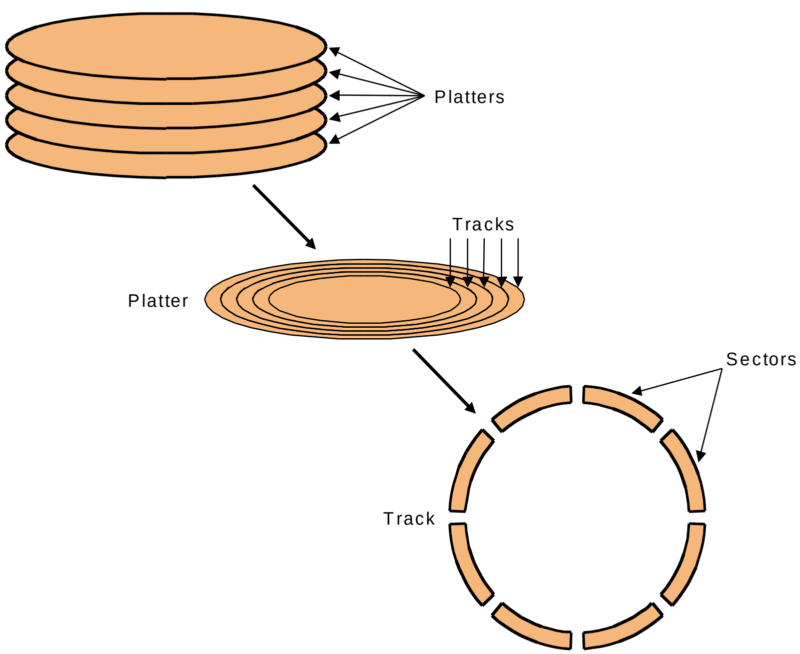
Lectures 26

- Finish up disks
- Parallelism

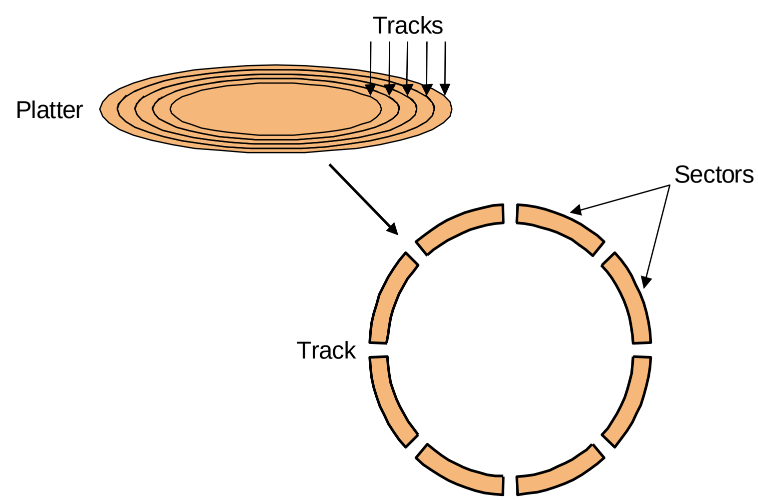
Hard drives

- The ugly guts of a hard disk.
  - Data is stored on double-sided magnetic disks called platters.
  - Each platter is arranged like a record, with many concentric tracks.
  - Tracks are further divided into individual sectors, which are the basic unit of data transfer.
  - Each surface has a read/write head like the arm on a record player, but all the heads are connected and move together.
- A 75GB IBM Deskstar has roughly:
  - 5 platters (10 surfaces),
  - 27,000 tracks per surface,
  - 512 sectors per track, and
  - 512 bytes per sector.



Accessing data on a hard disk

- Accessing a sector on a track on a hard disk takes a lot of time!
  - Seek time measures the delay for the disk head to reach the track.
  - A rotational delay accounts for the time to get to the right sector.
  - The transfer time is how long the actual data read or write takes.
  - There may be additional overhead for the operating system or the controller hardware on the hard disk drive.
- Rotational speed, measured in revolutions per minute or RPM, partially determines the rotational delay and transfer time.



Estimating disk latencies (seek time)

- Manufacturers often report *average* seek times of 8-10ms.
  - These times average the time to seek from any track to any other track.
- In practice, seek times are often much better.
  - For example, if the head is already on or near the desired track, then seek time is much smaller. In other words, locality is important!
  - Actual average seek times are often just 2-3ms.

