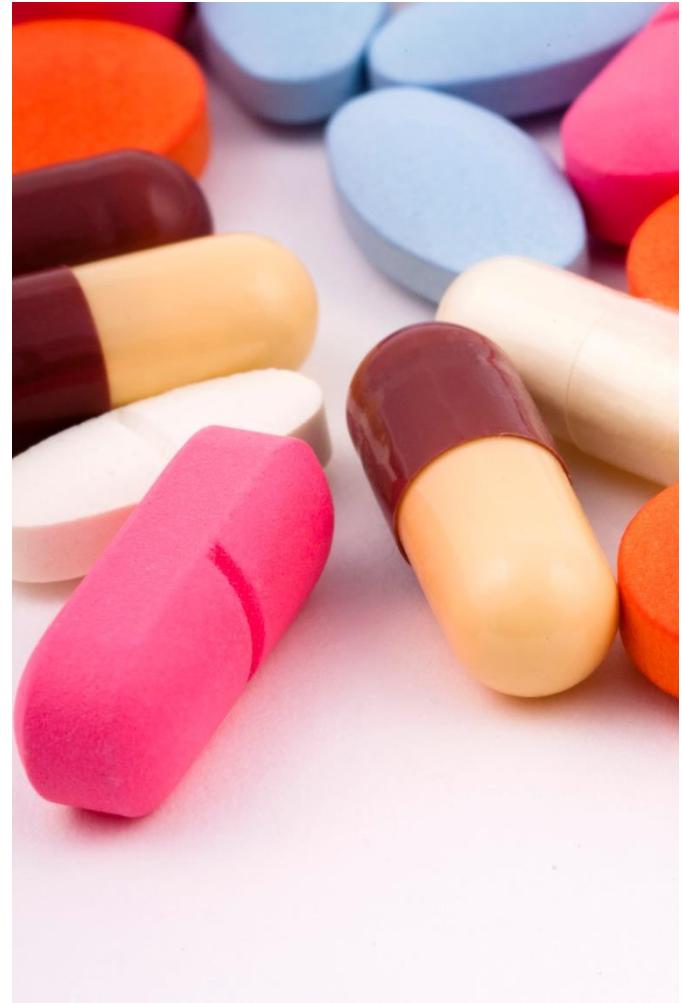
CHANGE IN PRECIPITATION BY END OF 21st CENTURY
inches of liquid water per year



Protein folding



Drug discovery



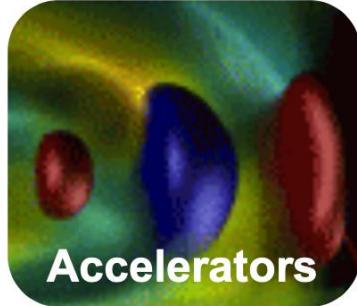
Energy research



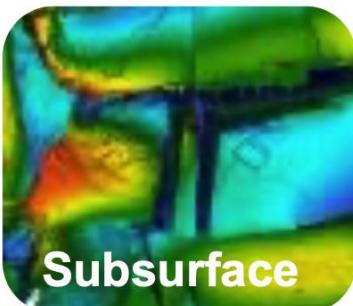
Data analysis



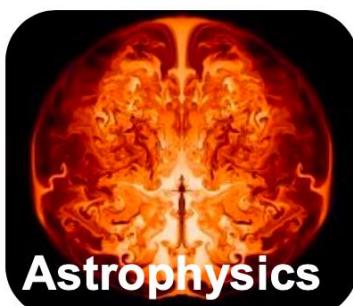
What supercomputing can do?



