

ECE 432/532
Programming for Parallel Processors

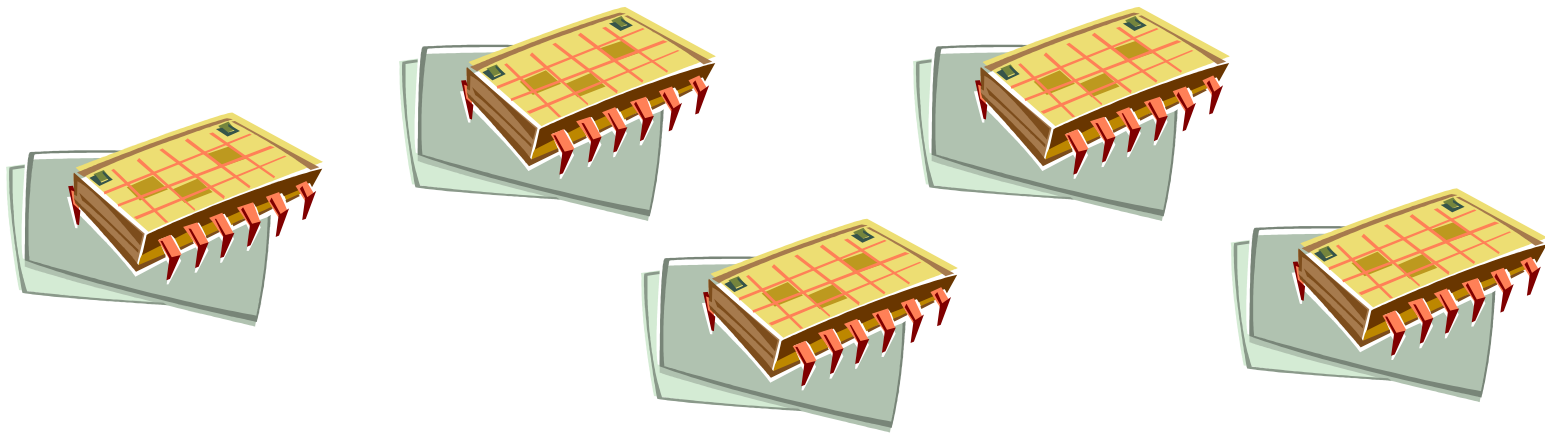
So far...

- 1986-2002: The performance of microprocessors increased, on average, 50% per year
- 2002: Single-processor performance improvement has slowed to about 20% per year
- 2005: Most of the major manufacturers decided that the road to rapidly increasing performance lay in the direction of parallelism
 - Rather than trying to continue to develop ever-faster monolithic processors, manufacturers started putting *multiple* complete processors on a single integrated circuit.

Simply adding more processors will **not** magically improve the performance of the vast majority of **serial programs**, that is, programs that were written to run on a single processor.

An intelligent solution

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



All of this raises a number of questions

- Why do we care? Aren't single processor systems fast enough?
- Why can't microprocessor manufacturers continue to develop much faster single processor systems? Why build **parallel systems**?
- Why can't we write programs that will automatically convert serial programs into **parallel programs**?

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).



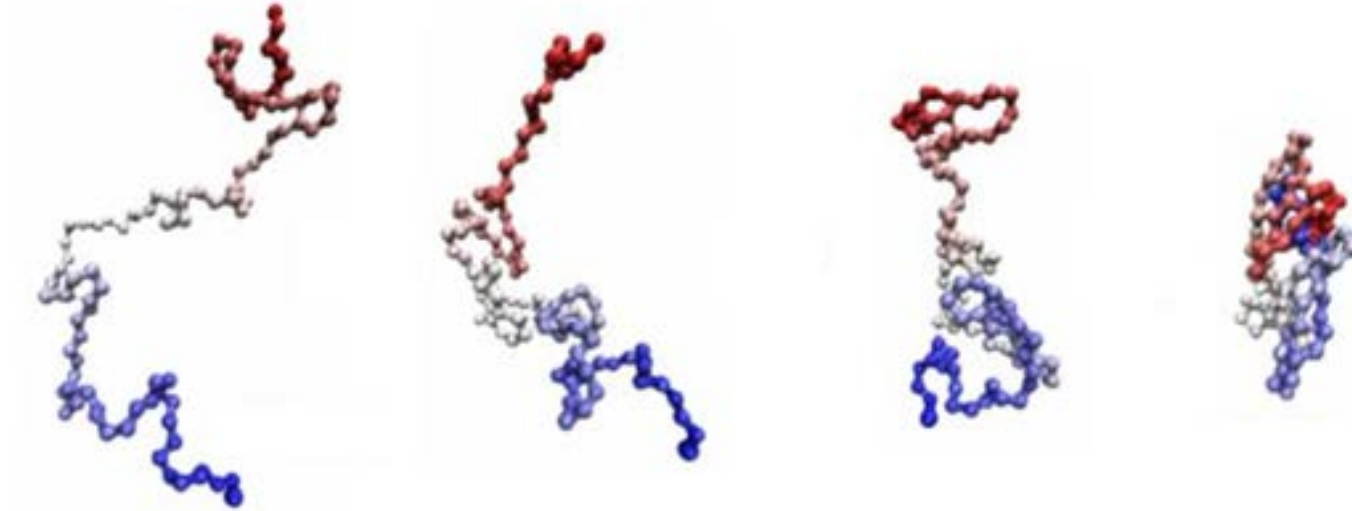
Why do we care?

