Parallel Programming

Overview of Parallel and Distributed Programming

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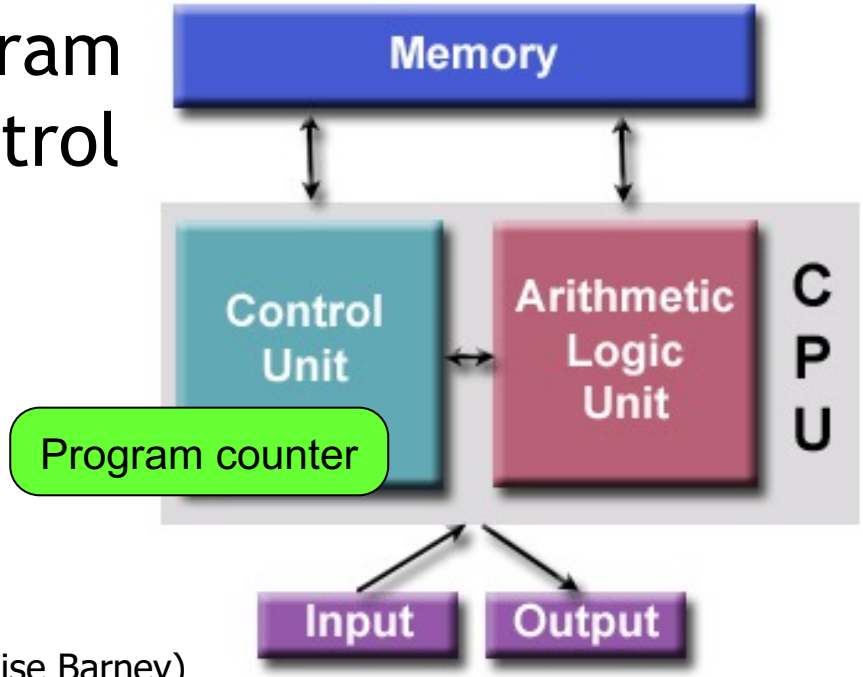
Outline

- The What and Why of Parallel Computing
- The Why and How of Parallel Programming
- Parallel Programming Models
- Performance Evaluation

Sequential Computing

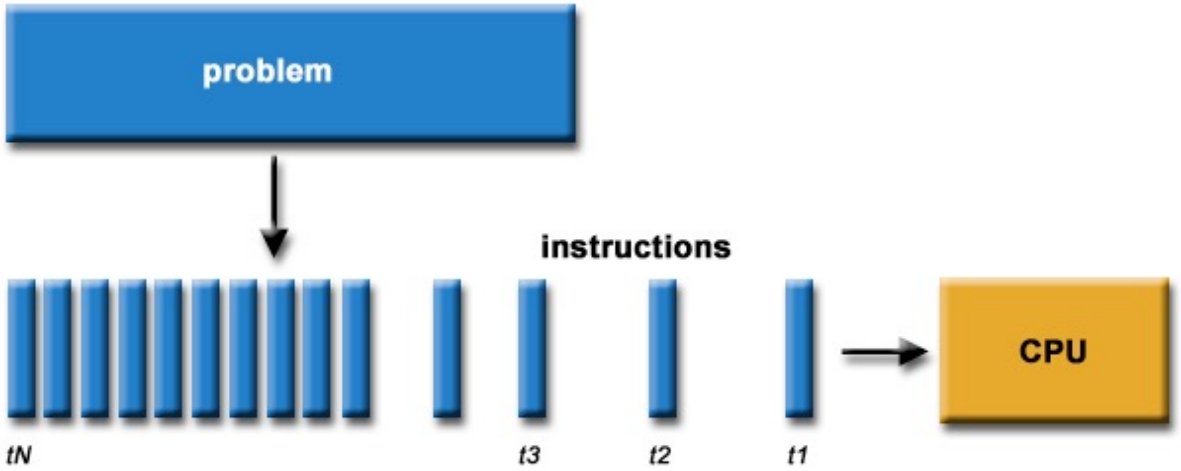
- von Neumann arch. with Program Counter (PC) dictates sequential execution
- Traditional programming thus follows a single thread of control
  - The sequence of program points reached as control flows through the program



(Introduction to Parallel Computing, Blaise Barney)

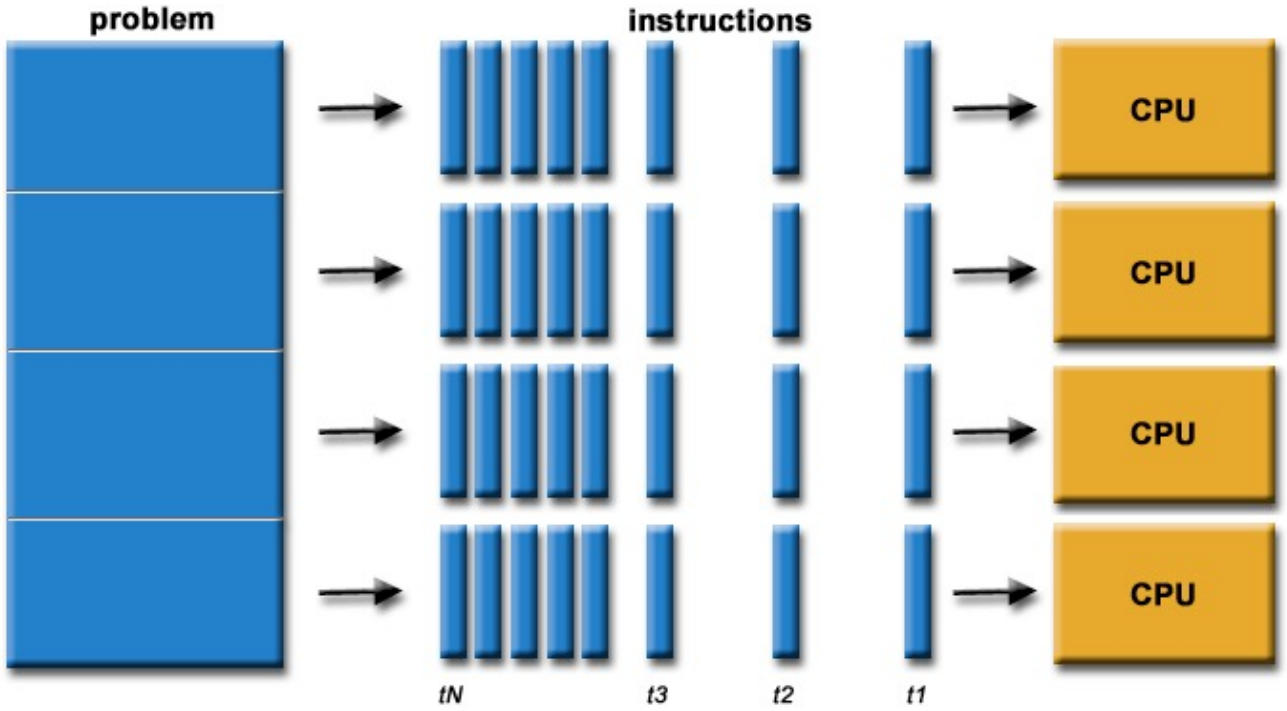
Sequential Computing (Cont'd)

- Traditionally, software has been written for serial computing:
  - To be run on a single computer having a single CPU
  - A problem is broken into a discrete series of instructions
  - Instructions are executed one after another
  - Only one instruction may execute at any moment in time



What is Parallel Computing?

- In the simplest sense, parallel computing is the simultaneous use of multiple compute resources to solve a computational problem

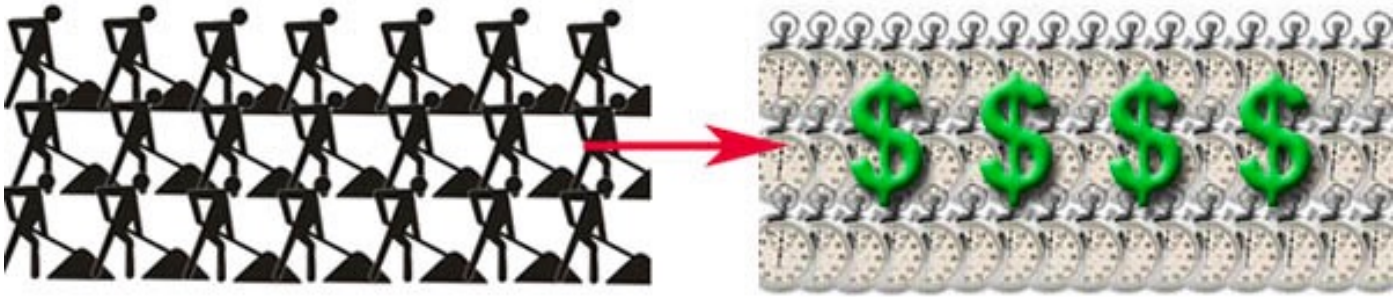


Concurrent, Parallel, and Distributed Computing

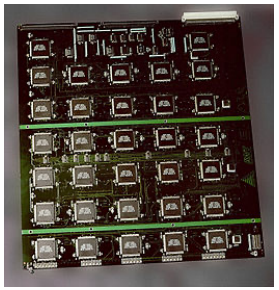
- Although there isn't complete agreement on the distinction between these terms, many authors make the following distinctions:
  - Concurrent computing: A program is one in which multiple tasks can be *in progress* at any instant
  - Parallel computing: A program is one in which multiple tasks *cooperate closely* to solve a problem
  - Distributed computing: A program may need to cooperate with other programs to solve a problem

Why Use Parallel Computing? (1/3)

- Save time and/or money
  - In theory, throwing more resources at a task will shorten its time to completion, with potential cost savings
    - Parallel computers can be built from cheap, commodity components



  - Time to brute force a 56-bit DES key has evolved from
    - 1998, 56 hours, $250,000
    - 2006, 6.4 hours, $10,000



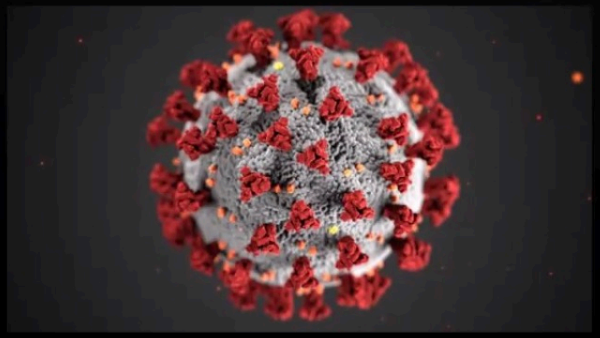
Why Use Parallel Computing? (2/3)

- Solve larger problems (applications demand it!)
  - Many problems are so large and/or complex that it is impractical or impossible to solve them on a single computer, especially given limited computer memory
    - Largest direct numerical solutions have evolved from meshes of 10243 to 80963 in the last ten years!
    - E.g., climate modeling, drug discovery, energy research, data analysis
  - Big data drivers

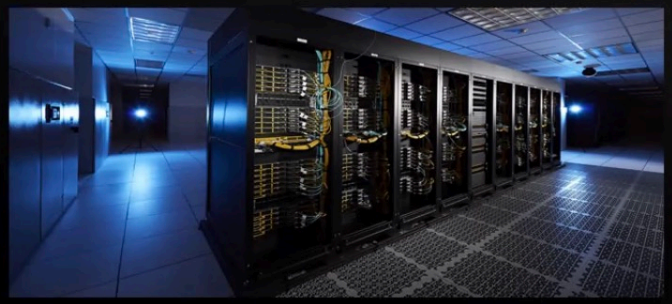
COVID-19 Drug Development

AMD'S COVID-19 HPC FUND

- Provides research institutions with computing resources to accelerate medical research on COVID-19 and other diseases
- Examples include:
  - NYU: Discovery of drugs that may be therapeutic for COVID-19, retrieval of relevant research from biomedical literature, and analysis of medical images
  - Rice: Exploration of how the coronavirus's surface proteins facilitate entrance to human cells and how to screen thousands of drug molecules to identify the best candidates for clinical tests
  - LLNL: Discovery of potential antibodies and anti-viral compounds for COVID-19 using molecular dynamics simulations and machine learning



Coronavirus



Corona Supercomputer

AMD

Source: Michael Schulte's keynote speech at ICPP '20

Big Data Phenomenon

- "Data are becoming the new raw material of business: an economic input almost on a par with capital and labor."