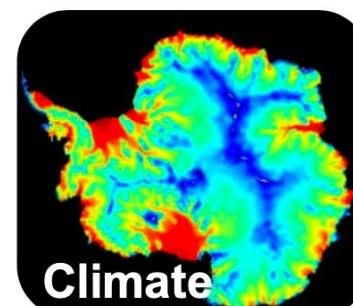
Accelerators



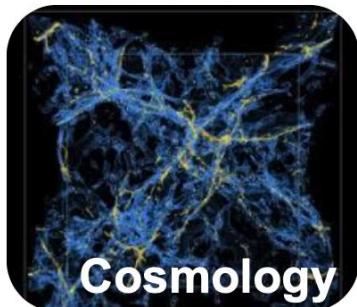
Subsurface



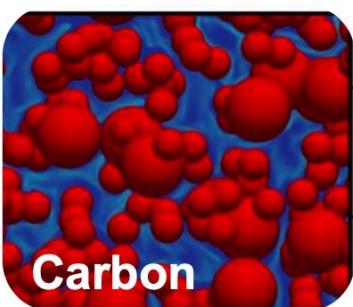
Astrophysics



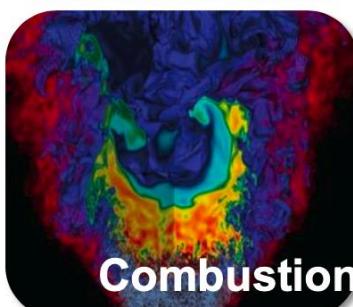
Climate



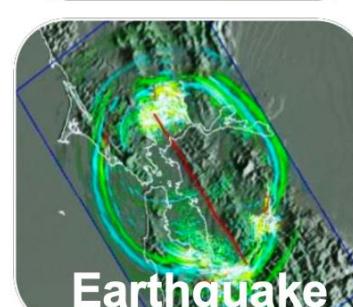
Cosmology



Carbon



Combustion



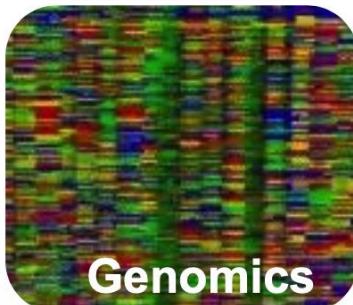
Earthquake



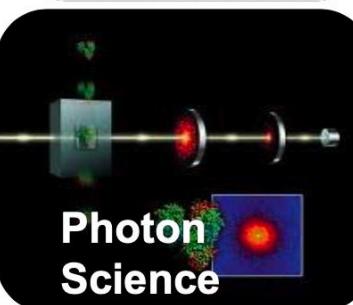
Chemistry



Urban



Genomics



Photon
Science

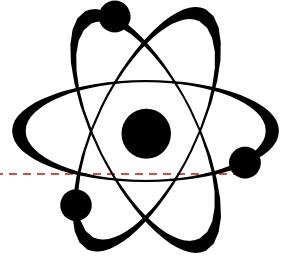


Why we're building parallel systems

- Up to now, performance increases have been attributable to increasing density of transistors.
- But there are inherent problems.



A little physics lesson

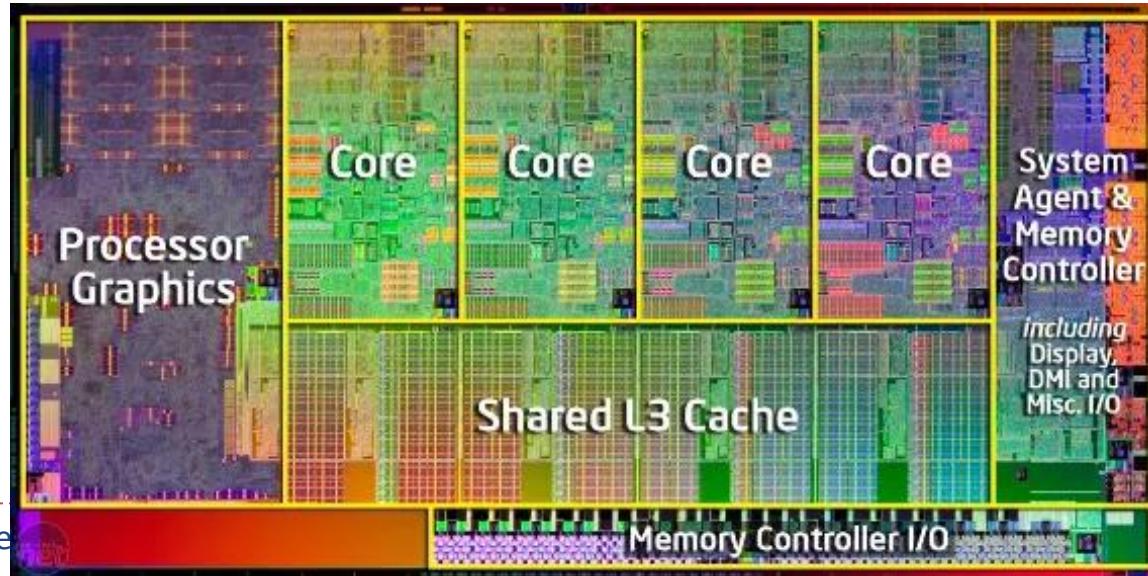


- Smaller transistors = faster processors.
- Faster processors = increased power consumption.
- Increased power consumption = increased heat.
- Increased heat = unreliable processors.