Estimating Disk Latencies (rotational latency)

- Once the head is in place, we need to wait until the right sector is underneath the head.
  - This may require as little as no time (reading consecutive sectors) or as much as a full rotation (just missed it).
  - On average, for random reads/writes, we can assume that the disk spins halfway on average.

- Rotational delay depends partly on how fast the disk platters spin.

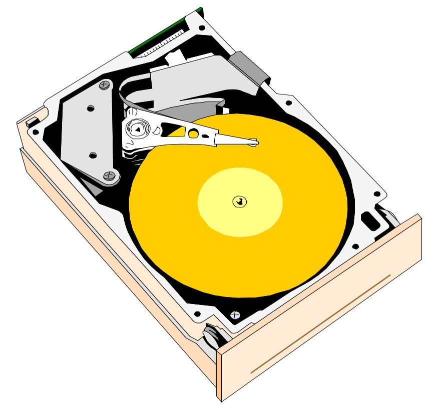
  Average rotational delay = 0.5 x rotations x rotational speed

  - For example, a 5400 RPM disk has an average rotational delay of:

  0.5 rotations / (5400 rotations/minute) = 5.55ms

Estimating disk times

- The overall response time is the sum of the seek time, rotational delay, transfer time, and overhead.
- Assume a disk has the following specifications.
  - An average seek time of 9ms
  - A 5400 RPM rotational speed
  - A 10MB/s average transfer rate
  - 2ms of overheads



- How long does it take to read a random 1,024 byte sector?
  - The average rotational delay is 5.55ms.
  - The transfer time will be about (1024 bytes / 10 MB/s) = 0.1ms.
  - The response time is then 9ms + 5.55ms + 0.1ms + 2ms = 16.7ms. That's 16,700,000 cycles for a 1GHz processor!
- One possible measure of throughput would be the number of random sectors that can be read in one second.

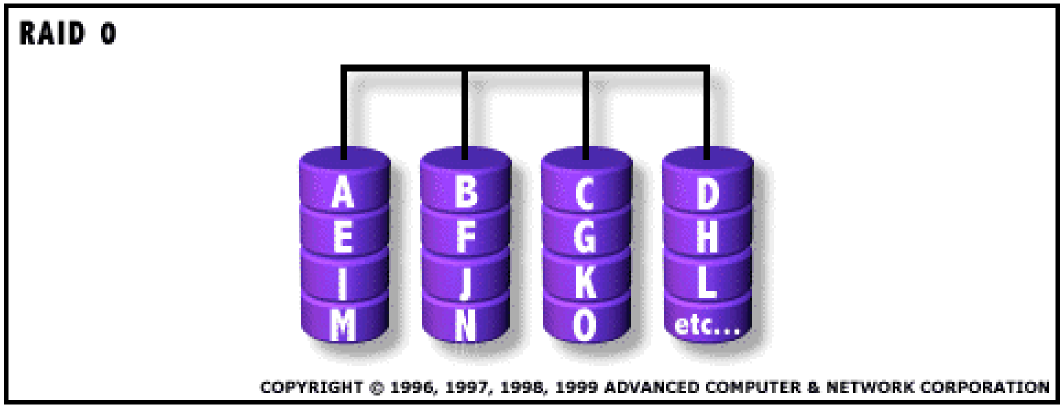
(1 sector / 16.7ms) x (1000ms / 1s) = 60 sectors/second.

Estimating disk times

- The overall response time is the sum of the seek time, rotational delay, transfer time, and overhead.
- Assume a disk has the following specifications.
  - An average seek time of 3ms
  - A 7200 RPM rotational speed
  - A 10MB/s average transfer rate
  - 2ms of overheads
- How long does it take to read a random 1,024 byte sector?
  - The average rotational delay is:
  - The transfer time will be about:
  - The response time is then:
- How long would it take to read a whole track (512 sectors) selected at random, if the sectors could be read in any order?

Parallel I/O

- Many hardware systems use parallelism for increased speed.
  - Pipelined processors include extra hardware so they can execute multiple instructions simultaneously.
  - Dividing memory into banks lets us access several words at once.
- A redundant array of inexpensive disks or RAID system allows access to several hard drives at once, for increased bandwidth.
  - The picture below shows a single data file with fifteen sectors denoted A-O, which are "striped" across four disks.
  - This is reminiscent of interleaved main memories from last week.