  —The Economist, 2010

- "Information will be the oil of the 21st century"

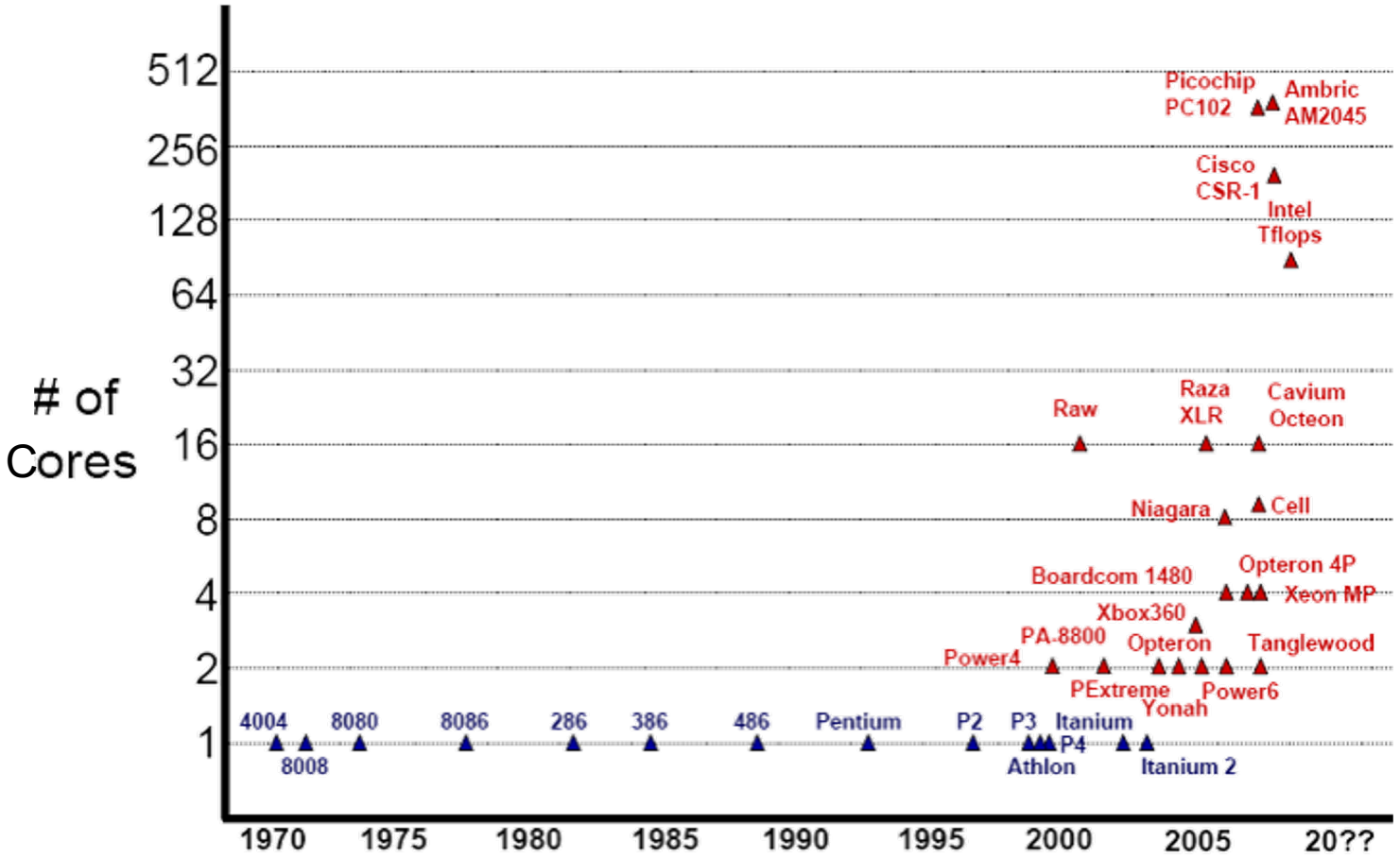
  —Gartner, 2010

Source：IDF2012

Why Use Parallel Computing? (3/3)

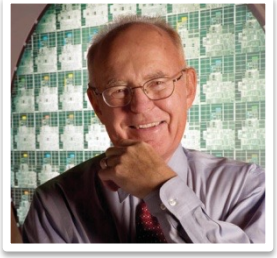
- Architectures demand it!
  - The free lunch is over
    - Clock speed increase is no longer an option
  - Multiple/many cores are future trend
  - Simply adding more processors will not magically improve the performance of the vast majority of **serial** programs

Multicore Trends

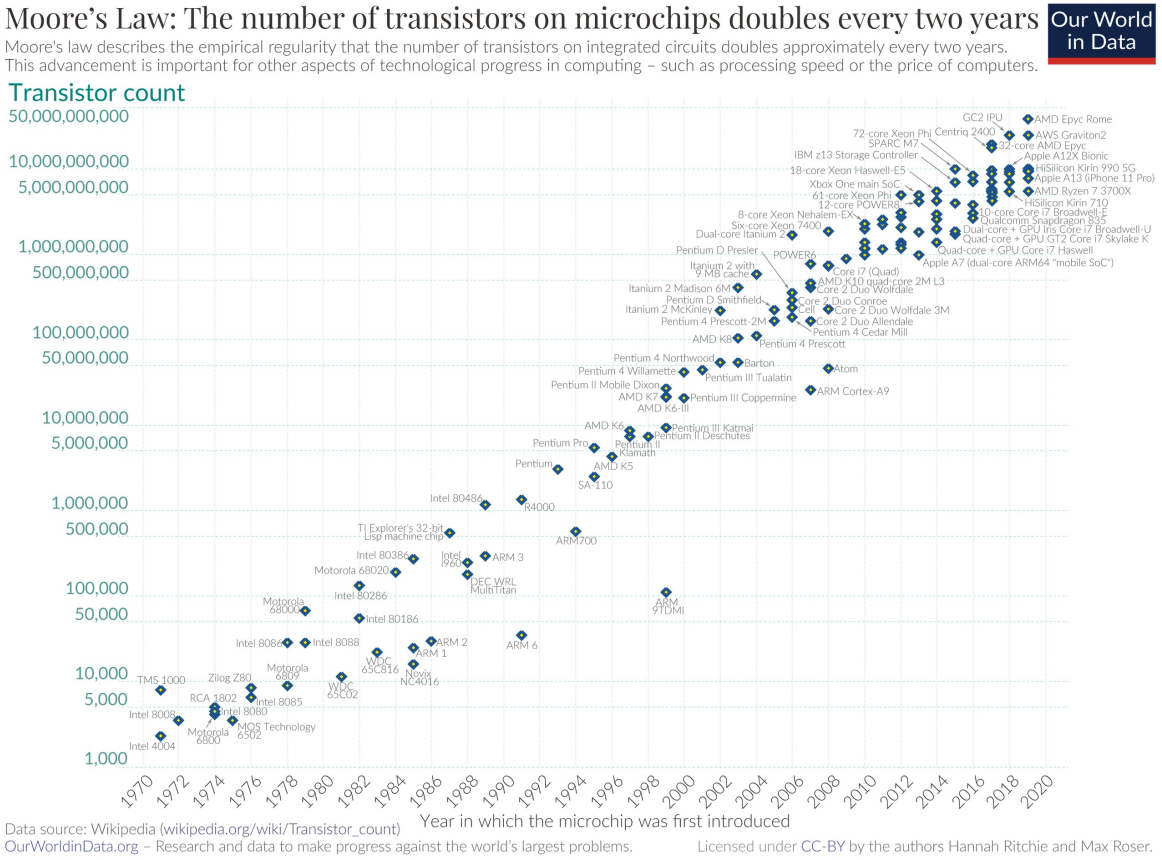


(Source) MIT Course 6.189, "Multi-core Programming Primer: Learn and Compete in Programming the PLAYSTATION®3 Cell Processor."

Moore's Law

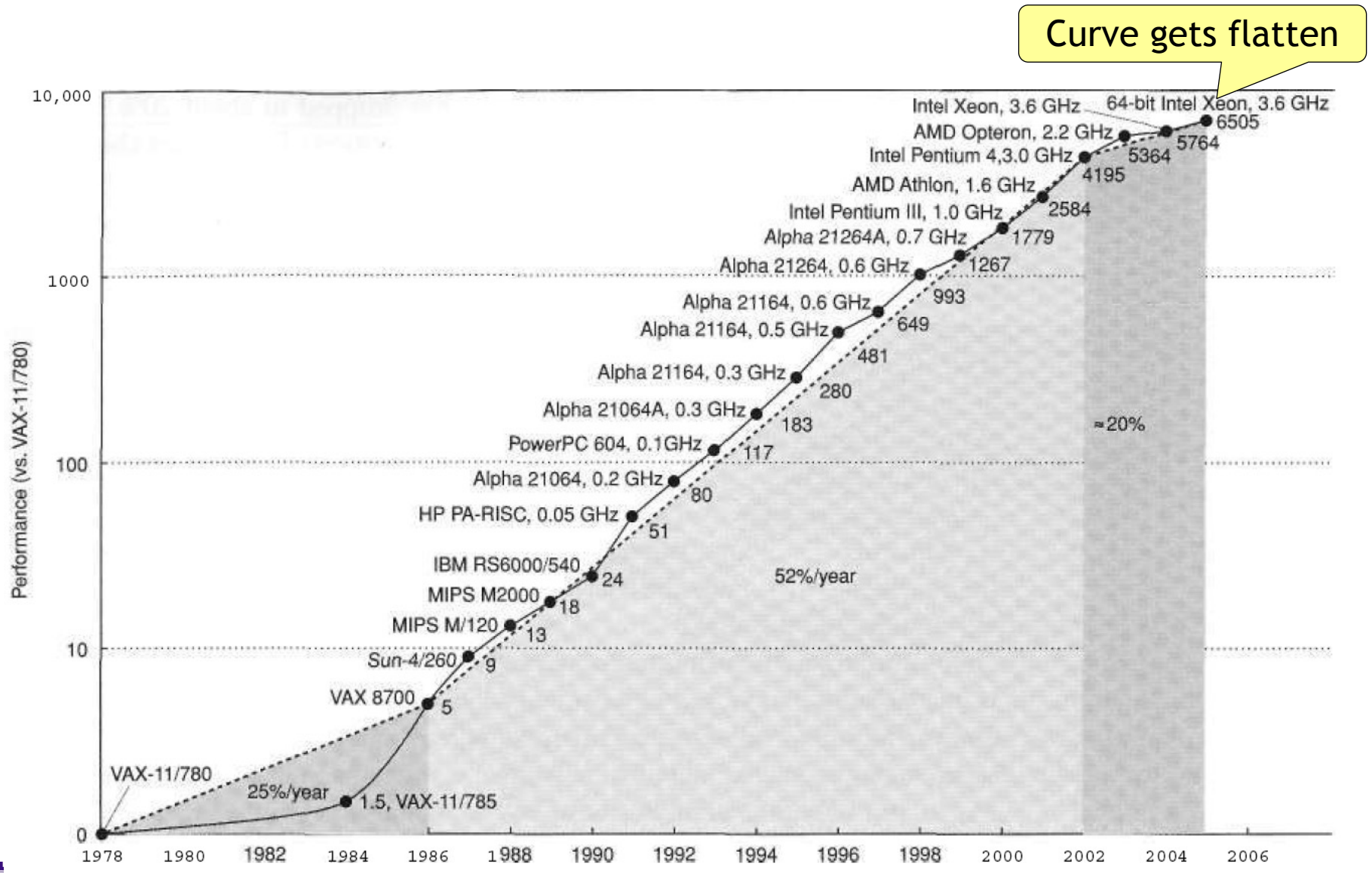


- Describes a trend in the history of computer hardware that the number of transistors can be inexpensively placed on an integrated circuit is increasing exponentially
  - Doubling every 18 month (Moore's original predication)
  - Doubling approximately every two years (actual growth of processors)



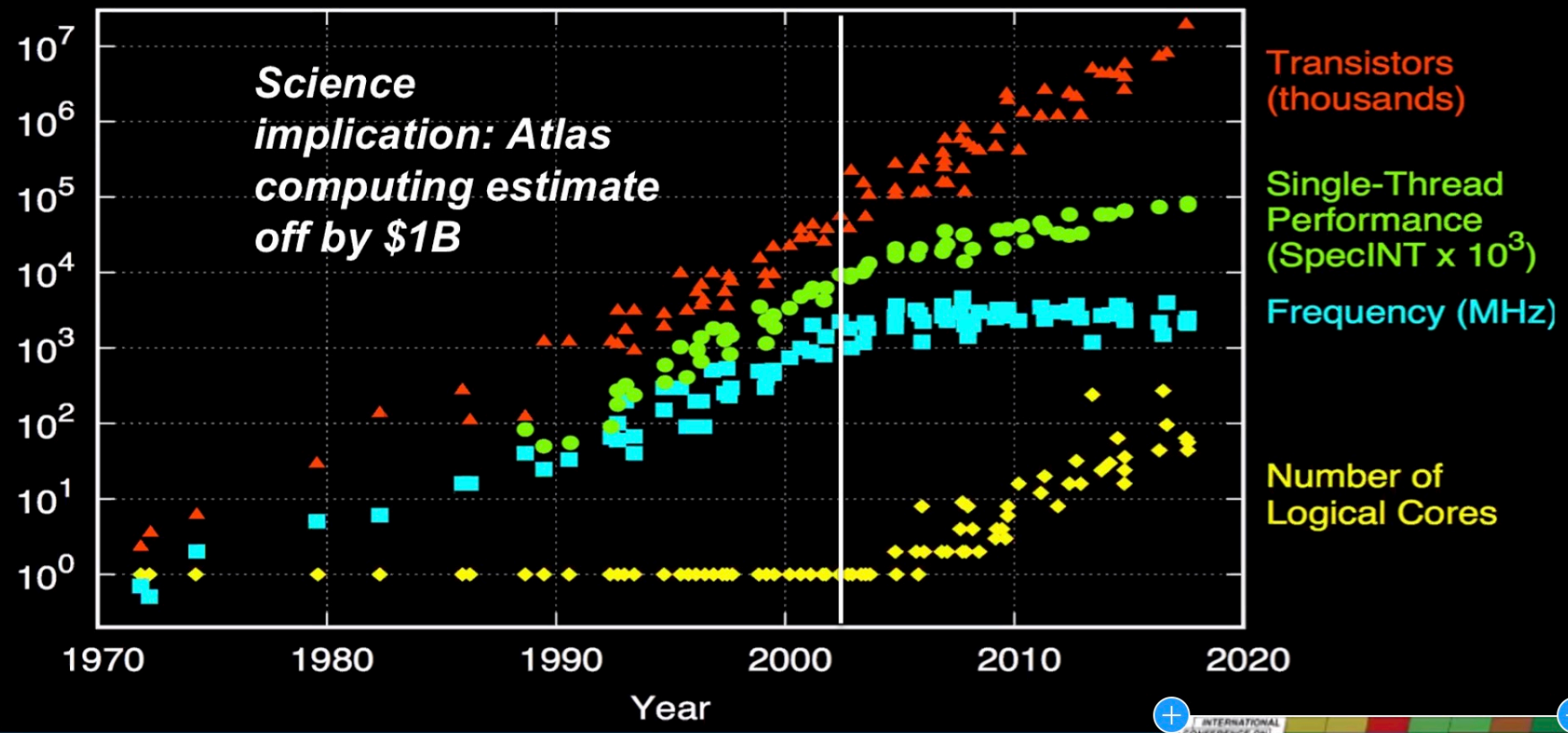
(Source) http://en.wikipedia.org/wiki/Moore%27s_law

Semiconductor Trends

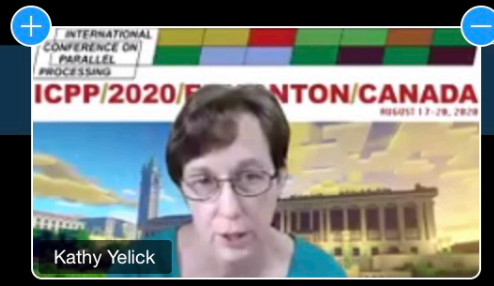


(Source) Hennessy & Patterson, Computer Architecture: A Quantitative Approach, 4th edition, Oct., 2006