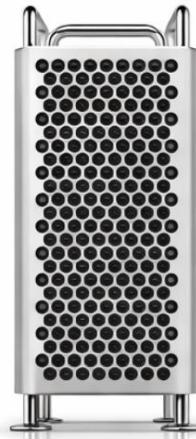
Solution

- Move away from single-core systems to multicore processors.
- “core” = central processing unit (CPU)
- Introducing parallelism!!!



Parallel Machines Today

Examples from Apple's product line:



Mac Pro
Apple M2 Ultra
24 CPU cores
76 GPU cores



14" MacBook Pro
Apple M3 Pro
12 CPU cores
18 GPU cores



24" iMac
Apple M3
8 CPU cores
10 GPU cores



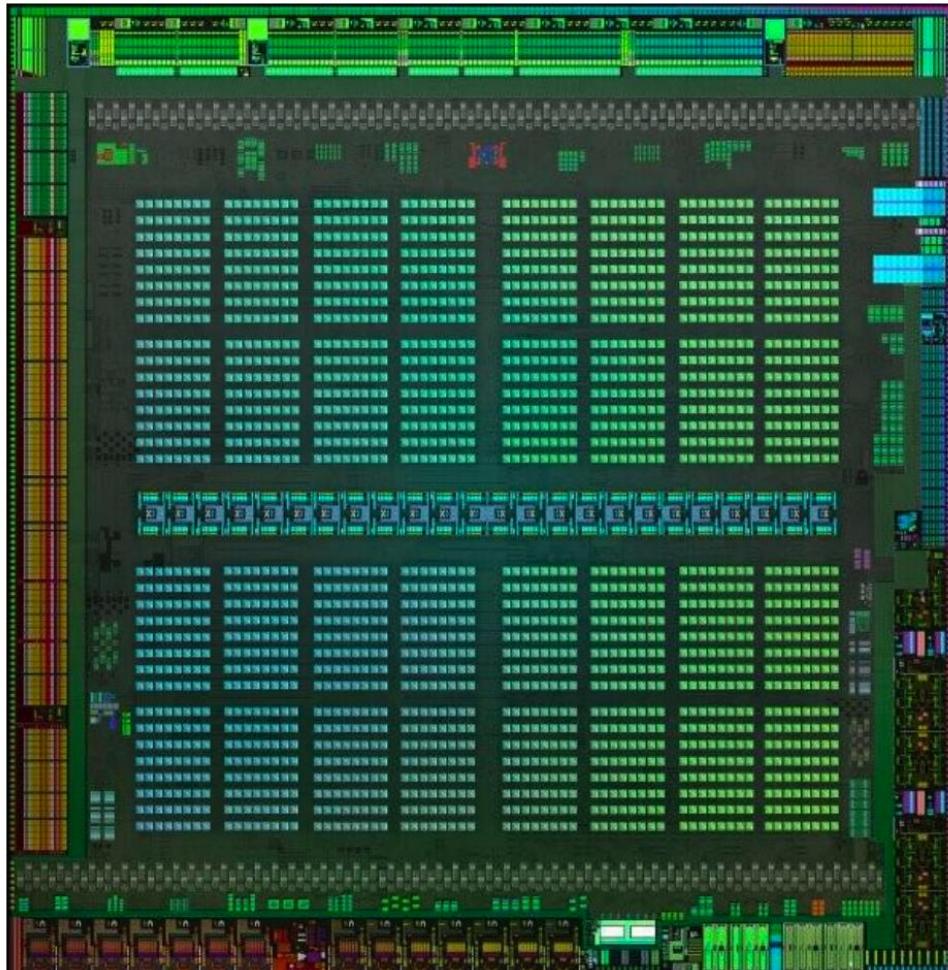
iPhone 15 Pro Max
A17 Pro Chip
6 CPU cores
6 GPU cores



Intel Core Ultra X9 388H (2025)



NVIDIA RTX 5090 (2025)

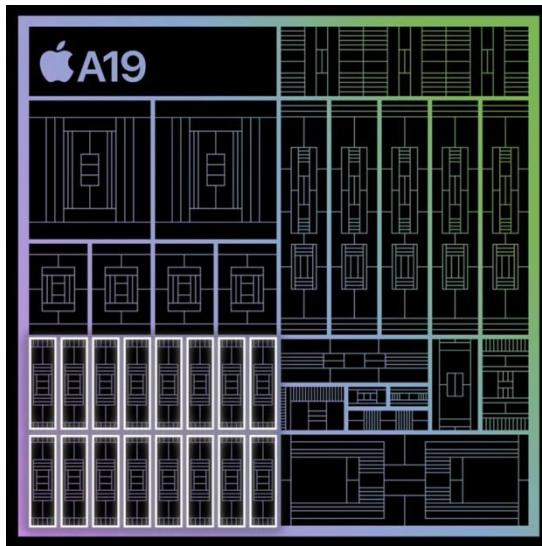


- High-end Blackwell architecture
- 21,760 CUDA cores
- Much more parallelism
- <https://www.youtube.com/watch?v=rCwgAGG2sZQ>