- Application needs:
 - *Climate modeling*
 - *Protein folding*
 - *Drug discovery*
 - *Data analysis*
 - *DNA analysis*
 - ...

Climate modeling



Protein folding



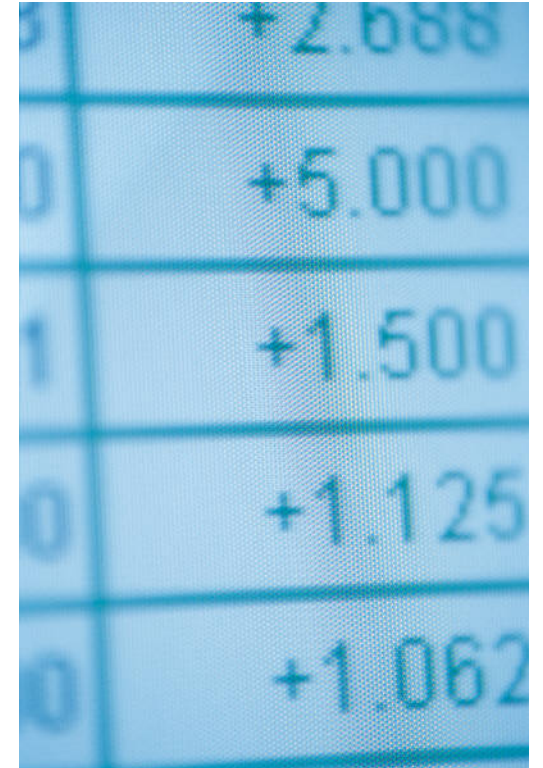