Pipelining vs. Parallel processing

- In both cases, multiple "things" processed by multiple "functional units"

  Pipelining: each thing is broken into a **sequence of pieces**, where each piece is handled by a **different** (specialized) functional unit

  Parallel processing: each thing is processed **entirely** by a single functional unit

- We will briefly introduce the key ideas behind parallel processing
  - instruction level parallelism
  - data-level parallelism
  - thread-level parallelism

Exploiting Parallelism

- Of the computing problems for which performance is important, many have inherent parallelism

- Best example: computer games
  - Graphics, physics, sound, AI etc. can be done separately
  - Furthermore, there is often parallelism within each of these:
    - Each pixel on the screen's color can be computed independently
    - Non-contacting objects can be updated/simulated independently
    - Artificial intelligence of non-human entities done independently

- Another example: Google queries
  - Every query is independent
  - Google is read-only!!

Parallelism at the Instruction Level

```
add     $2 <- $3, $4
or      $2 <- $2, $4
lw      $6 <- 0($4)
addi    $7 <- $6, 0x5
sub     $8 <- $8, $4
```

Dependences?
RAW
WAW
WAR

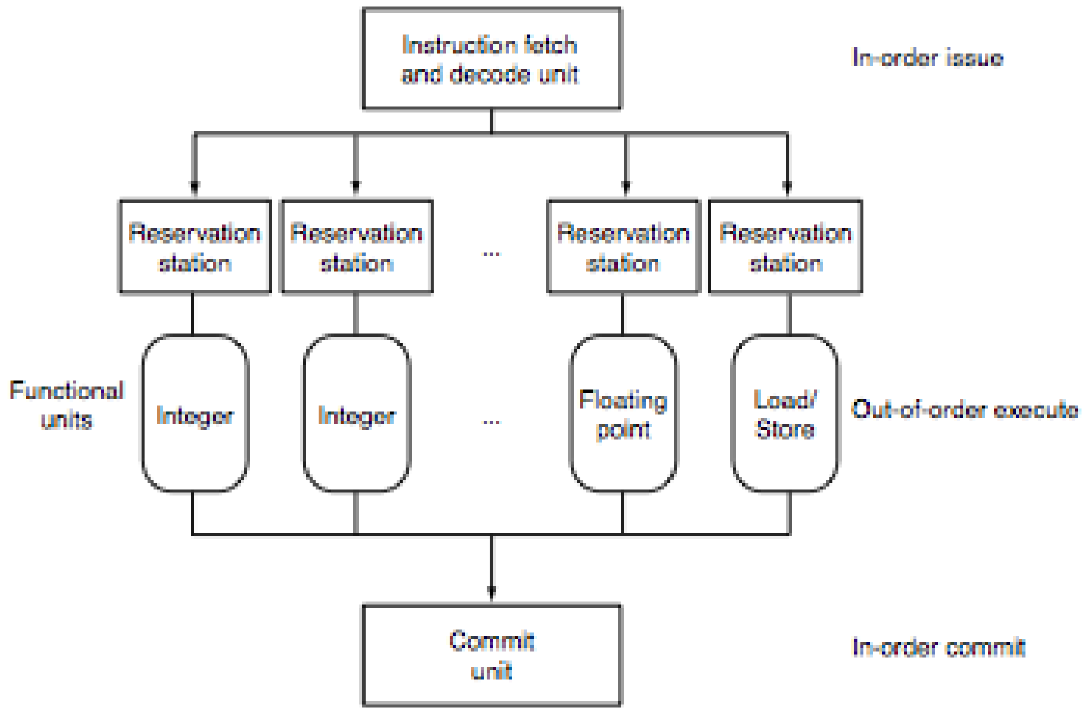
When can we reorder instructions?

When should we reorder instructions?

```
add     $2 <- $3, $4
or      $5 <- $2, $4
lw      $6 <- 0($4)
sub     $8 <- $8, $4
addi    $7 <- $6, 0x5
```

Surperscalar Processors:
Multiple instructions executing in parallel at *same* stage