Mobile parallel processing

- Power constraints heavily influence design of mobile systems



- **CPU:** 6 cores total – 2 *performance* cores + 4 *efficiency* cores
- **GPU:** 5 cores (Apple-designed GPU with Neural Accelerators)
- **NPU:** 16-core Neural Engine
- **CPU:** 8 (2+6 Oryon)
- **GPU:** Adreno 840
- **NPU:** Qualcomm Hexagon NPU



Why we need to write parallel programs

- Running multiple instances of a serial program often isn't very useful.
- Rewrite serial programs so that they're parallel.
- Write translation programs that automatically convert serial programs into parallel programs.
 - This is very difficult to do.
 - Success has been limited.



More problems

- Some coding constructs can be recognized by an automatic program generator and converted to a parallel construct.
- However, it's likely that the result will be a very inefficient program.
- Sometimes the best parallel solution is to step back and devise an entirely new algorithm.



Example

- Serial solution:

```
sum = 0;  
for (i = 0; i < n; i++) {  
    x = Compute_next_value(. . .);  
    sum += x;  
}
```

- What does this program do?
 - Compute n values and add them together.



Example (cont.): How to parallel the code?

- We have p cores, p much smaller than n .
- Each core performs a partial sum of approximately n/p values.

```
my_sum = 0;  
my_first_i = . . . ;  
my_last_i = . . . ;  
for (my_i = my_first_i; my_i < my_last_i; my_i++) {  
    my_x = Compute_next_value( . . . );  
    my_sum += my_x;  
}
```

Each core uses its own **private variables** and executes this block of code **independently** of the other cores.



Example (cont.)

- After each core completes execution of the code, is a private variable `my_sum` contains the sum of the values computed by its calls to `Compute_next_value`.
- Ex., 8 cores, $n = 24$, then the calls to `Compute_next_value` return:

1,4,3, 9,2,8, 5,1,1, 5,2,7, 2,5,0, 4,1,8, 6,5,1, 2,3,9



Example (cont.)

- Once all the cores are done computing their private `my_sum`, they form a global sum by sending results to a designated “master” core which adds the final result.



Example (cont.)

```
if (I'm the master core) {  
    sum = my_x;  
    for each core other than myself {  
        receive value from core;  
        sum += value;  
    }  
} else {  
    send my_x to the master;  
}
```



Example (cont.)

1,4,3, 9,2,8, 5,1,1, 5,2,7, 2,5,0, 4,1,8, 6,5,1, 2,3,9

Core	0	1	2	3	4	5	6	7
my_sum	8	19	7	15	7	13	12	14

Global sum

$$8 + 19 + 7 + 15 + 7 + 13 + 12 + 14 = 95$$

Core	0	1	2	3	4	5	6	7
my_sum	95	19	7	15	7	13	12	14



But wait!

- There's a much better way to compute the global sum.

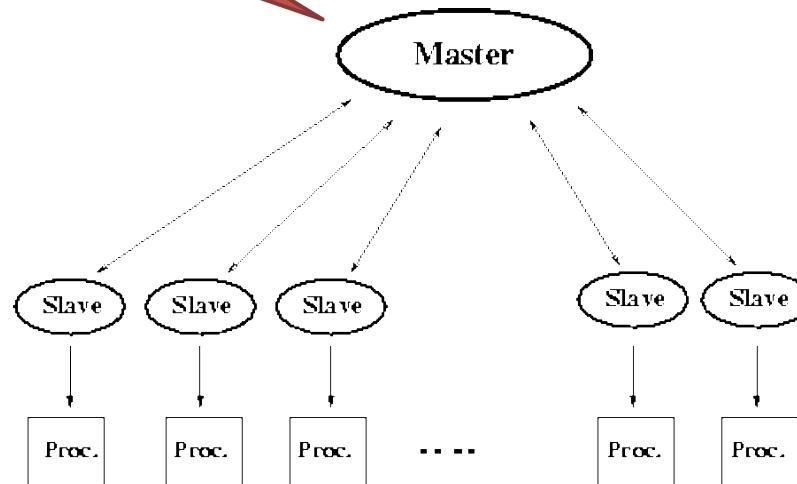


Problems?

Potential bottleneck!