Dennard Scaling is Dead; Moore's Law Will Follow



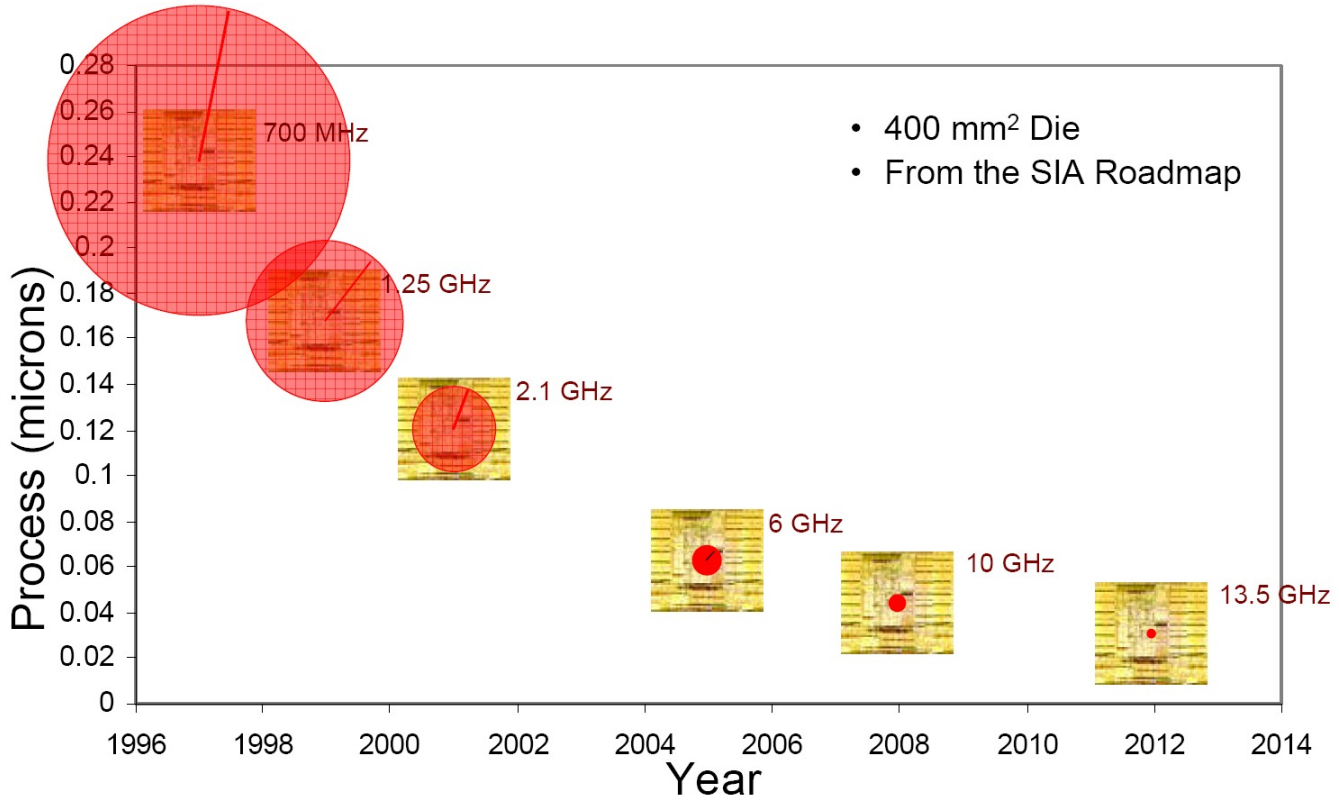
M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, C. Batten, and K. Rupp



Source: Kathy Yelick's keynote speech at ICPP '20

Challenges:
Wire Delay becomes issue when clock rate raised

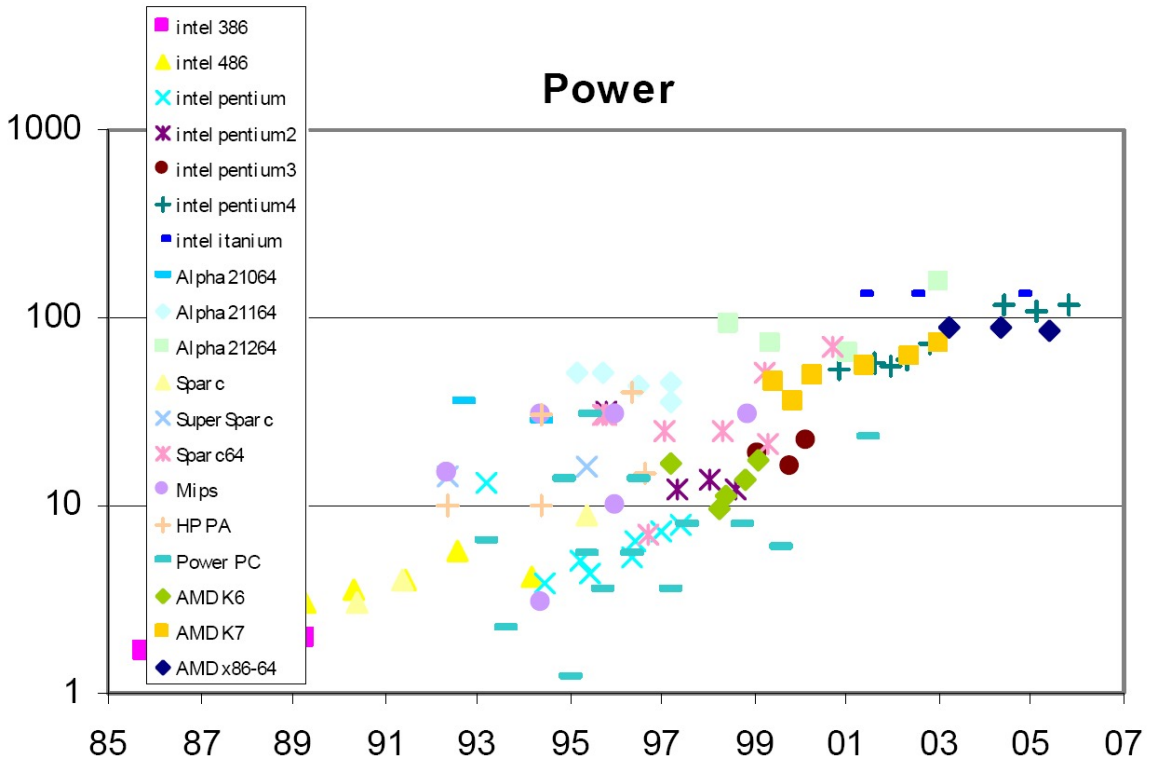
- The signal delay for a wire increases in proportion to the product of its resistance and capacitance (R*C)
  - Feature size shrinks → shorter wires → higher resistance and capacitance per unit length



(Source) MIT Course 6.189, "Multi-core Programming Primer: Learn and Compete in Programming the PLAYSTATION®3 Cell Processor."

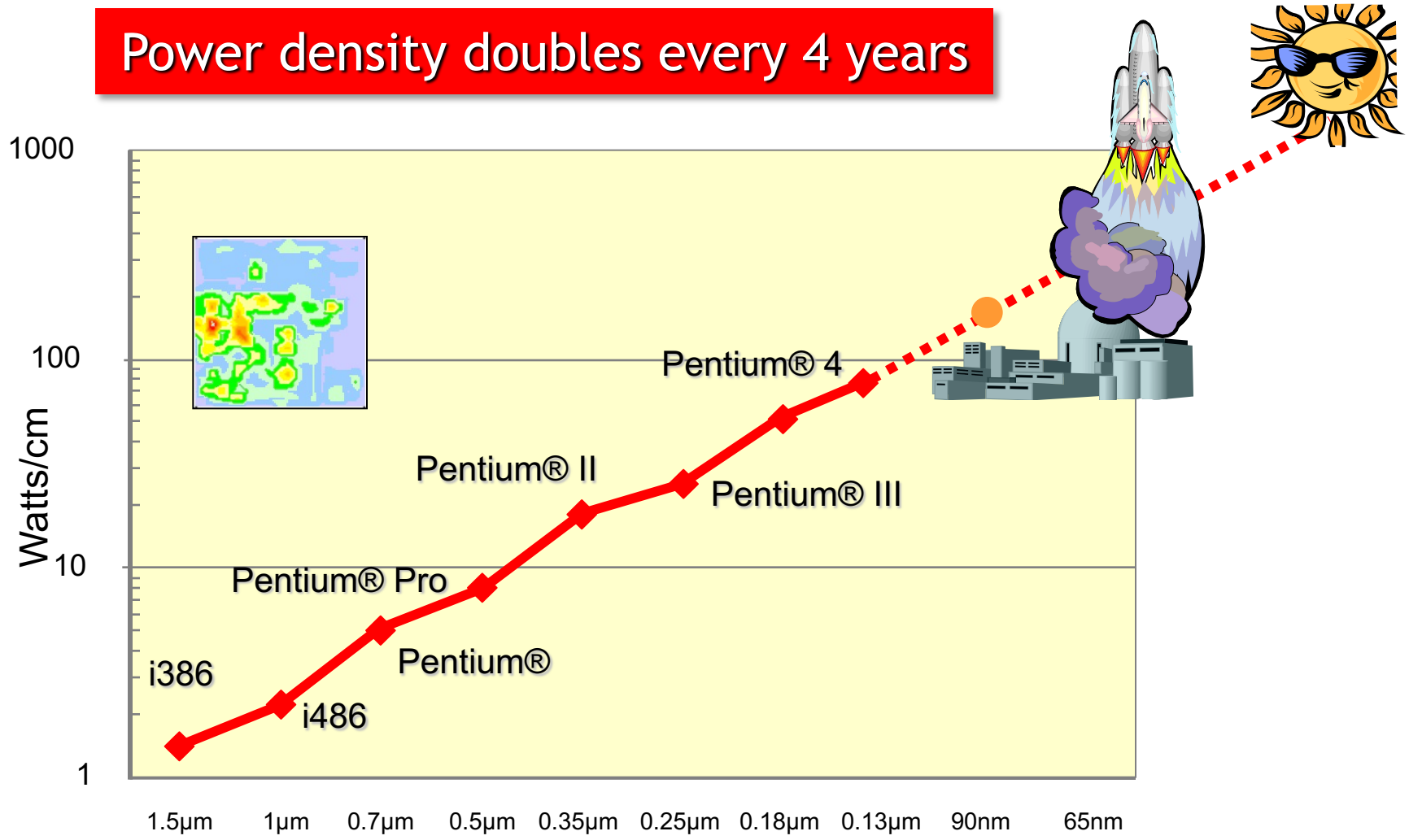
Challenges: Power Consumption

- Power consumption becomes a problem:
  - Operation energy of transistors (cost, environment)
  - Heat dissipation reaching its limitation (cooling, space, cost)



(Source) MIT Course 6.189, "Multi-core Programming Primer: Learn and Compete in Programming the PLAYSTATION®3 Cell Processor."

Power Density Trend



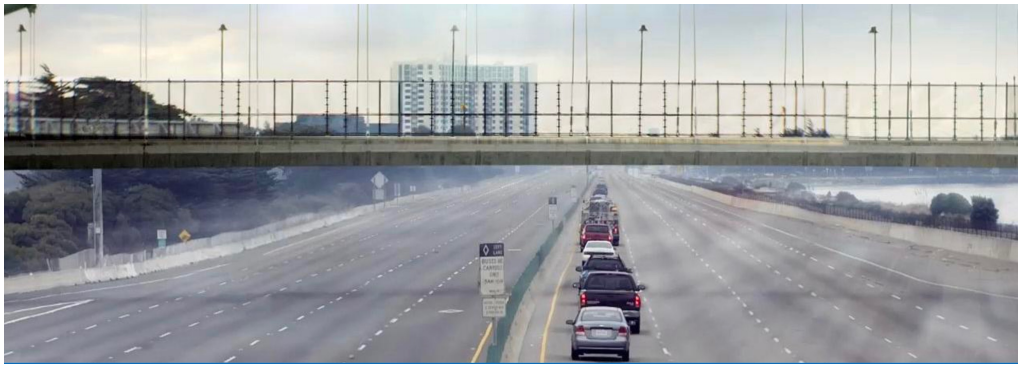
Source: Intel

Outline

- The What and Why of Parallel Computing
- The Why and How of Parallel Programming
- Parallel Programming Models
- Performance Evaluation

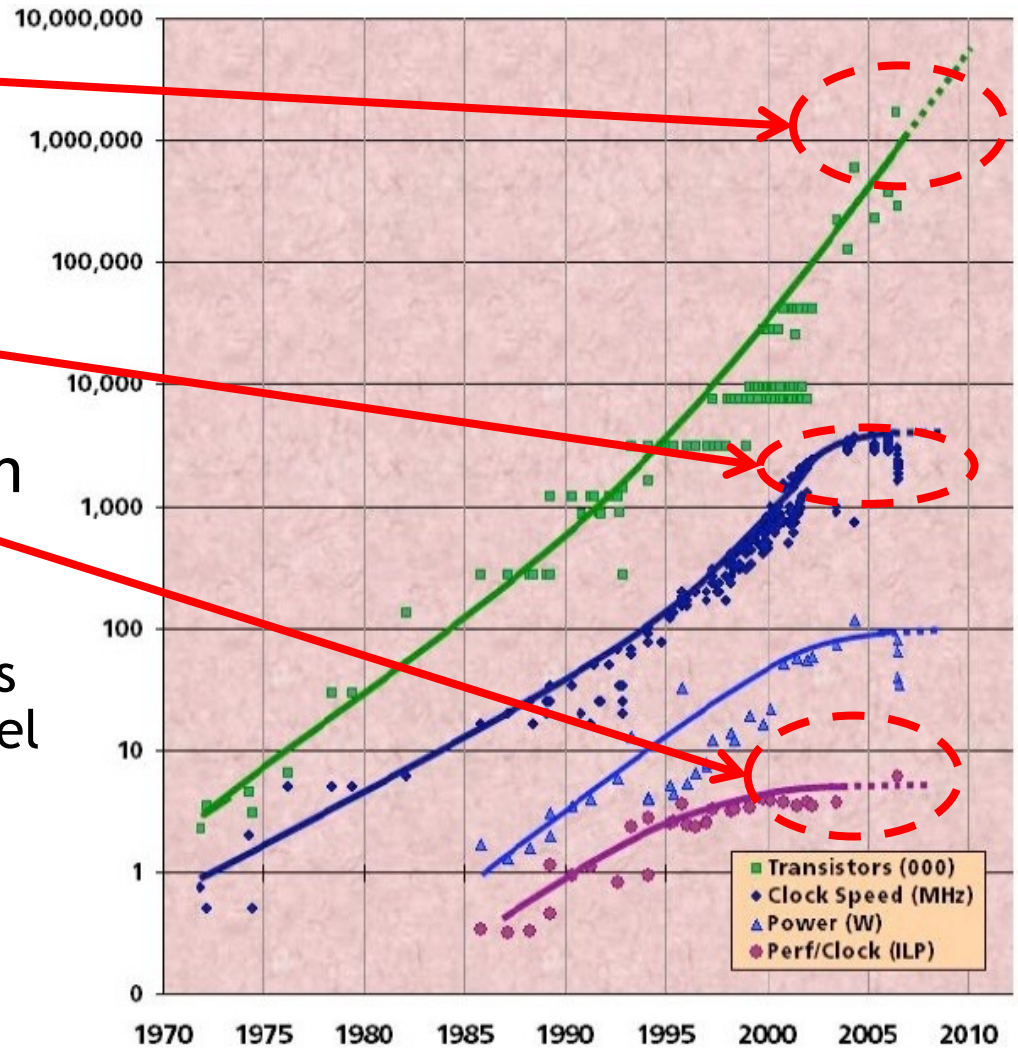
Why We Need to Write Parallel Programs?