Drug discovery



Energy research



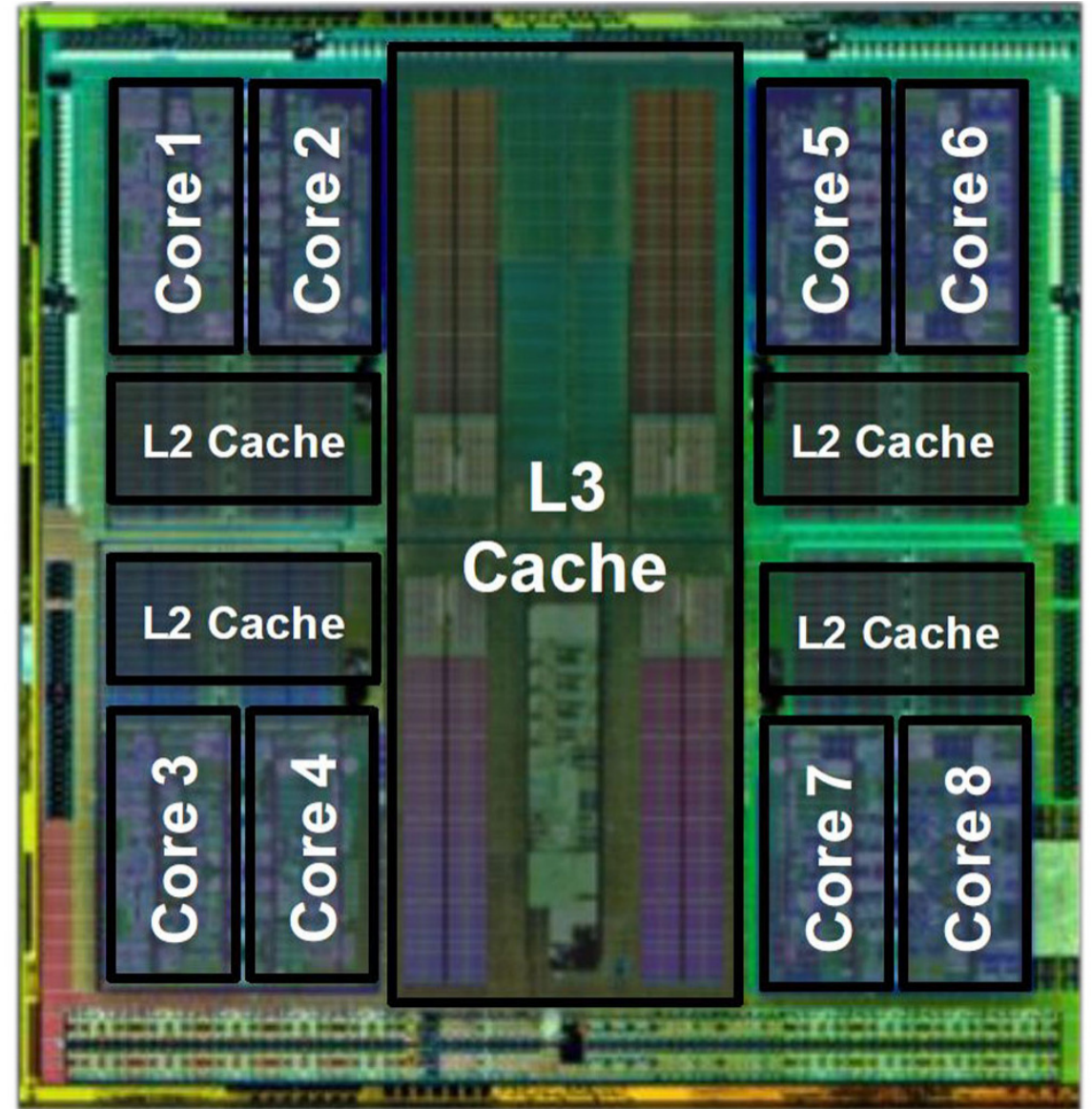
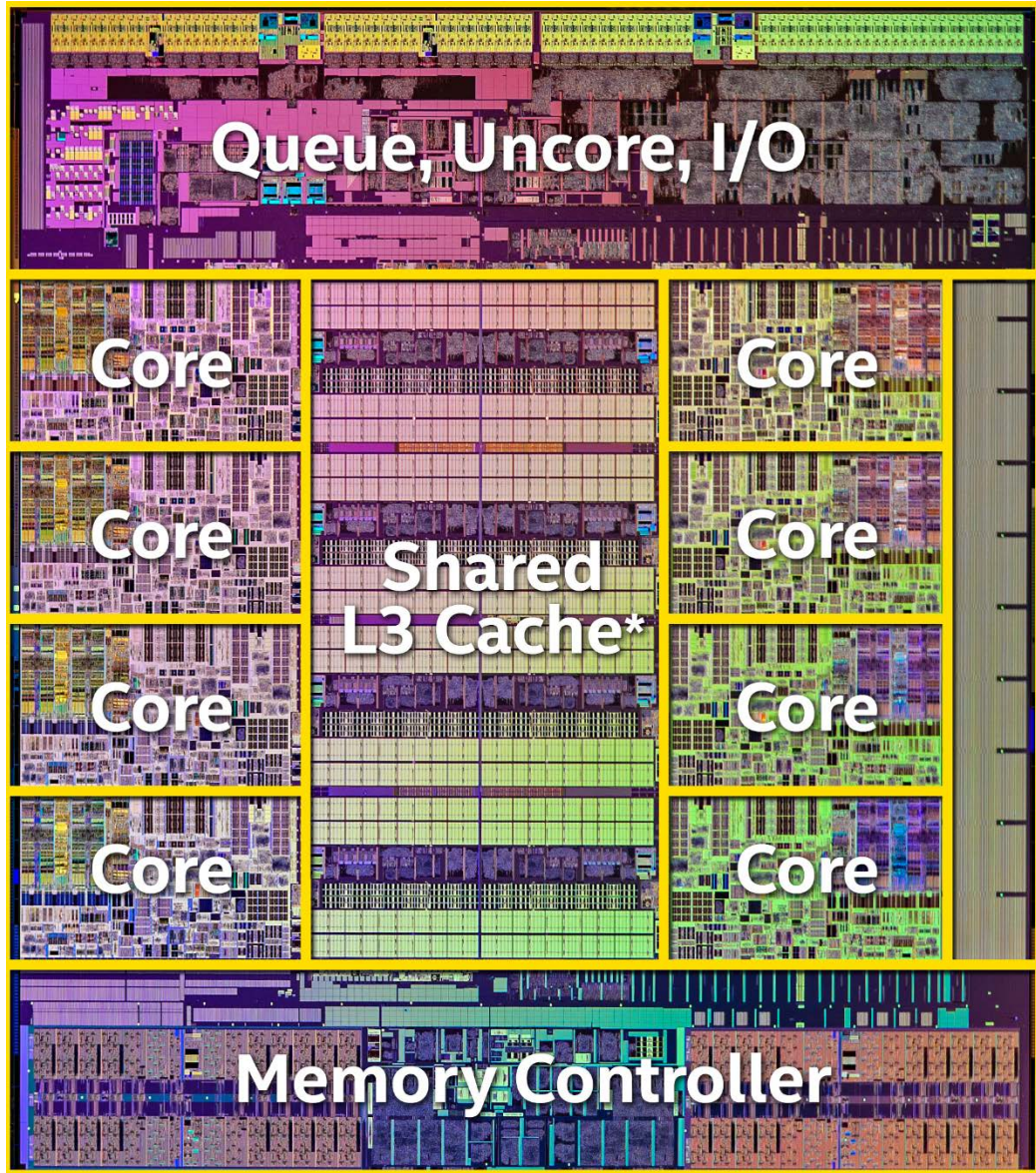
Data analysis



5	+2.688
0	+5.000
1	+1.500
0	+1.125
0	+1.062

Why build parallel systems?