Global sum

$$8 + 19 + 7 + 15 + 7 + 13 + 12 + 14 = 95$$



Core	0	1	2	3	4	5	6	7
my_sum	8	19	7	15	7	13	12	14

1,4,3, 9,2,8, 5,1,1, 5,2,7, 2,5,0, 4,1,8, 6,5,1, 2,3,9



Better parallel algorithm

- Don't make the master core do all the work.
- Share it among the other cores.
- Pair the cores so that core 0 adds its result with core 1's result.
- Core 2 adds its result with core 3's result, etc.
- Work with odd and even numbered pairs of cores.

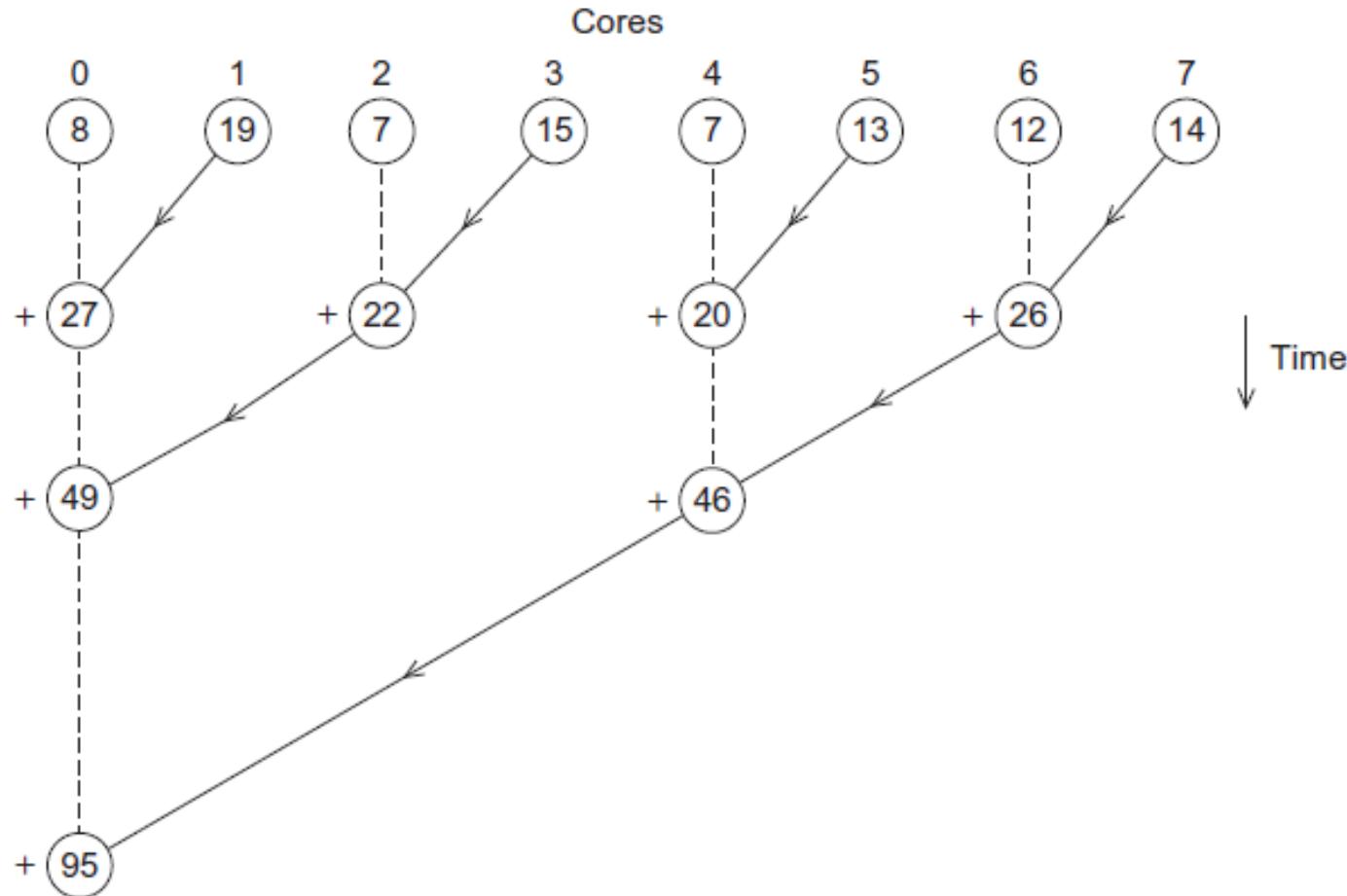


Better parallel algorithm (cont.)

- Repeat the process now with only the evenly ranked cores.
- Core 0 adds result from core 2.
- Core 4 adds the result from core 6, etc.
- Now cores divisible by 4 repeat the process, and so forth, until core 0 has the final result.