- Most programs that have been written for single-core systems cannot exploit the presence of multiple cores
- The bad news is that researchers have had very limited success writing programs that convert serial programs in languages such as C and C++ into parallel programs



Limiting Forces: Clock Speed and ILP

- Chip density is continuing increase ~2x every 2 years
  - # processors/chip (cores) may double instead
- Clock speed is not
- There is little or no more instruction-level parallelism (ILP) to be found
  - Can no longer allow programmer to think in terms of a serial programming model
- Conclusion:
  - Parallelism must be exposed to software!



Source: Intel, Microsoft (Sutter) and Stanford (Olukotun, Hammond)

Parallelizing A Program: An Example

- As an example, suppose that we need to compute *n* values and add them together
- We know that this can be done with the following serial code:

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

Partitioning Step

- Now suppose we also have *p* cores and *p* is much smaller than *n*. Then each core can form a partial sum of approximately *n*/*p* values:

```
my_n = n/p;
my_first_i = my_n * my_rank;
my_last_i = my_first_i + my_n;
```

```
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;
}
```

- Here the prefix *my* indicates that each core is using its own, private variables, and each core can execute this block of code independently of the other cores

An Example

- For example, if there are eight cores, $n = 24$, and the 24 calls to Compute next value return the values

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

- Then the values stored in my sum might be

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

- When the cores are done computing their values of *my_sum*, they can form a global sum by sending their results to a designated "master" core, which can add their results

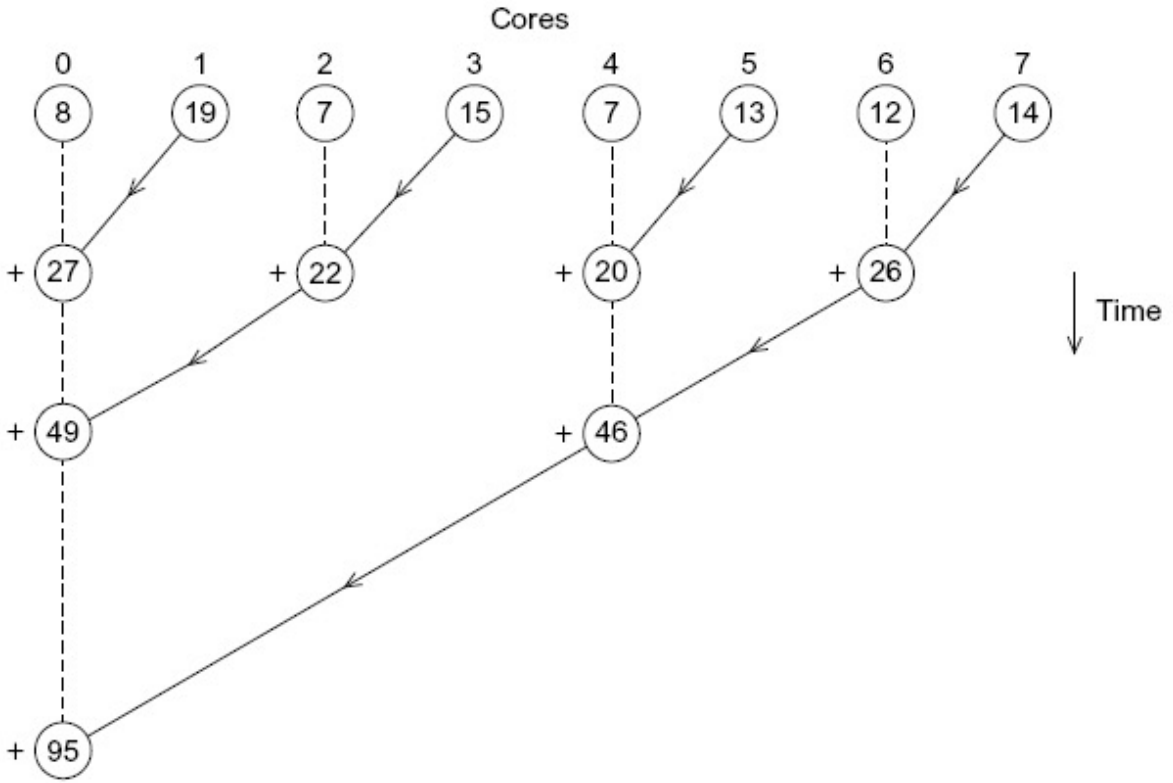
Aggregation Step

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

```
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;
}
```

A Better Aggregation

- Instead of making the master core do all the work of computing the final sum, we can pair the cores so that while core 0 adds in the result of core 1, core 2 can add in the result of core 3, core 4 can add in the result of core 5 and so on



Comparison between Two Aggregation Methods

- With eight cores, the master will carry out **seven** receives and adds using the first method, while with the second method it will only carry out **three**
- The difference becomes much more dramatic with large numbers of cores
  - With 1000 cores, the first method will require 999 receives and adds, while the second will only require 10, an improvement of almost a factor of **100**!

Writing Parallel Software to Exploit Parallelism

- The point here is that it's unlikely that a translation program would "discover" the second global sum
- We cannot simply continue to write serial programs
- We must write parallel programs that exploit the power of multiple processors

How Do We Write Parallel Programs?

- There are two widely used approaches:
  1) Task-parallelism
     - We partition the various tasks carried out in solving the problem among the cores
  2) Data-parallelism
     - We partition the data used in solving the problem among the cores, and each core carries out more or less similar operations on its part of the data
- The theme of the course focuses on data parallelism, which mostly exists within loops

How Do We Write Parallel Programs?

- Currently, the most powerful parallel programs are written using *explicit* parallel constructs
- They are written using extensions to languages such as C and C++
  - These programs include explicit instructions for parallelism

Coordination

- In both global sum examples, the coordination involves three types:
  1) Communication
     - One or more cores send their current partial sums to another core
  2) Load Balancing
     - We want the cores all to be assigned roughly the same number of values to compute
  3) Synchronization
     - Sometimes we want that each core will wait until all the cores have entered a given point

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Parallel Programming Models

- Programming model is made up of the languages and libraries that create an abstract view of the machine
- Control
  - How is parallelism created?
  - What orderings exist between operations?
- Data
  - What data are private vs. shared?
  - How is logically shared data accessed or communicated?
- Synchronization
  - What operations can be used to coordinate parallelism?
  - What are the atomic (indivisible) operations?

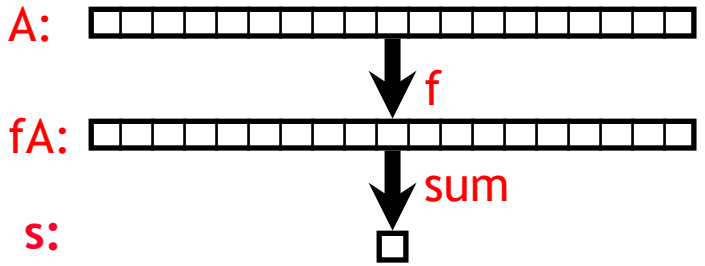
Simple Example of Data Parallelism

- Consider applying a function f to the elements of an array A and then computing its sum:

$$\sum_{i=0}^{n-1} f(A[i])$$

- Questions:
  - Where does *A* live? All in single memory? Partitioned?
  - What work will be done by each processors?
  - They need to coordinate to get a single result, how?

A = array of all data
fA = f(A)
s = sum(fA)



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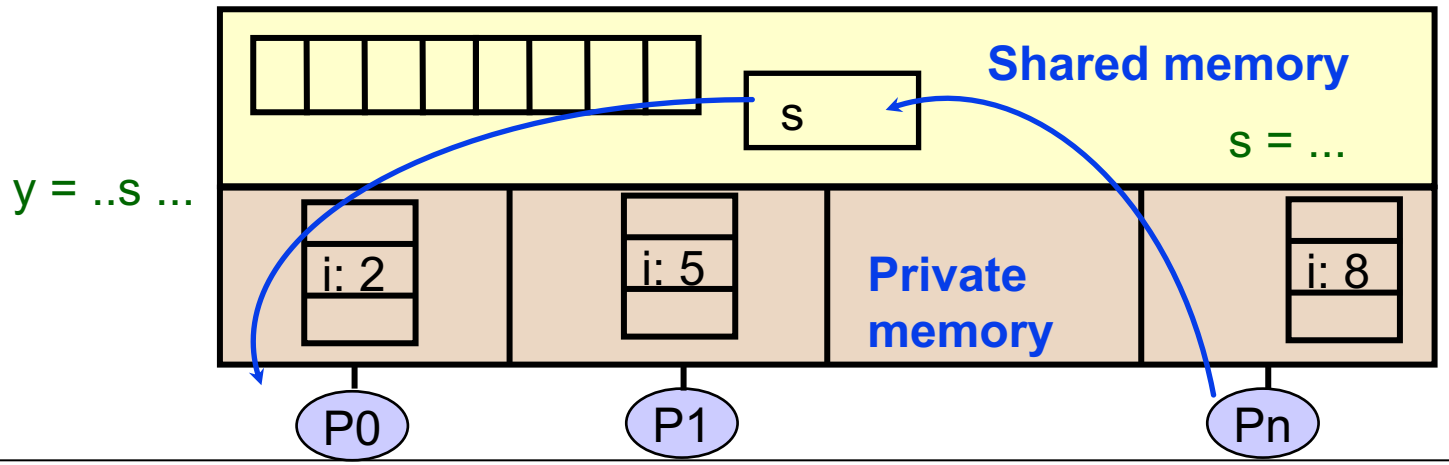
  - Shared-memory model
  - Distributed-memory model
  - Data-parallel model
- Performance Evaluation

Programming Model 1: Shared Memory

- Program is a collection of threads of control
  - Can be created dynamically, mid-execution, in some languages
- Each thread has a set of private variables, e.g., local stack variables
- Also a set of shared variables, e.g., static variables, shared common blocks, or global heap
  - Threads communicate implicitly by writing and reading shared variables
  - Threads coordinate by synchronizing on shared variables



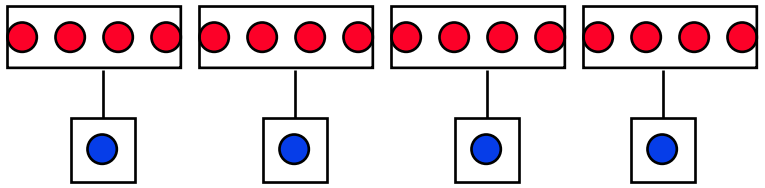
Simple Example of Data Parallelism

- Shared memory strategy:
  - small number p << n=size(A) processors
  - attached to single memory

$$\sum_{i=0}^{n-1} f(A[i])$$

- Parallel decomposition:
  - Each evaluation and each partial sum is a task
- Assign n/p numbers to each of p procs
  - Each computes independent "private" results and partial sum
  - Collect the p partial sums and compute a global sum

Two Classes of Data:



- Logically Shared
  - The original n numbers, the global sum
- Logically Private
  - The individual function evaluations
  - What about the individual partial sums?

Shared Memory "Code" for Computing a Sum

```
fork(sum,a[0:n/2-1]);
sum(a[n/2,n-1]);
```

```
static int s = 0;
```

```
Thread 1

  for i = 0, n/2-1
      s = s + f(A[i])
```

```
Thread 2

  for i = n/2, n-1
      s = s + f(A[i])
```

- What is the problem with this program?