- Much of the increase in single processor performance has been driven by the ever-increasing density of transistors
- As the size of transistors decreases, their speed can be increased
 - Smaller transistors = faster processors
 - Faster processors = increased power consumption.
- However, as the speed of transistors increases, their power consumption also increases → Heat problems, unreliability
- *Parallelism*: put multiple, relatively simple, complete processors on a single chip. Such integrated circuits are called multicore processors



Fun facts

- **1978:** Intel introduces the 16-bit 8086 microprocessor. It will become an industry standard
- **2003:** AMD introduces the x86-64, a 64-bit superset of the x86 instruction set
- **2004:** AMD demonstrates an x86 dual-core processor chip
- **2005:** Intel ships its first dual-core processor chip

Why we need to write parallel programs?

- Most programs that have been written for single-core systems
 - We can run multiple instances of a program on a multicore system, but this is often of little help
- Example: Video games
 - We can run multiple instances of our favorite game program
or
 - run faster with more realistic graphics

Why we need to write parallel programs?

- Solutions:
 - Rewrite the serial programs so that they're *parallel*
 - write translation programs → automatically convert serial to parallel code

Why we need to write parallel programs?

- Solutions:

- Rewrite the serial programs so that they're *parallel*

- ~~• write translation programs → automatically convert serial to parallel code~~

Researchers have had very limited success writing programs that convert serial programs in languages such as C and C++ into parallel programs

Serial to parallel

- We can view the multiplication of two $n \times n$ matrices as a sequence of dot products

$$\begin{array}{c} \left[\begin{array}{c|c} a & b \\ \hline c & d \end{array} \right] \times \left[\begin{array}{c|c} e & f \\ \hline g & h \end{array} \right] = \left[\begin{array}{c|c} ae + bg & af + bh \\ \hline ce + dg & cf + dh \end{array} \right] \\ A \qquad \qquad B \qquad \qquad \qquad C \end{array}$$

A, B and C are square matrices of size $N \times N$
a, b, c and d are submatrices of A, of size $N/2 \times N/2$
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Serial to parallel

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but parallelizing a matrix multiplication as a sequence of parallel dot products is likely to be very slow on many systems

Serial to parallel

- An efficient parallel implementation of a serial program may not be obtained by finding efficient parallelizations of each of its steps.
- Rather, the best parallelization may be obtained by stepping back and devising an entirely new algorithm

Example

- Compute n values and add them together:

Example

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Serial code

```
sum = 0;
for (i = 0; i < n; i++) {
    x = Compute_next_value(. . .);
    sum += x;
}
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What about the parallel version?

Example

- Compute n values and add them together:
- Parallel code \rightarrow We have p cores and $p \ll n \rightarrow$ each core forms 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;
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Each core uses it's own private variables and executes this block of code independently of the other cores.

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Each core uses it's own private variables and executes this block of code independently of the other cores.

Example

- For $p=8$ and $n=24$, calls to *Compute_next_value* return the values

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

Example

- How do you find the final sum?
 - When the cores are done, they can form a global sum by sending their results to a designated “master” core, which can add their results

```
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

- If the master core is core 0, it would add the values:
 $8 + 19 + 7 + 15 + 7 + 13 + 12 + 14 = 95$.

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Is this an effective way?