OoO Execution Hardware

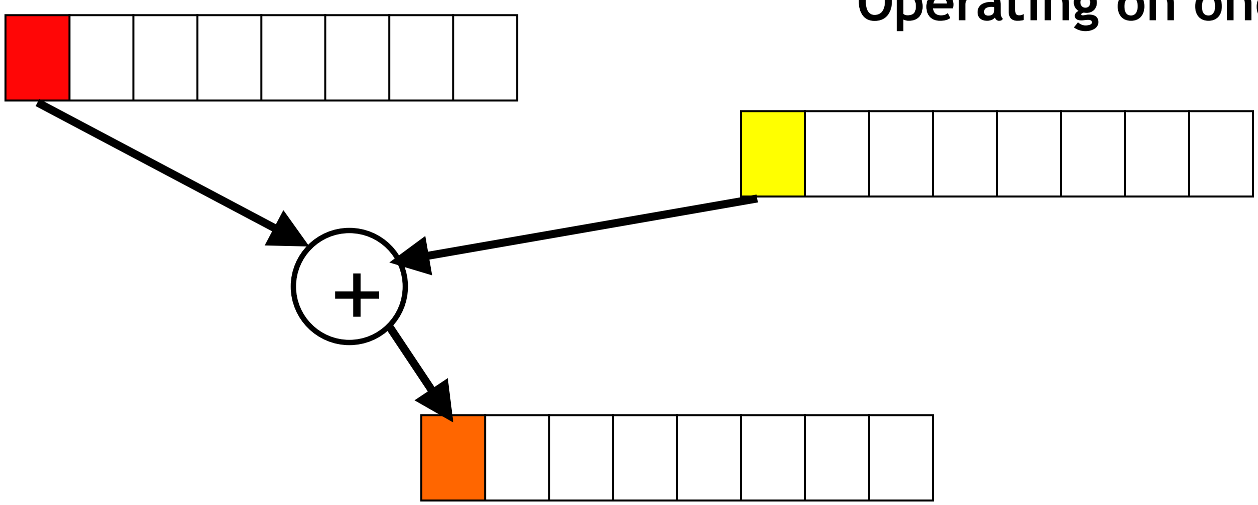


Exploiting Parallelism at the Data Level

- Consider adding together two arrays:

```
void
array_add(int A[], int B[], int C[], int length) {
  int i;
  for (i = 0 ; i < length ; ++ i) {
   C[i] = A[i] + B[i];
  }
}
```

Operating on one element at a time



Exploiting Parallelism at the Data Level

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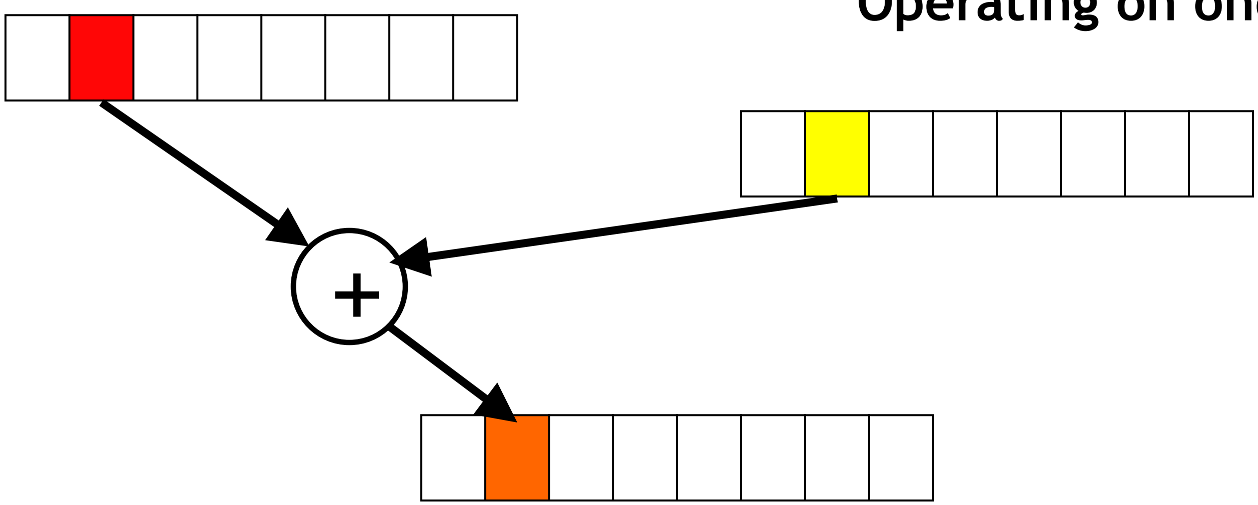
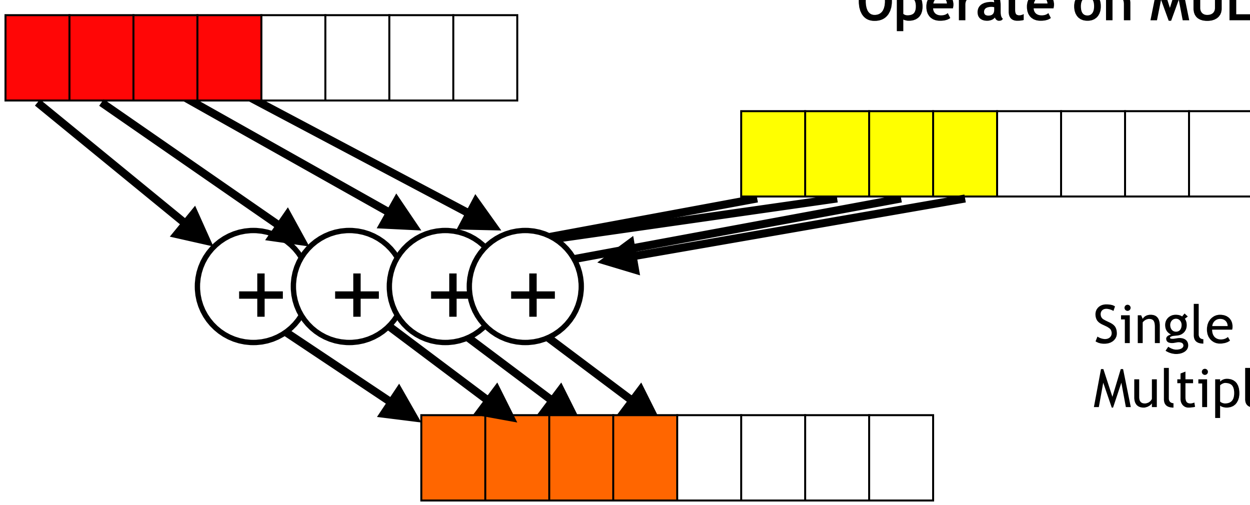
Operating on one element at a time