- A race condition or data race occurs when:
  - Two processors (or two threads) access the same variable, and at least one does a write
  - The accesses are concurrent (not synchronized) so they could happen simultaneously

An Example of Race Condition

A= | 3 | 5 |

$f(x) = x^2$

```
static int s = 0;
```

Thread 1		Thread 2	
….		…	
compute f([A[i]) and put in reg0	9	compute f([A[i]) and put in reg0	25
reg1 = s	0	reg1 = s	0
reg1 = reg1 + reg0	9	reg1 = reg1 + reg0	25
s = reg1	9	s = reg1	25
…		…	

- Assume A = [3,5], $f(x) = x^2$, and s=0 initially
- For this program to work, s should be $3^2 + 5^2 = 34$ at the end
  - but it may be 34, 9, or 25
- The atomic operations are reads and writes
  - Never see ½ of one number, but += operation is not atomic
  - All computations happen in (private) register

Improved Code for Computing a Sum

```
static int s = 0;
static lock lk;
```

Why not do lock inside the loop?

```
Thread 1

    local_s1= 0
    for i = 0, n/2-1
        local_s1 = local_s1 + f(A[i])
    lock(lk);
    s = s + local_s1
    unlock(lk);
```

```
Thread 2

    local_s2 = 0
    for i = n/2, n-1
        local_s2= local_s2 + f(A[i])
    lock(lk);
    s = s +local_s2
    unlock(lk);
```

- Since addition is associative, it's OK to rearrange order
- Most computation is on private variables
  - Sharing frequency is also reduced, which might improve speed
  - But there is still a race condition on the update of shared s
  - The race condition can be fixed by adding locks (only one thread can hold a lock at a time; others wait for it)

POSIX Threads

- POSIX: Portable Operating System Interface for UNIX
  - Interface to Operating System utilities
- Pthreads: The POSIX threading interface
  - System calls to create and synchronize threads
  - Should be relatively uniform across UNIX-like OS platforms
  - Originally IEEE POSIX 1003.1c
- Pthreads contain support for
  - Creating parallelism
  - Synchronizing
  - No explicit support for communication, because shared memory is implicit; a pointer to shared data is passed to a thread
    - Only for static variables and HEAP! Stacks not shared

Pthreads Example: Hello World

```
void* SayHello(void *foo) {
    printf( "Hello, world!\n" );
    return NULL;
}
int main() {
    pthread_t threads[16];
    int tn;
    for(tn=0; tn<16; tn++) {
        pthread_create(&threads[tn], NULL, SayHello, NULL);
    }
    for(tn=0; tn<16 ; tn++) {
        pthread_join(threads[tn], NULL);
    }
    return 0;
}
```

Shared Data and Threads

- Variables declared outside of main are shared
- Objects allocated on the heap may be shared (if pointer is passed)
- Variables on the stack are private: passing pointer to these around to other threads can cause problems
- Often done by creating a large “thread data” struct, which is passed into all threads as argument

```
char *message = "Hello World!\n";
pthread_create(&thread1, NULL,
               print_fun,(void*) message);
```

OpenMP

C$OMP FLUSH

#pragma omp critical

C$OMP

C$OMP

C$OM

C$C

#pra

C$OMP PARALLEL COPYIN(/blk/)

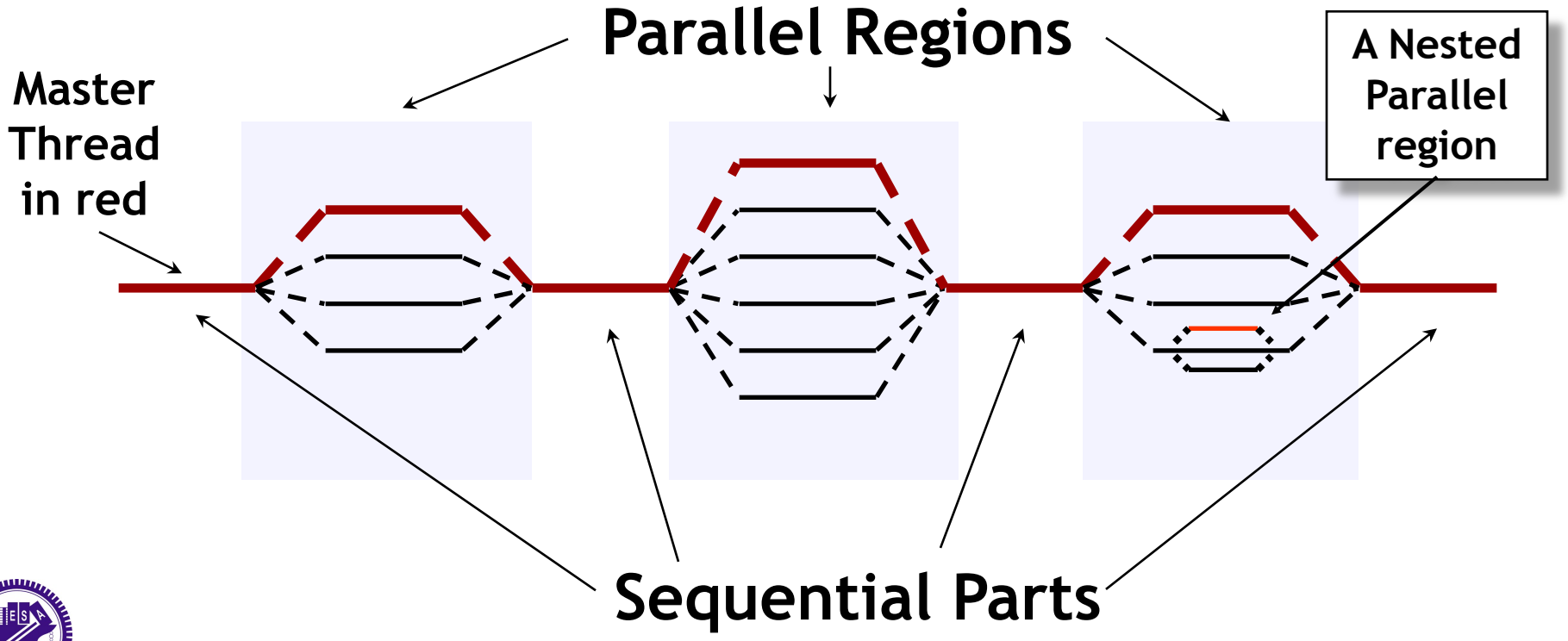
C$OMP DO lastprivate(XX)

OpenMP: An API for Writing Multithreaded Applications

- A set of compiler directives and library routines for parallel application programmers
- Makes writing multi-threaded applications in Fortran, C and C++ as easy as we can make it
- Standardizes last 20 years of SMP practice

OpenMP Execution Model:

- Fork-Join Parallelism:
  - Master thread spawns a team of threads as needed
  - Parallelism added incrementally until performance are met: i.e. the sequential program evolves into a parallel program



OpenMP Example: Hello World

- Write a multithreaded program where each thread prints “hello world”

```
void main() {



    printf(“ hello(%d) ”, ID);
    printf(“ world(%d) \n”, ID);

}
```

OpenMP Example: Hello World

- Tell the compiler to pack code into a function, fork the threads, and join when done ...

```
#include “omp.h”
void main() {
#pragma omp parallel
  {
    int ID = omp_get_thread_num();
    printf(“ hello(%d) ”, ID);
    printf(“ world(%d) \n”, ID);
  }
}
```

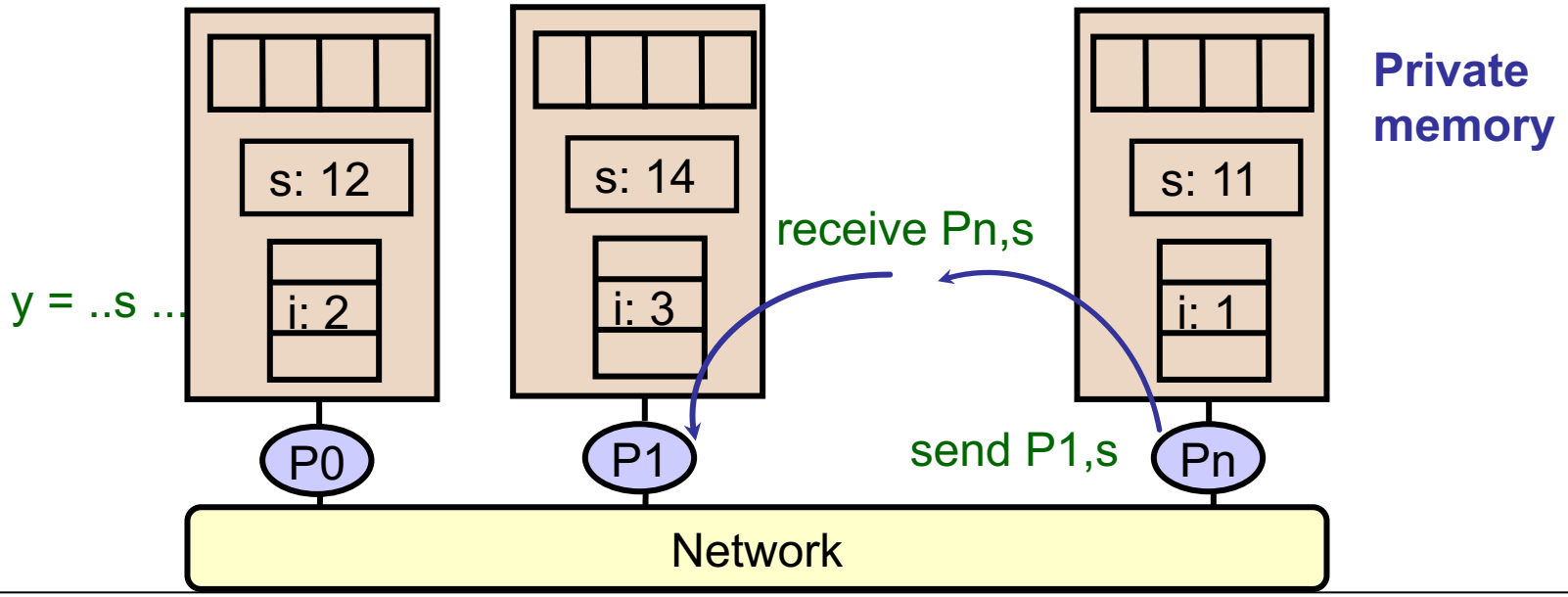
Sample Output:
hello(1) hello(0) world(1)
world(0)
hello(3) hello(2) world(3)
world(2)

Outline

- The What and Why of Parallel Computing
- The Why and How of Parallel Programming
- Parallel Programming Models
  - Shared-memory model
  - Distributed-memory model
  - Data-parallel model
- Performance Evaluation

Programming Model 2: Message Passing

- Program consists of a collection of named processes
  - Usually fixed at program startup time
  - Thread of control plus local address space -- NO shared data
  - Logically shared data is partitioned over local processes
- Processes communicate by explicit send/receive pairs
  - Coordination is implicit in every communication event
  - MPI (Message Passing Interface) is the most commonly used SW



Computing s = f(A[1])+f(A[2]) on each processor

- First possible solution - what could go wrong?

```
Processor 1
   xlocal = f(A[1])
   send xlocal, proc2
   receive xremote, proc2
   s = xlocal + xremote
```

```
Processor 2
   xlocal = f(A[2])
   send xlocal, proc1
   receive xremote, proc1
   s = xlocal + xremote
```

- If send/receive acts like the telephone system? The post office?
- Second possible solution

```
Processor 1
   xlocal = f(A[1])
   send xlocal, proc2
   receive xremote, proc2
   s = xlocal + xremote
```

```
Processor 2
   xlocal = f(A[2])
   receive xremote, proc1
   send xlocal, proc1
   s = xlocal + xremote
```

MPI – the de facto standard

- MPI has become the de facto standard for parallel computing using message passing
- Example:

```
for (i=1;i<numprocs;i++) {
   sprintf(buff, "Hello %d! ", i);
   MPI_Send(buff, BUFSIZE, MPI_CHAR, i, TAG, MPI_COMM_WORLD);
}
for(i=1;i<numprocs;i++) {
   MPI_Recv(buff, BUFSIZE, MPI_CHAR, i, TAG, MPI_COMM_WORLD, &stat);
   printf("%d: %s\n", myid, buff);
}
```

- Pros and Cons of standards
  - MPI created finally a standard for applications development in the HPC community => portability
  - The MPI standard is a least common denominator building on mid-80s technology, so may discourage innovation

Which is better? SM or MP?

- Which is better, Shared Memory or Message Passing?
  - Depends on the program!
  - Both are "communication Turing complete"
    - i.e. can build Shared Memory with Message Passing and vice-versa
- Advantages of Shared Memory
  - Implicit communication (loads/stores)
  - Low overhead when cached
- Disadvantages of Shared Memory
  - Complex to build in way that scales well
  - Requires synchronization operations
  - Hard to control data placement within caching system
- Advantages of Message Passing
  - Explicit Communication (sending/receiving of messages)
  - Easier to control data placement (no automatic caching)
- Disadvantages of Message Passing
  - Message passing overhead can be quite high
  - More complex to program
  - Introduces question of reception technique (interrupts/polling)

Outline

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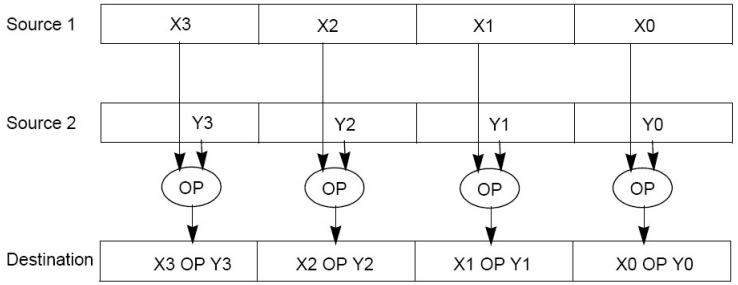
Programming Model 3: Data Parallel

- Single thread of control consisting of parallel operations
  - A = B + C could mean adding two arrays in parallel
- Parallel operations applied to all (or a defined subset) of a data structure, usually an array
  - Communication is implicit in parallel operators
  - Elegant and easy to understand and reason about
  - Coordination is implicit – statements executed synchronously
  - Similar to Matlab language for array operations
- Drawbacks:
  - Not all problems fit this model
  - Difficult to map onto coarse-grained machines