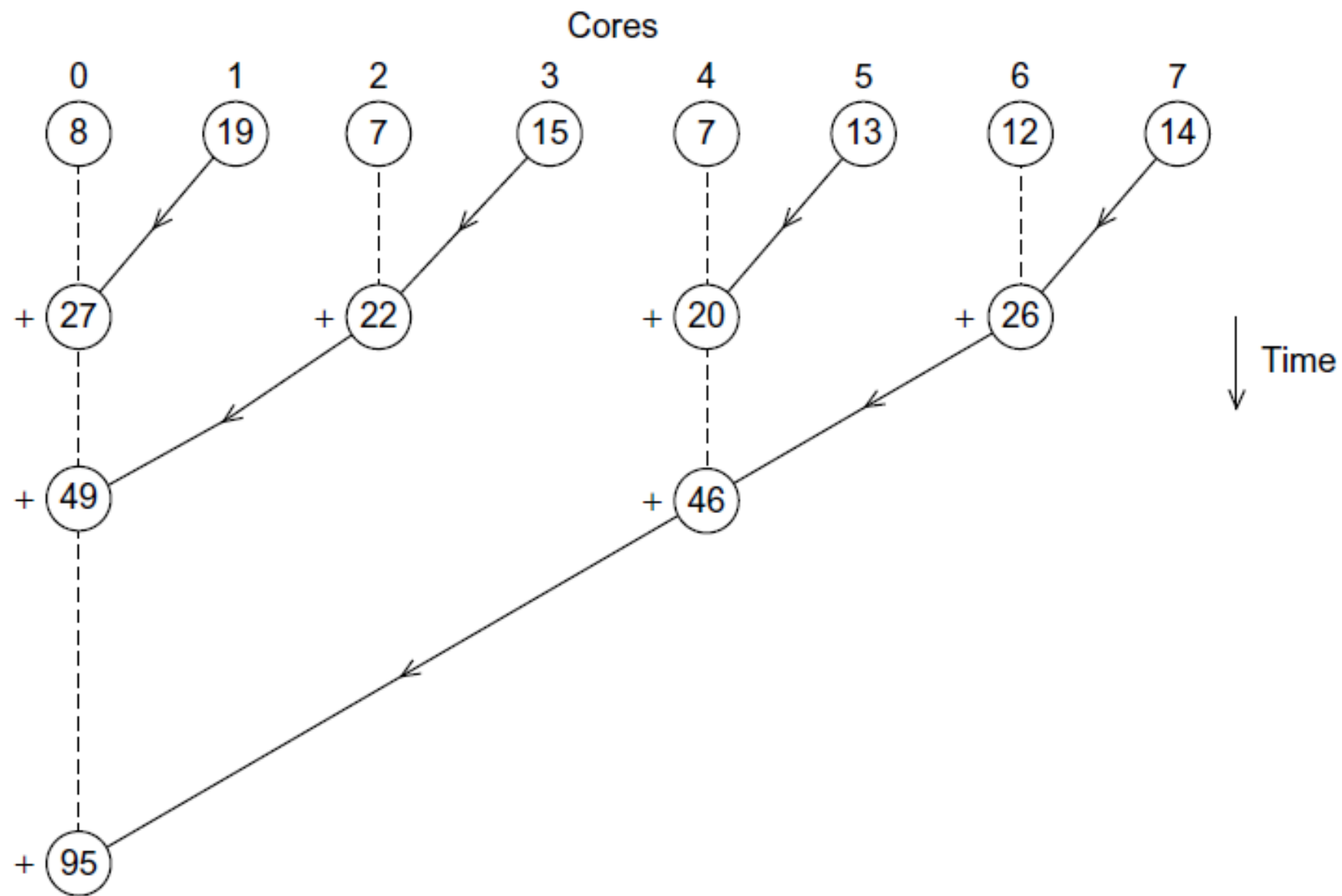
What happens when $p \gg 0$

```
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

- Don't make the master core do all the work.
- Alternative solution: pair the cores so that
 - core 0 adds in the result of core 1
 - core 2 can in the result of core 3
 - core 4 can add in the result of core 5
 - and so on.

Example



Analysis

- In the first example, the master core performs 7 receives and 7 additions.
- In the second example, the master core performs 3 receives and 3 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 999 receives and 999 additions.
 - The second example would only require 10 receives and 10 additions.
- That's an improvement of almost a factor of 100!

Conclusions

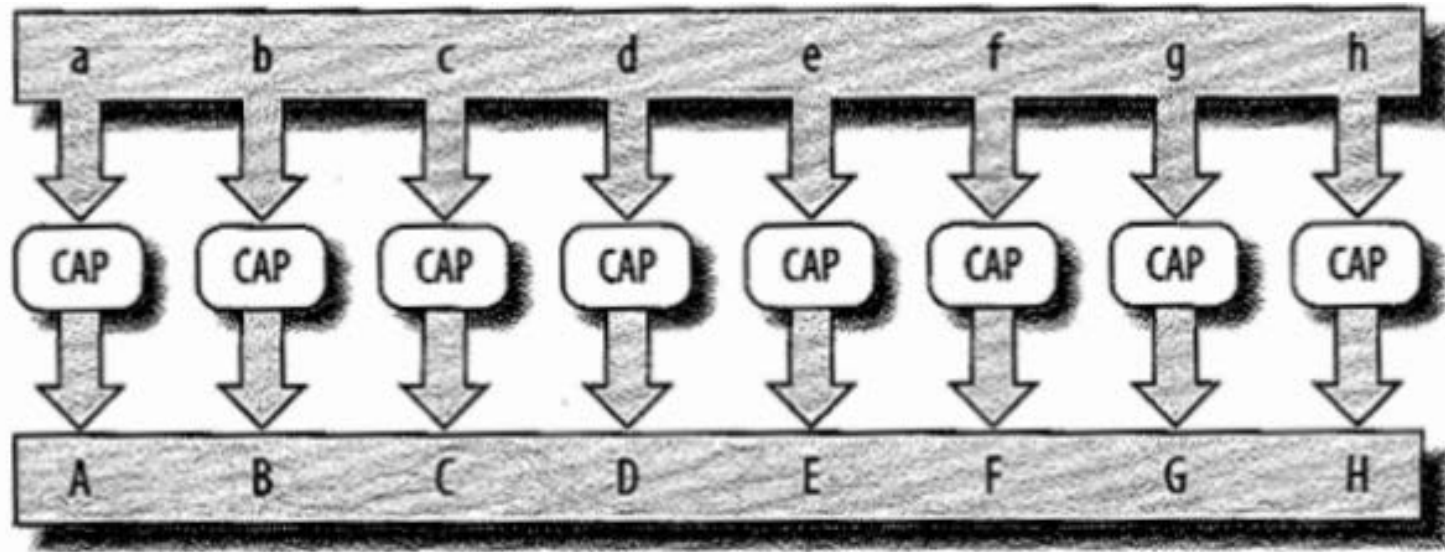
- The first global sum is a fairly obvious generalization of the serial global sum
- The point here is that it's unlikely that a translation program would "discover" the second global sum
- Rather there would more likely be a predefined efficient global sum that the translation program would have access to
 - It could "recognize" the original serial loop and replace it with a precoded, efficient, parallel global sum.

How do we write parallel programs?

- Partition the work to be done among the cores:
 - **task-parallelism**
 - **data-parallelism**