Exploiting Parallelism at the Data Level (SIMD)

- Consider adding together two arrays:

```
void
array_add(int A[], int B[], int C[], int length) {
  int i;
  for (i = 0 ; i < length ; ++ i) {
   C[i] = A[i] + B[i];
  }
}
```



Operate on MULTIPLE elements

Single Instruction,
Multiple Data (**SIMD**)

Intel SSE/SSE2 as an example of SIMD

- Added new 128 bit registers (XMM0 – XMM7), each can store
  - 4 single precision FP values (SSE) 4 * 32b
  - 2 double precision FP values (SSE2) 2 * 64b
  - 16 byte values (SSE2) 16 * 8b
  - 8 word values (SSE2) 8 * 16b
  - 4 double word values (SSE2) 4 * 32b
  - 1 128-bit integer value (SSE2) 1 * 128b

	4.0 (32 bits)	4.0 (32 bits)	3.5 (32 bits)	-2.0 (32 bits)
+	-1.5 (32 bits)	2.0 (32 bits)	1.7 (32 bits)	2.3 (32 bits)
	2.5 (32 bits)	6.0 (32 bits)	5.2 (32 bits)	0.3 (32 bits)

Is it always that easy?

- Not always… a more challenging example:

```
unsigned
sum_array(unsigned *array, int length) {
  int total = 0;
  for (int i = 0 ; i < length ; ++ i) {
         total += array[i];
  }
  return total;
}
```

- Is there parallelism here?