Vector/SIMD operations

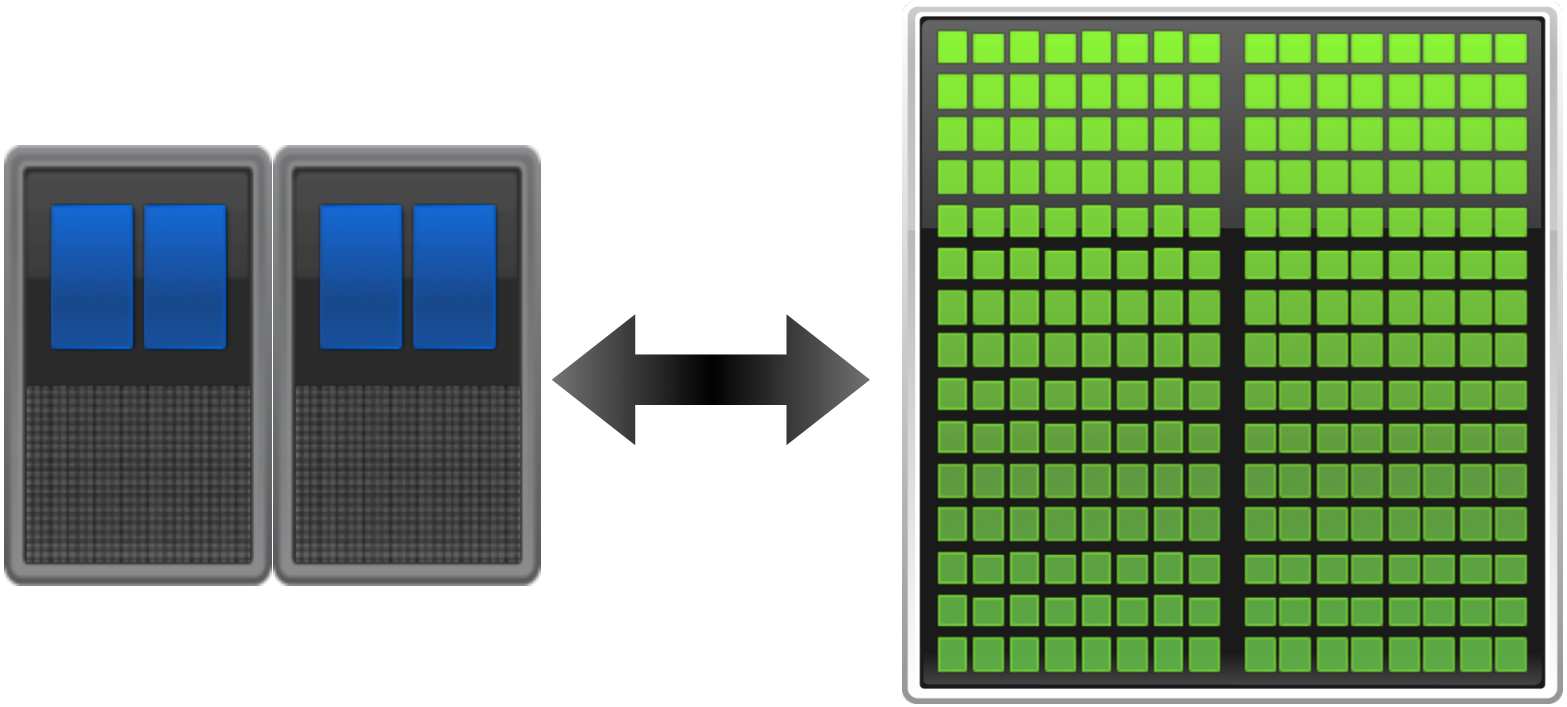


What about GPU and Cloud?

- GPU's big performance opportunity is data parallelism
  - Most programs have a mixture of highly parallel operations, and some not so parallel
  - GPUs provide a threaded programming model (CUDA) for data parallelism to accommodate both
  - Current research attempting to generalize programming model to other architectures, for portability (OpenCL)

- Cloud computing allows large numbers of people easily share O(10^5) machines
  - MapReduce was first programming model: data parallel on distributed memory
  - More flexible models (Hadoop…) invented since then

CPU-GPU: Heterogeneous Parallel Computing



Latency-optimized CPU

Fast serial processing

Throughput-optimized GPU

Scalable parallel processing

CUDA (Compute Unified Device Architecture)

- ***Data-parallel*** programming interface to GPU
  - Data to be operated on is discretized into independent partition of memory
  - Each thread performs roughly same computation to different partition of data
- Programmer expresses
  - Thread programs to be launched on GPU, and how to launch
  - Data organization and movement between host and GPU
  - Synchronization, memory management, …
- CUDA is one of first to support ***heterogeneous*** architectures (more later in the semester)

OpenCL

- Open Computing Language
- A framework for writing programs that execute across heterogeneous platforms consisting of CPUs, GPUs and other processors

CUDA Example: Vector Add

```
int main() {
  int A[ ] = {…};
  int B[ ] = {…};

  for (i = 0; i < N; i++) {
    C[i] = A[i] + B[i];
  }
}
```

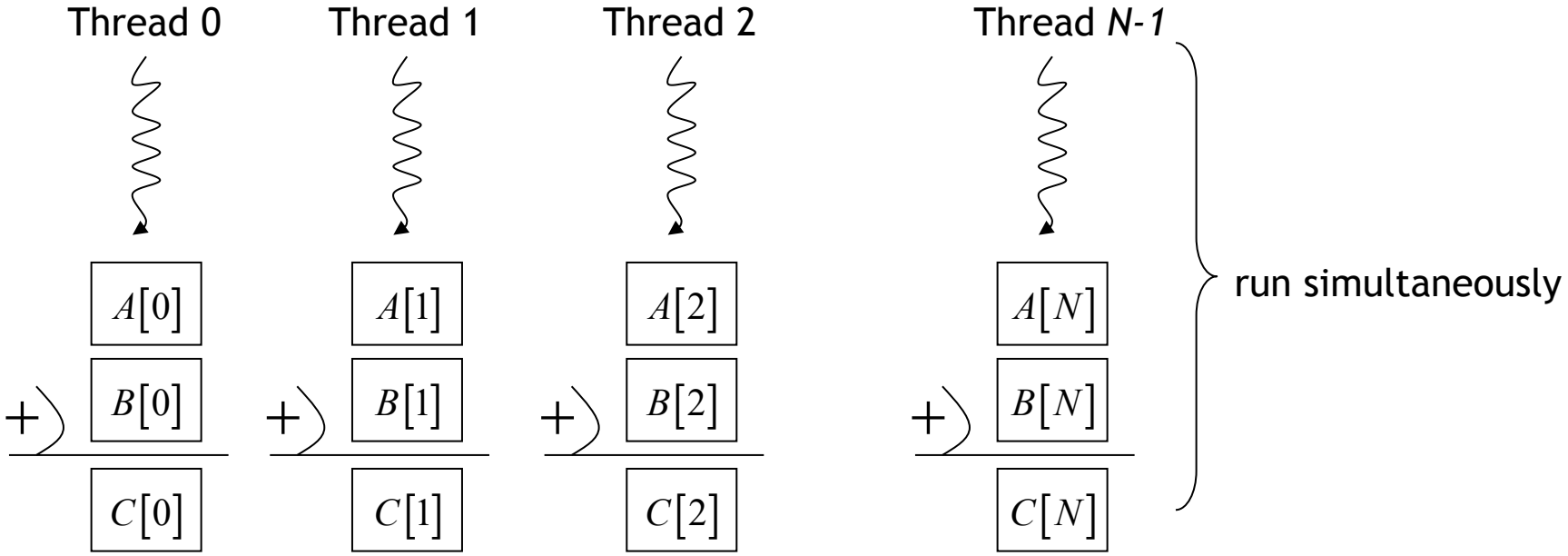
Sequential version

```
__global__ void vecAdd(int A[ ], int B[ ], int C[ ]) {
  int i = threadIdx.x;
  C[i] = A[i] + B[i];
}

int main() {
  int hA[ ] = {…};
  int hB[ ] = {…};

  cudaMemcpy(dA, hA, sizeof(hA), HostToDevice);
  cudaMemcpy(dB, hB, sizeof(hB), HostToDevice);

  vecAdd<<<1, N>>>(dA, dB, dC);

  cudaMemcpy(dC, hC, sizeof(hC), DeviceToHost);
}
```

Parallel version

CUDA Example: Vector Add

```
__global__ void vecAdd(int A[ ], int B[ ], int C[ ]) {
  int i = threadIdx.x;
  C[i] = A[i] + B[i];
}
```



MapReduce

- MapReduce is a programming model for processing large data sets with a parallel, distributed algorithm on a cluster
- The model is inspired by the map and reduce functions commonly used in functional programming

Map and Reduce

- Map
  - The master node takes the input, divides it into smaller sub-problems, and distributes them to worker nodes
  - The worker node processes the smaller problem, and passes the answer back to its master node

  Map function:

  $$(K_{in}, V_{in}) \rightarrow \text{list}<(K_{inter}, V_{inter})>$$

- Reduce
  - The master node then collects the answers to all the sub-problems and combines them in some way to form the output, the answer to the problem it was originally trying to solve

  Reduce function:

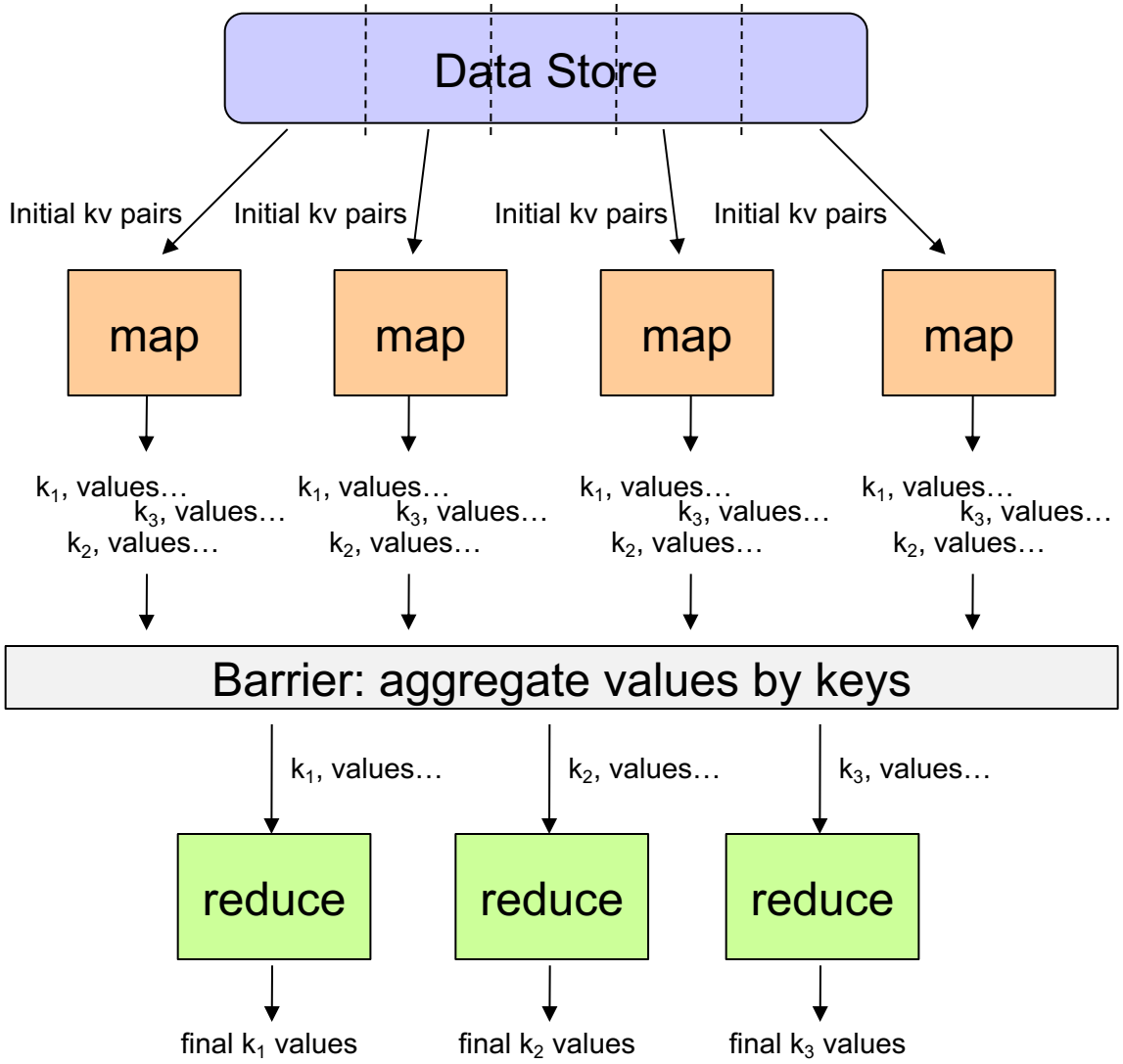
  $$(K_{inter}, \text{list}<V_{inter}>) \rightarrow \text{list}<(K_{out}, V_{out})>$$

Typical Problem

- Iterate over a large number of records
- Map: extract something of interest from each
- Shuffle and sort intermediate results
- Reduce: aggregate intermediate results
- Generate final output

Key idea: provide an abstraction at the point of these two operations

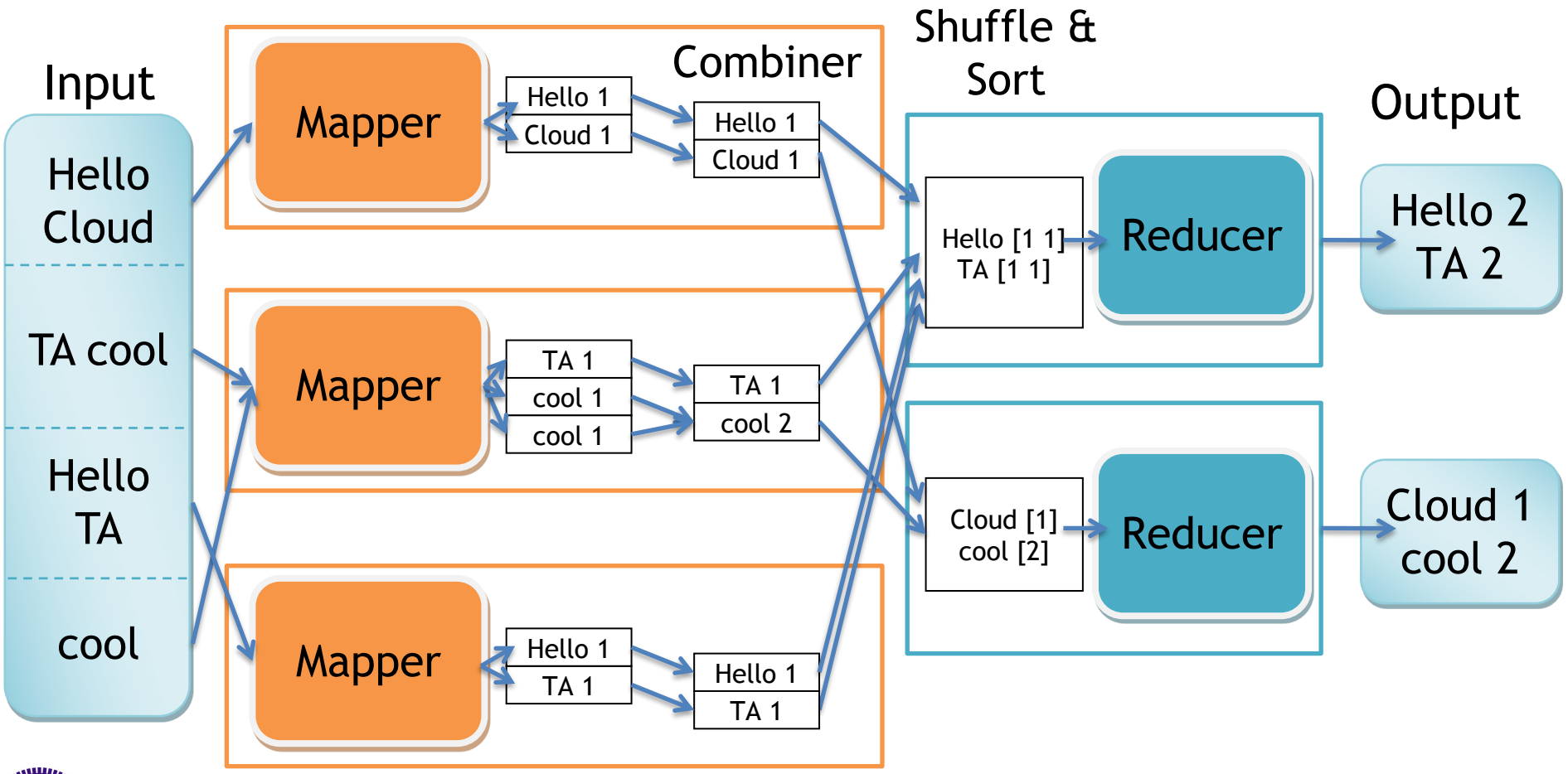
It's just divide and conquer!