- Task parallelism:
 - Different tasks running on the same data
- Data parallelism:
 - The same task runs on different data in parallel

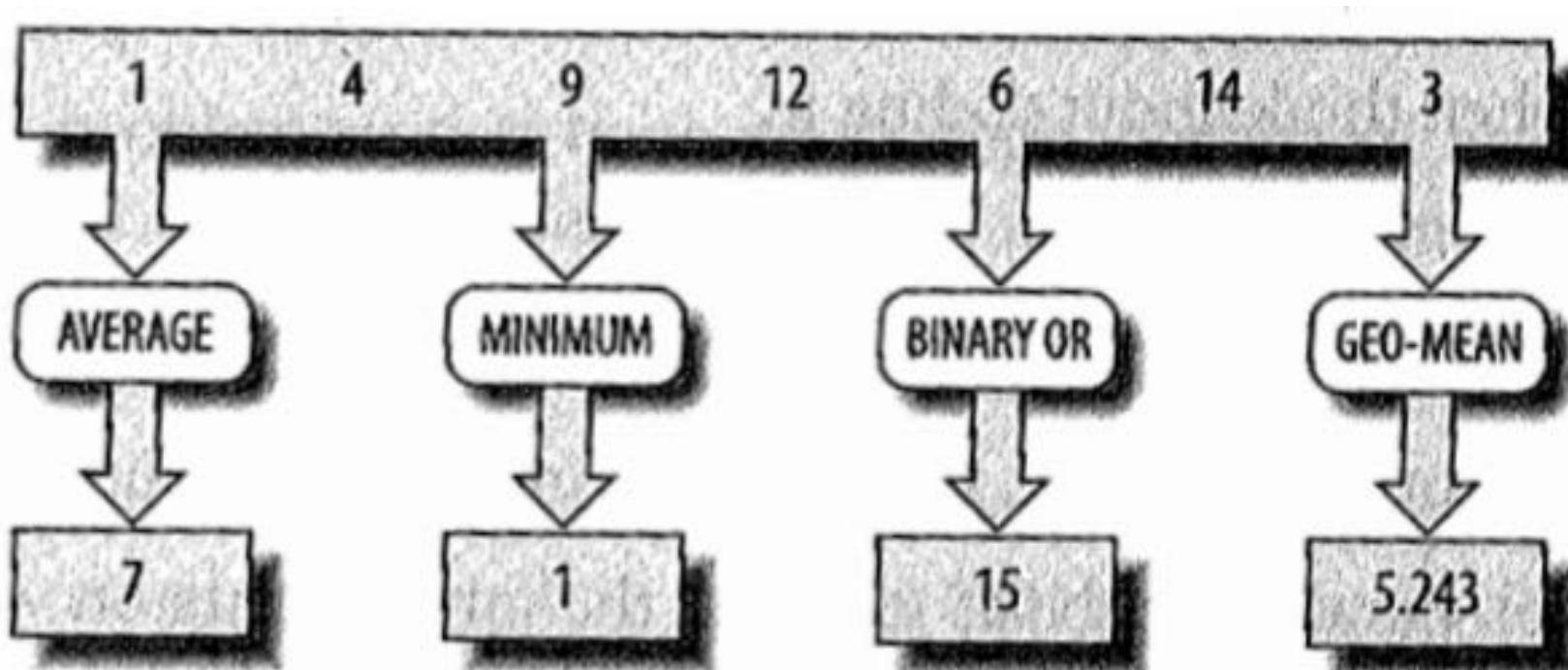
Data parallelism

- Example: convert all characters in an array to upper-case
 - Can divide parts of the data between different tasks and perform the tasks in parallel
 - Key: no dependencies between the tasks that cause their results to be ordered



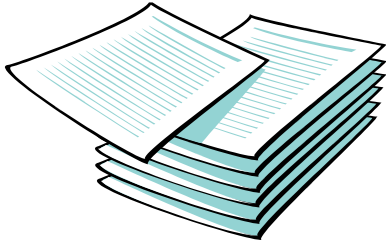
Task parallelism

- Example:
 - Several functions on the same data: average, minimum, binary or, geometric mean
 - No dependencies between the tasks, so all can run in parallel



Professor P

15 questions
300 exams



Professor P's grading assistants



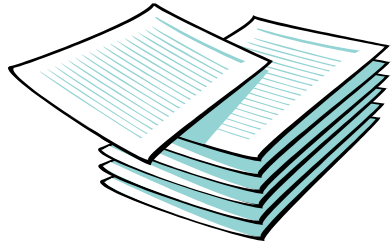
TA#1

TA#2

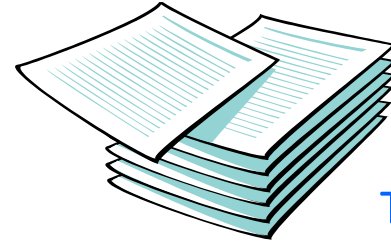
TA#3

Division of work – data parallelism

TA#1

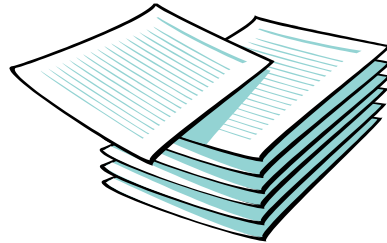


100 exams



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

Coordination

- When the cores can work independently, writing a parallel program is much the same as writing a serial program
- Things get a good deal more complex when the cores need to coordinate their work

Coordination

- **Communication:** one or more cores send their current partial sums to another core