Multiple cores forming a global sum



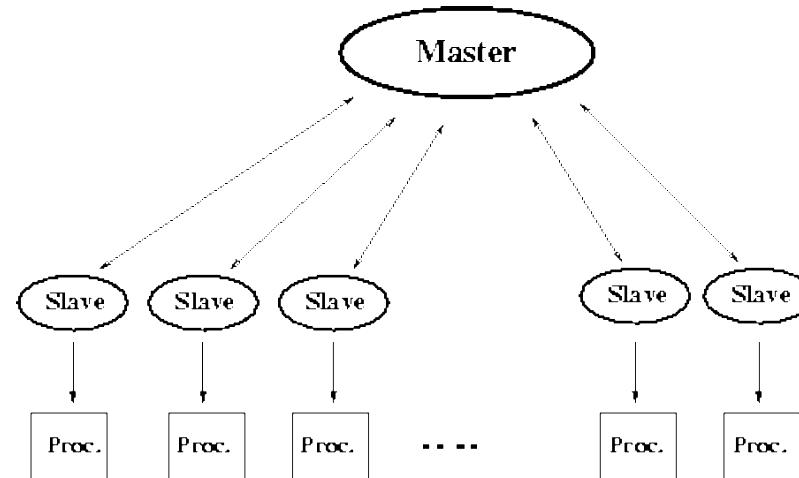
Analysis

- In the first example, the master core performs receives and additions.
- In the second example, the master core performs receives and additions.
- The improvement is more than a factor of 2!



Analysis (cont.)

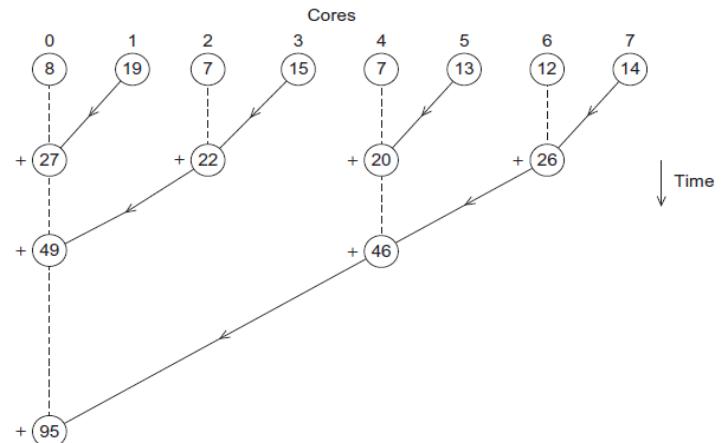
- The difference is more dramatic with a larger number of cores.
- If we have 1000 cores:
 - The first example would require the master to perform receives and additions.



Analysis (cont.)

- The difference is more dramatic with a larger number of cores.
- If we have 1000 cores:
 - The second example would only require receives and additions.

$$(2^{10}=1024)$$



- That's an improvement of almost a factor of 100!



How do we write parallel programs?

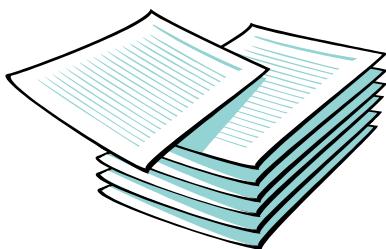
- Task parallelism
 - Partition various tasks carried out solving the problem among the cores.
- Data parallelism
 - Partition the data used in solving the problem among the cores.
 - Each core carries out similar operations on it's part of the data.



Professor P

15 questions

300 exams



Professor P's grading assistants



TA#1

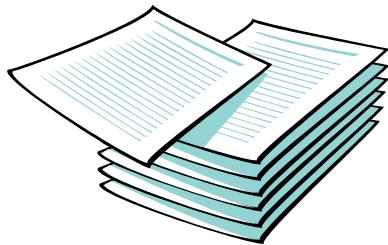
TA#2

TA#3



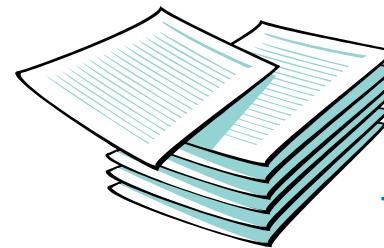
Division of work – data parallelism

TA#1



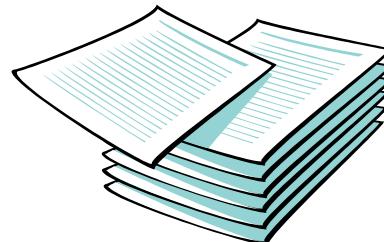
100 exams

TA#3



100 exams

TA#2



100 exams



Division of work – task parallelism

TA#1



Questions 1 - 5



TA#3

Questions 11 - 15

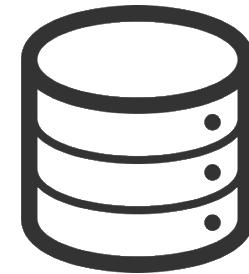
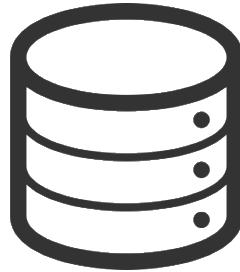