Example: Word Count

```
def map(line_num, line):
    foreach word in line.split():
        output(word, 1)
```

```
def reduce(word, counts):
    output(word, sum(counts))
```



Hadoop

- Hadoop (High-availability distributed object-oriented platform)
- An open-source software framework that supports data-intensive distributed applications
- Distributed File System (HDFS)
  - Runs on same machines
  - Replicates data 3x for fault-tolerance
- It supports the running of applications on large clusters of commodity hardware

Hadoop

- Hadoop was derived from Google's MapReduce and Google File System (GFS) papers
- Hadoop is written in the Java programming language

Remark

- Three basic conceptual models
  - Shared memory
  - Distributed memory
  - Data parallel

  and hybrids of these models
- All of these models rely on dividing up work into parts that are:
  - Mostly independent (little synchronization)
  - About same size (load balanced)
  - Have good locality (little communication)

Outline

- The What and Why of Parallel Computing
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Performance

- Of course our main purpose in writing parallel programs is usually increased performance
- So what can we expect? And how can we evaluate our programs?
  - Speedup
  - Efficiency
  - Scalability

Speedup

- We run our program with *p* cores, one thread or process on each core, then our parallel program will run *p* times faster than the serial program
- When this happens, we say that our parallel program has **linear speedup**

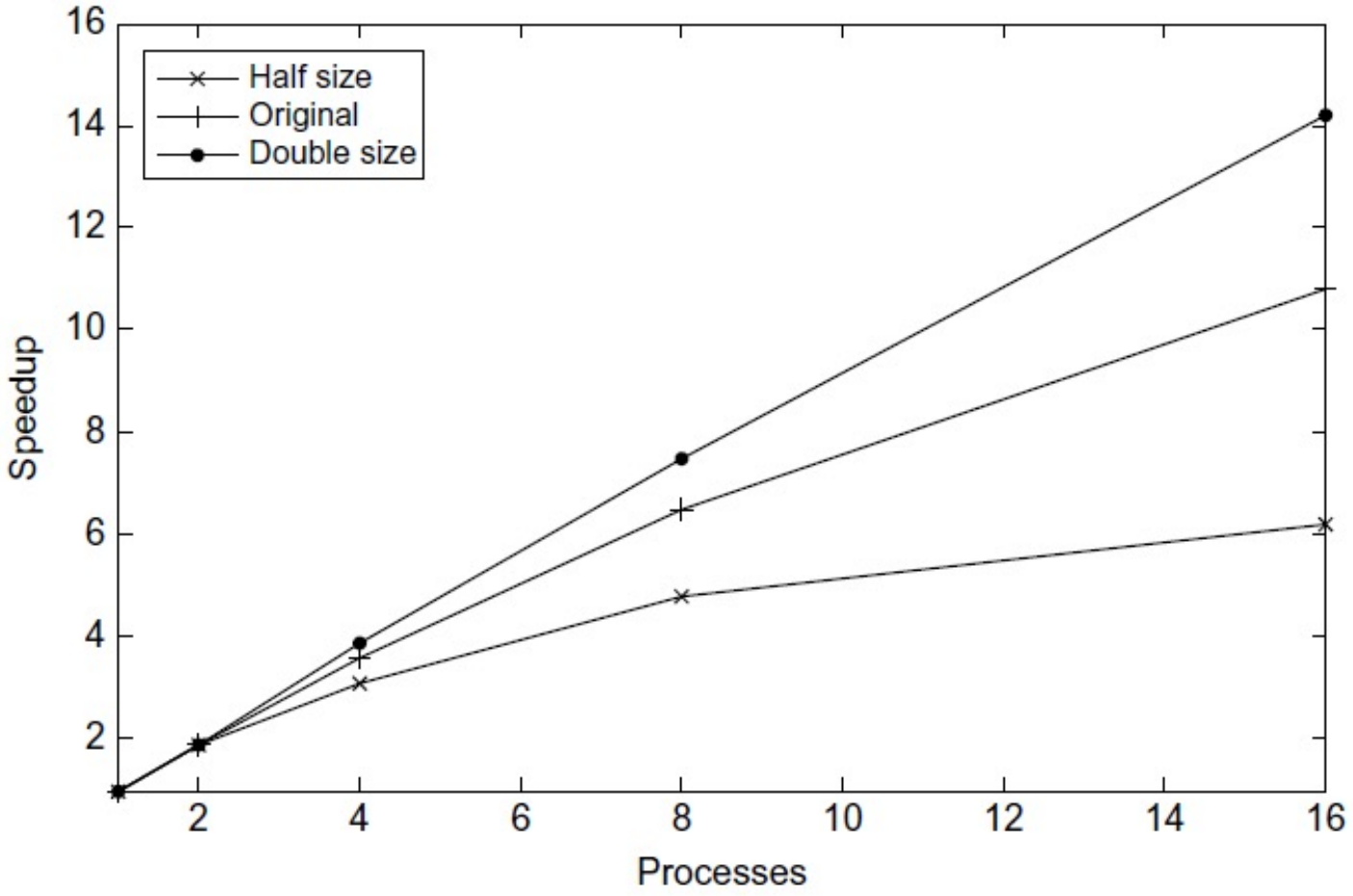
Speedup

- In practice, we're unlikely to get linear speedup because the use of multiple processes almost invariably introduces some overhead
- We define the speedup of a parallel program to be:

$$S = \frac{T_{\text{serial}}}{T_{\text{parallel}}}$$

- Then linear speedup has S = *p*

Speedup



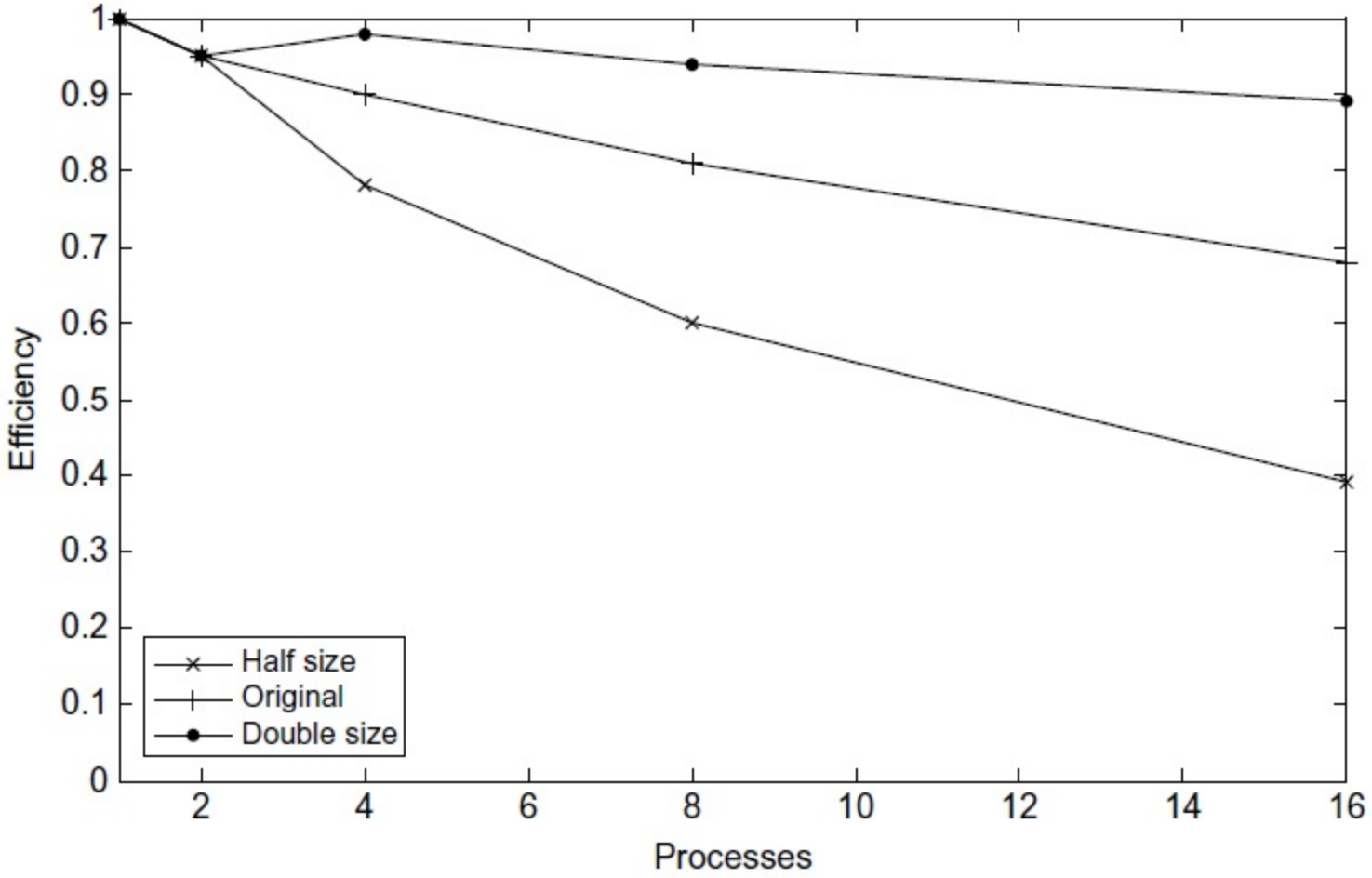
Speedups of parallel program on different problem sizes

Efficiency

- S/p, is sometimes called the **efficiency** of the parallel program

$$E = \frac{S}{p} = \frac{\left(\frac{T_{\text{serial}}}{T_{\text{parallel}}}\right)}{p} = \frac{T_{\text{serial}}}{p \cdot T_{\text{parallel}}}$$

Efficiency



Efficiencies of parallel program on different problem sizes

Scalability

- If we increase the problem size at the same rate that we increase the number of processes/threads, then the efficiency will be unchanged, and our program is scalable

AUTO SCALE

Grows without requiring developers to re-architect their algorithms/applications

Strongly Scalable and Weakly Scalable

- There are a couple of cases that have special names:
  1) Strongly scalable
     - When we increase the number of processes/threads, we can keep the efficiency fixed *without* increasing the problem size
  2) *Weakly scalable*
     - We can keep the efficiency fixed by increasing the problem size at the same rate as we increase the number of processes/threads

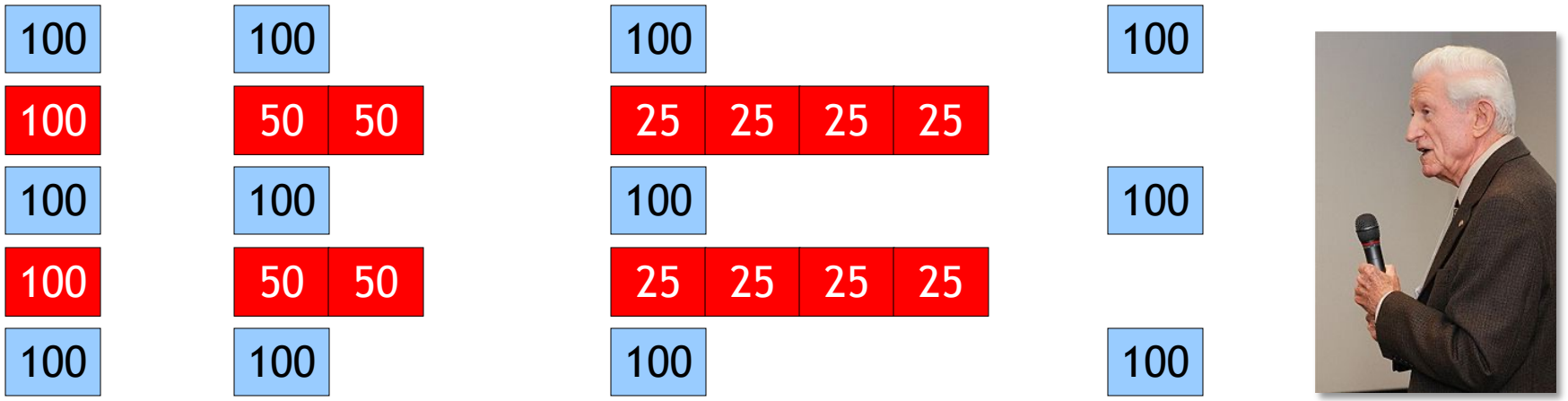
A Word of Warning

- Every parallel program contains at least one serial program
- Since we almost always need to coordinate the actions of multiple cores, writing parallel programs is almost always more complex than writing a serial program that solves the same problem