- **Load balancing:** we want the cores all to be assigned roughly the same number of values to compute
- **Synchronization:** we don't want the other cores to race ahead

What we will see

- We'll be focusing on learning to write programs that are *explicitly* parallel
- Learn the basics of programming parallel computers using the C/C++ language and three different extensions to C/C++:
 - **Message-Passing Interface** or **MPI**
 - **POSIX threads** or **Pthreads**
 - **OpenMP**
- MPI and Pthreads are libraries of type definitions, functions, and macros that can be used in C programs
- OpenMP consists of a library and some modifications to the C compiler.

What we will see

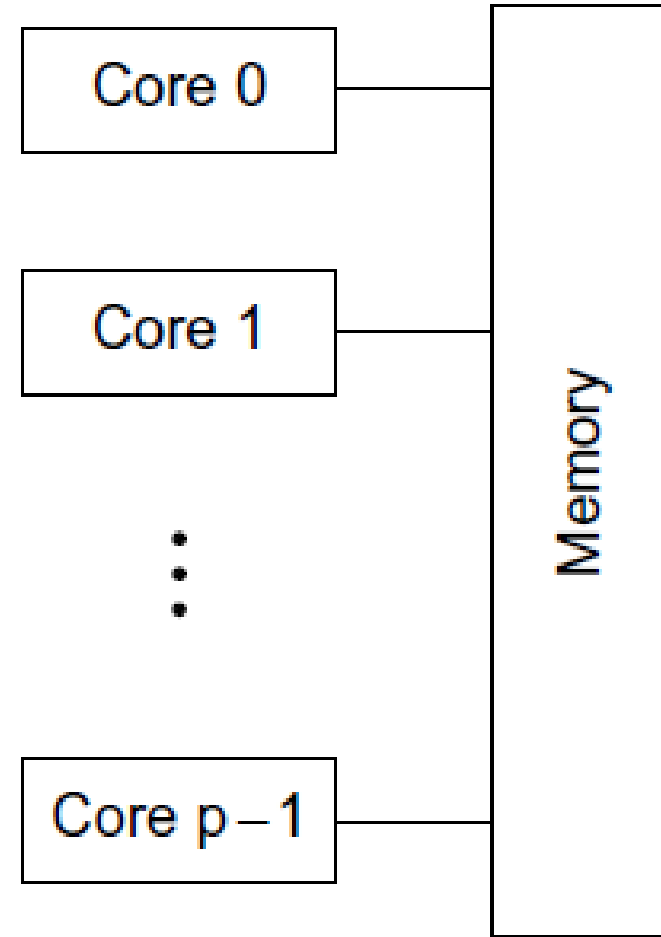
- Q: Why do we need 3 different extensions to C/C++ instead of just one?

What we will see

- Q: Why do we need 3 different extensions to C/C++ instead of just one?
- A: Don't forget hardware!!
- There are two main types of parallel systems:
 - **Shared memory** systems
 - **Distributed-memory** systems

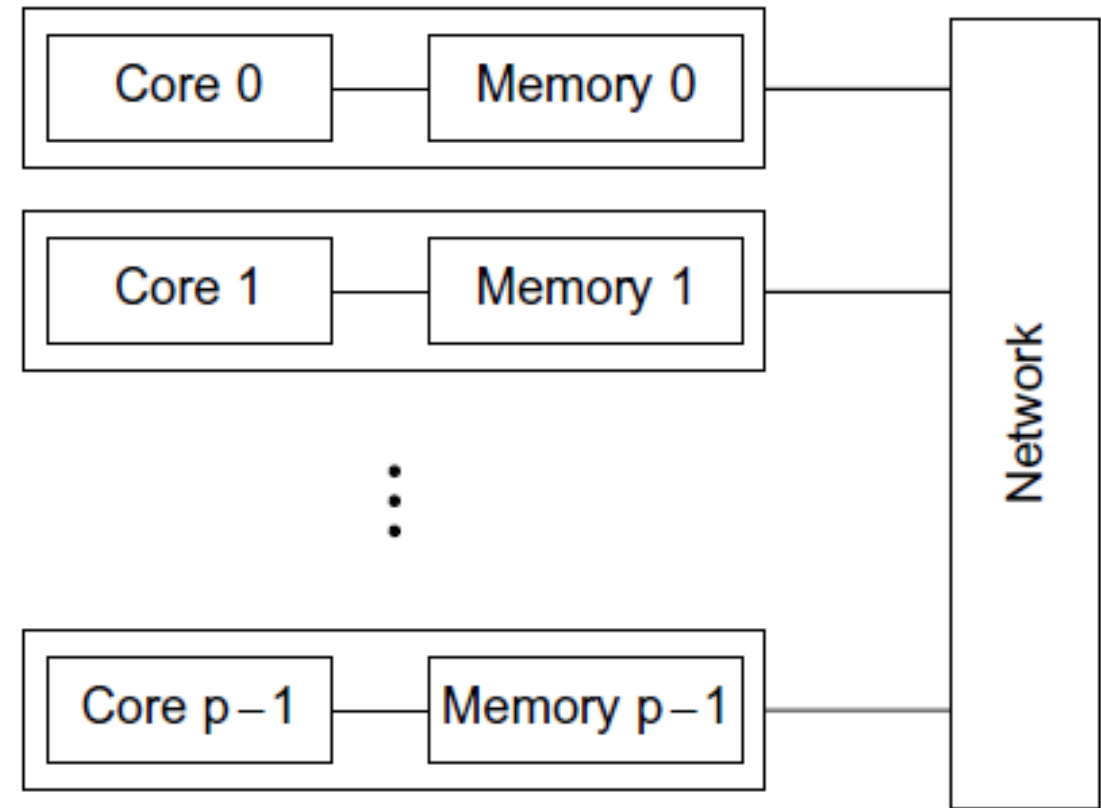
Shared memory

- In a **shared-memory** system, the cores can share access to the computer's memory
 - each core can read and write each memory location
- In a **shared-memory** system, we can coordinate the cores by having them examine and update shared-memory locations
- Pthreads and OpenMP were designed for programming shared-memory systems



Distributed memory

- In a **distributed-memory** system each core has its own, private memory
- Cores must communicate explicitly by doing something like sending messages across a network
- MPI was designed for programming distributed-memory systems.



Concurrent, parallel and distributed computing

- In **concurrent** computing, a program is one in which multiple tasks can be *in progress* at any instant
- In **parallel** computing, a program is one in which multiple tasks *cooperate closely* to solve a problem
- In **distributed** computing, a program may need to cooperate with other programs to solve a problem

Concurrent, parallel and distributed computing

- Parallel and distributed programs are concurrent
- A program such as a multitasking operating system is also concurrent, even when it is run on a machine with only one core, since multiple tasks can be *in progress* at any instant
- A parallel program usually runs multiple tasks simultaneously on cores
- On the other hand, distributed programs tend to be more “loosely coupled.” The tasks may be executed by multiple computers that are separated by large distances

Concluding Remarks (1)

- 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.

Concluding Remarks (2)

- 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.