TA#2

Questions 6 - 10



Division of work – data parallelism



```
sum = 0;  
for (i = 0; i < n; i++) {  
    x = Compute_next_value(. . .);  
    sum += x;  
}
```

Same task (program), different data



Division of work – task parallelism

```
if (I'm the master core) {  
    sum = my_x;  
    for each core other than myself {  
        receive value from core;  
        sum += value;  
    }  
} else {  
    send my_x to the master;  
}
```

different tasks (program): program A and B could be totally different logic

different data

Tasks

- 1) Receiving
- 2) Addition



Coordination

- Cores usually need to coordinate their work.
- **Communication** – one or more cores send their current partial sums to another core.
- **Load balancing** – share the work evenly among the cores so that one is not heavily loaded.
- **Synchronization** – because each core works at its own pace, make sure cores do not get too far ahead of the rest.



What we'll be doing

- Using the C language.
- Using three different extensions to C.
 - Message-Passing Interface (MPI)
 - Posix Threads (Pthreads)
 - OpenMP
- Write programs that are explicitly parallel.

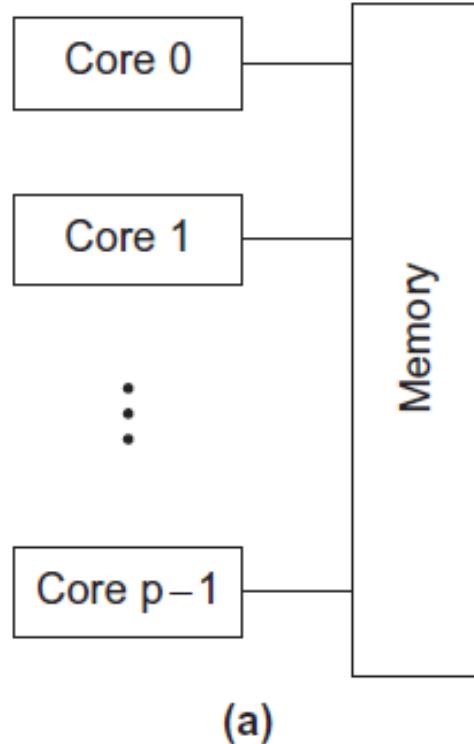


Type of parallel systems

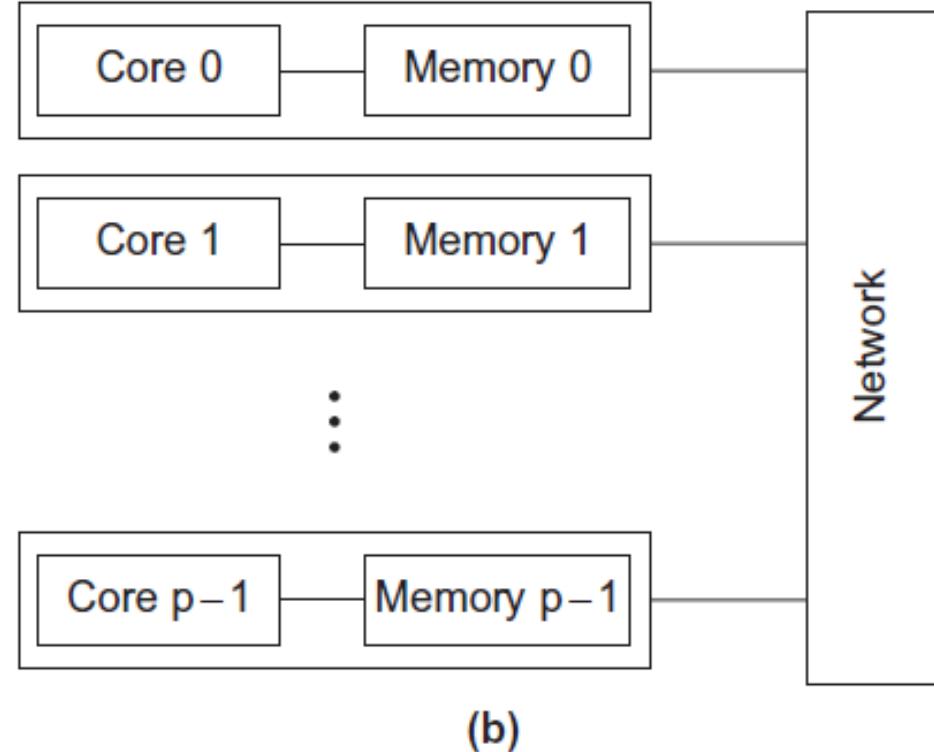
- Shared-memory
 - The cores can share access to the computer's memory.
 - Coordinate the cores by having them examine and update shared memory locations.
- Distributed-memory
 - Each core has its own, private memory.
 - The cores must communicate explicitly by sending messages across a network.