Amdahl's Law

- The speedup of a program using multiple processors in parallel computing is limited by the time needed for the sequential fraction of the program

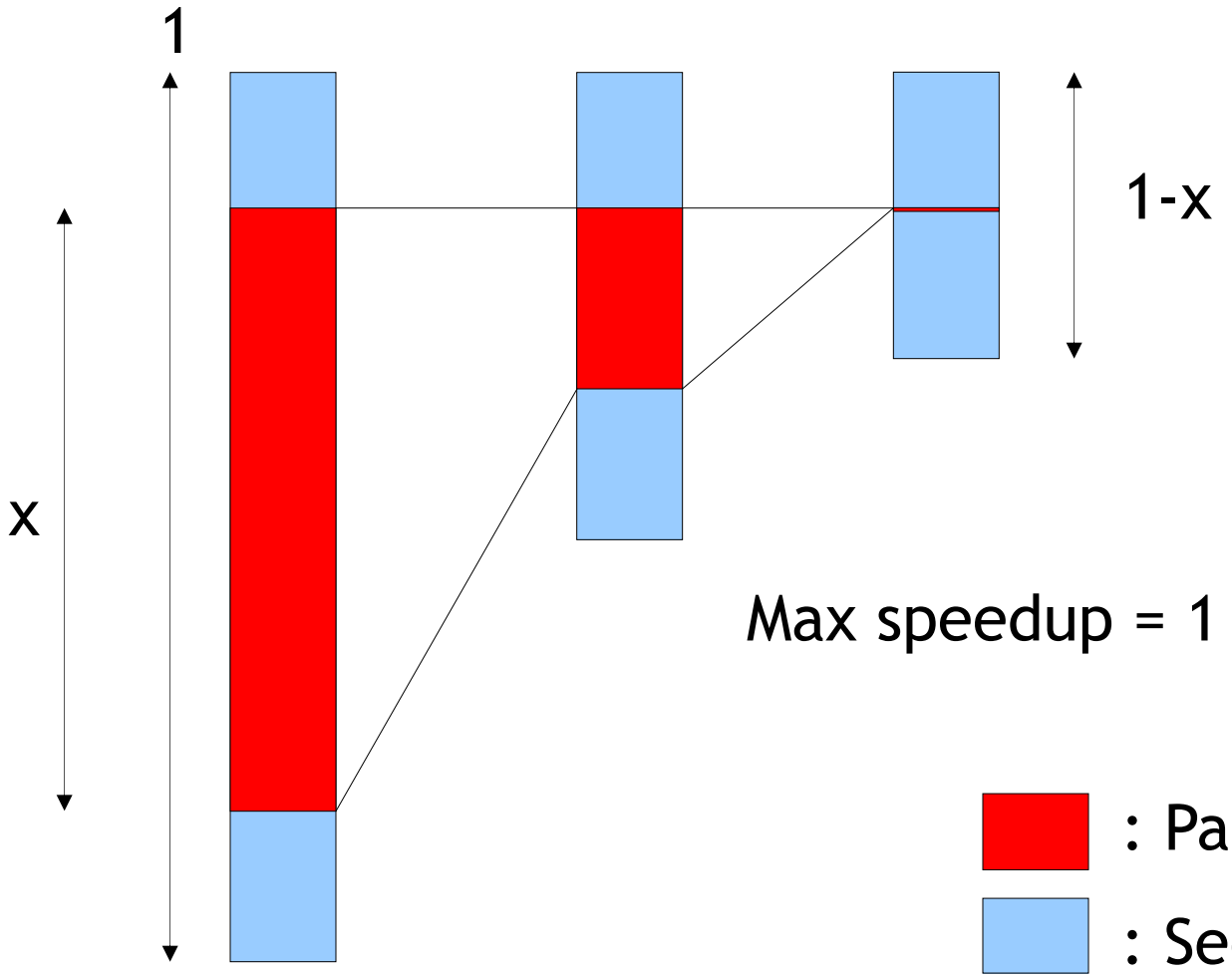
$$\text{Speedup} = \frac{\text{Sequential execution time}}{\text{Parallel execution time}}$$



: Parallel portion

: Sequential portion

Amdahl's Law (Cont'd)



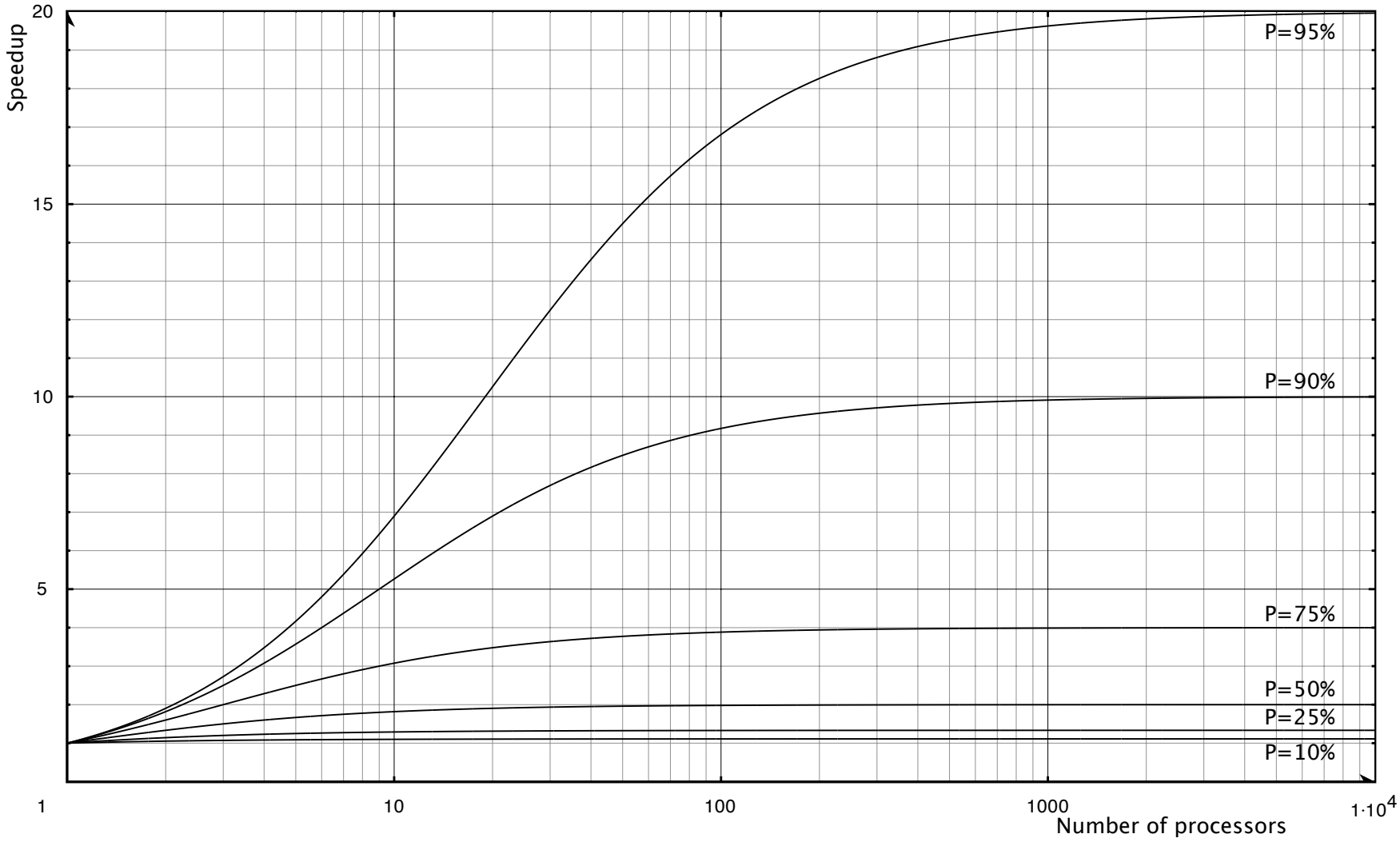
Max speedup = 1 / (1-x)

: Parallel portion

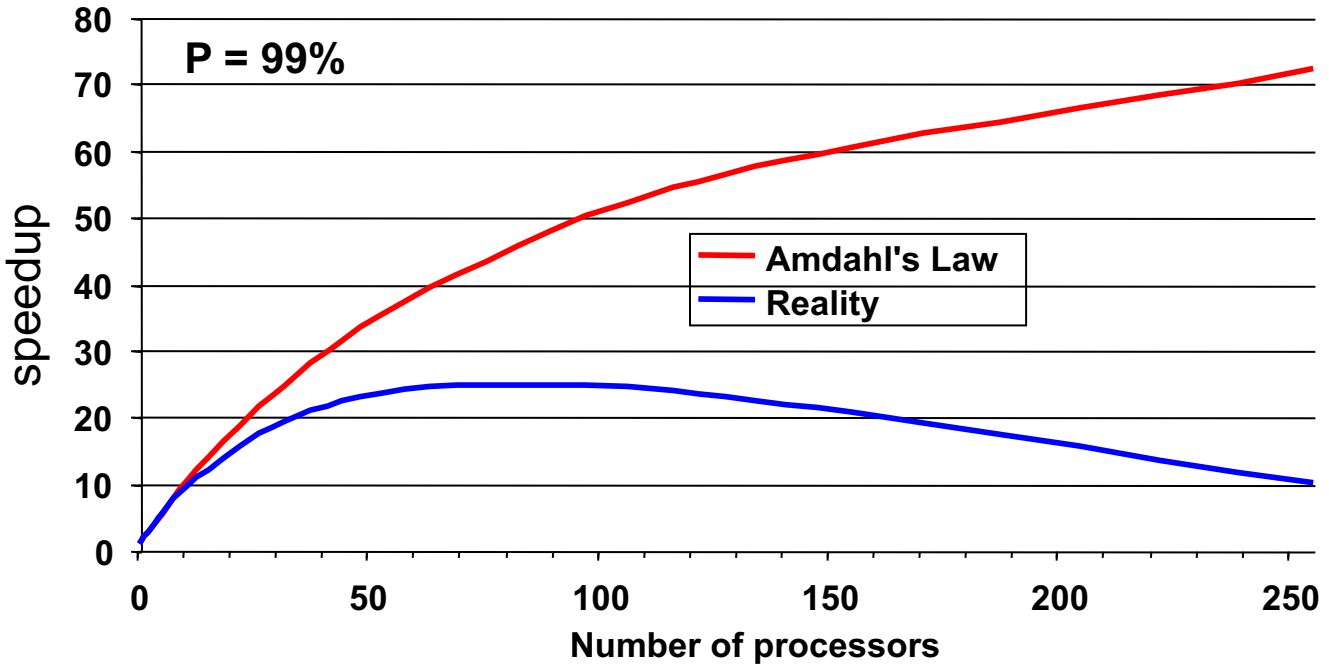
: Sequential portion

$$S(n) = \frac{s+p}{s+p/n} = \frac{1}{(1-p)+p/n}$$

Amdahl's Law (Cont'd)



Amdahl's Law vs Reality



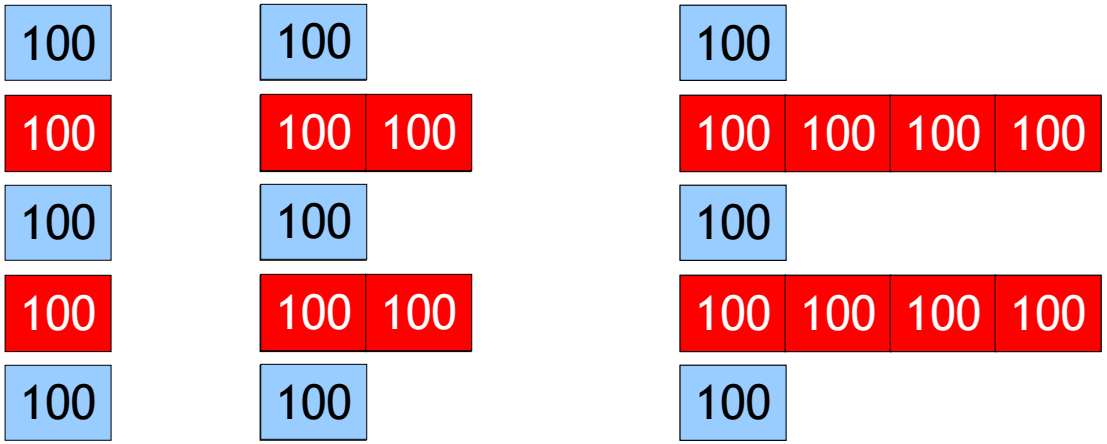
- Amdahl's Law provides a theoretical upper limit on parallel speedup assuming that there are no costs for communications
  - In reality, communications will result in a further degradation of performance

More on Amdahl's Law

- Amdahl's Law works on a *fixed* problem size
  - This is reasonable if your only goal is to solve a problem faster
  - What if you also want to solve a larger problem?
- Gustafson's Law:
  - The proportion of the computations that are sequential normally decreases as the problem size increases

Gustafson's Law

- Rather than assume that the problem size is fixed, assume that the parallel execution time is fixed
  - In increasing the problem size, Gustafson also makes the case that the serial section of the code does not increase as the problem size



  - Scaled speedup

$$S_s(n) = \frac{s + np}{s + p} = s + np = (1 - p) + np = 1 + (n - 1)p$$

Example of Gustafson's Law

- Suppose a parallel section of 95% and 20 processors; the speedup according to the formula is 19.05 instead of 10.26 according to Amdahl's law
  - Note, however, the different assumptions

$$S(n) = \frac{1}{(1-p) + p/n} = \frac{1}{0.05 + 0.95/20} \approx 10.26$$

$$S_s(n) = 1 + (n-1)p = 1 + (20-1) * 0.95 = 19.05$$

Summary

- In order to increase the power of processors, chipmakers have turned to **multicore** integrated circuits
- Ordinary **serial** programs usually cannot exploit the presence of multiple cores

Summary

- When we write parallel programs, we usually need to **coordinate** the work of the cores. This can involve **communication** among the cores, **load balancing**, and **synchronization** of the cores
- Parallel programs are usually very complex. So it's even more important to use good program development techniques with parallel programs

References

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