Type of parallel systems



Shared-memory



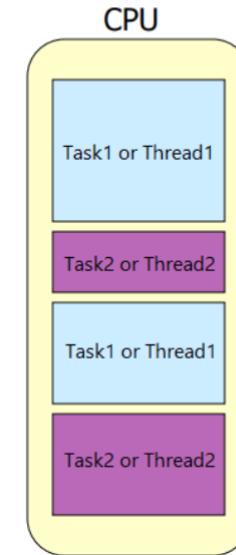
Distributed-memory



Terminology

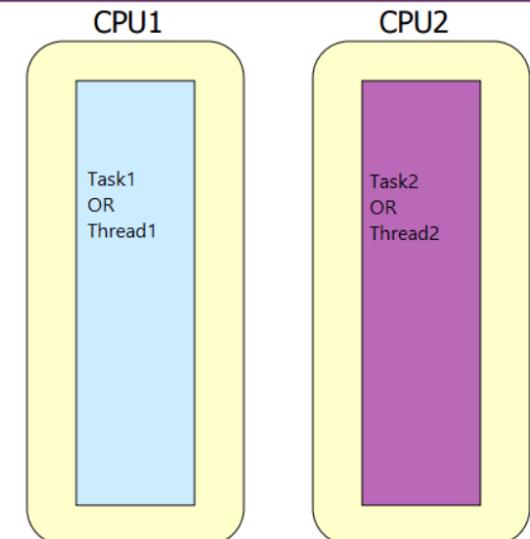
- **Concurrent computing** – a program is one in which multiple tasks can be in progress at any instant.

Concurrent



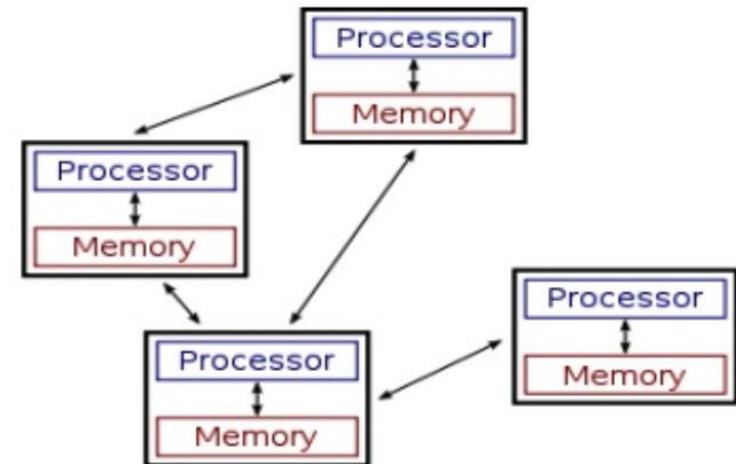
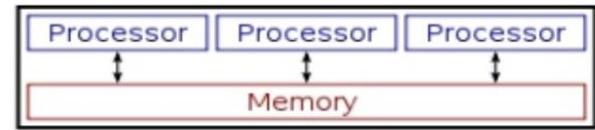
- **Parallel computing** – a program is one in which multiple tasks cooperate closely to solve a problem

Concurrent [also] Parallel



Terminology

- **Parallel computing** – a program is one in which multiple tasks cooperate closely to solve a problem
- **Distributed computing** – a program may need to cooperate with other programs to solve a problem.



Conclusion

- The laws of physics have brought us to the doorstep of multicore technology.
- Serial programs typically don't benefit from multiple cores.
- Automatic parallel program generation from serial program code isn't the most efficient approach to get high performance from multicore computers.



Conclusion (cont.)

- Learning to write parallel programs involves learning how to coordinate the cores.
- Parallel programs are usually very complex and therefore, require sound program techniques and development.