We first need to restructure the code

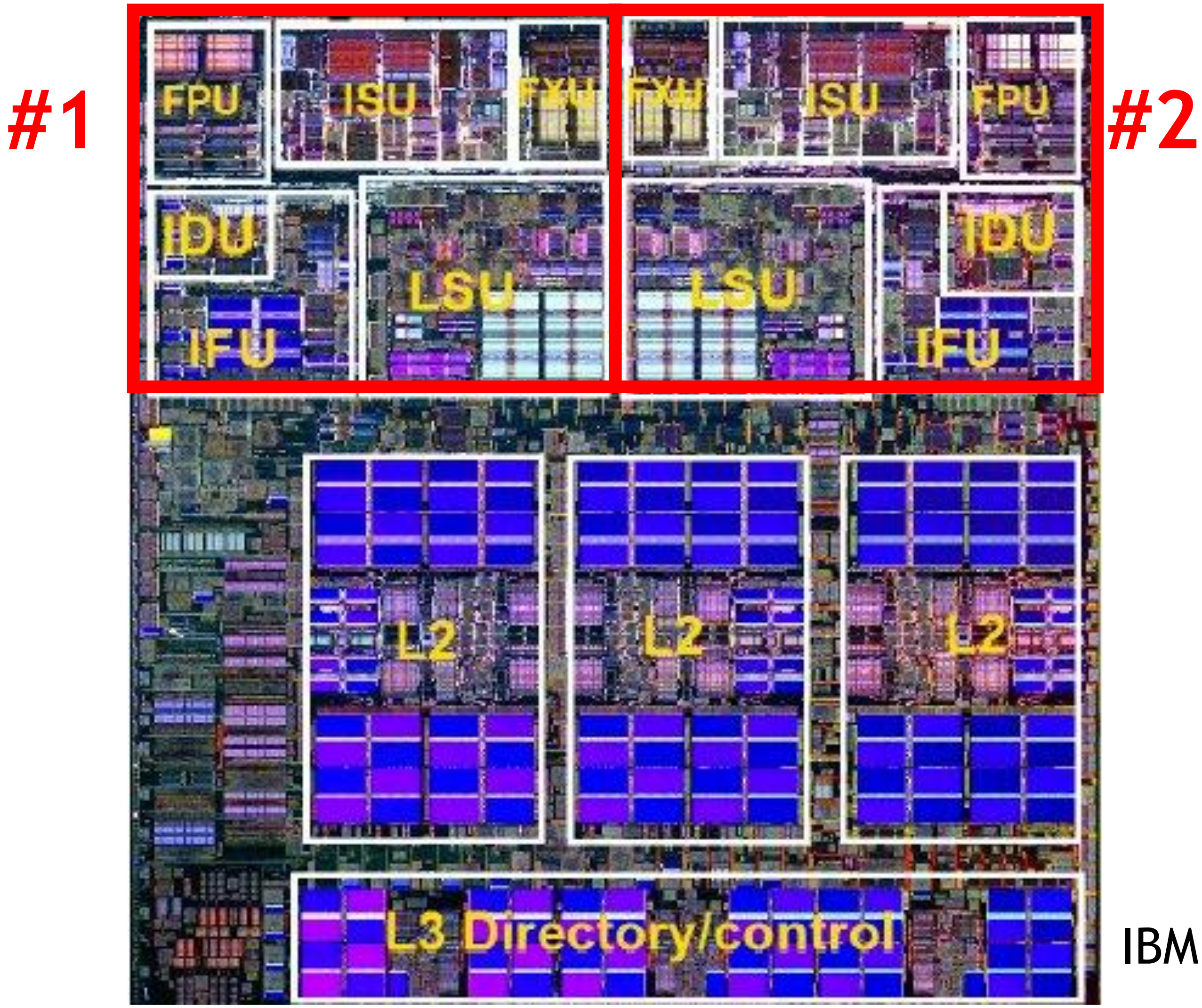
```
unsigned
sum_array2(unsigned *array, int length) {
  unsigned total, i;
  unsigned temp[4] = {0, 0, 0, 0};
  for (i = 0 ; i < length & ~0x3 ; i += 4) {
    temp[0] += array[i];
    temp[1] += array[i+1];
    temp[2] += array[i+2];
    temp[3] += array[i+3];
  }
  total = temp[0] + temp[1] + temp[2] + temp[3];
  for ( ; i < length ; ++ i) {
    total += array[i];
  }
  return total;
}
```

Then we can write SIMD code for the hot part

```
unsigned
sum_array2(unsigned *array, int length) {
  unsigned total, i;
  unsigned temp[4] = {0, 0, 0, 0};
  for (i = 0 ; i < length & ~0x3 ; i += 4) {
    temp[0] += array[i];
    temp[1] += array[i+1];
    temp[2] += array[i+2];
    temp[3] += array[i+3];
  }
  total = temp[0] + temp[1] + temp[2] + temp[3];
  for ( ; i < length ; ++ i) {
    total += array[i];
  }
  return total;
}
```

Thread level parallelism: Multi-Core Processors

- Two (or more) complete processors, fabricated on the same silicon chip
- Execute instructions from two (or more) programs/threads at same time



IBM Power5

Multi-Cores are Everywhere

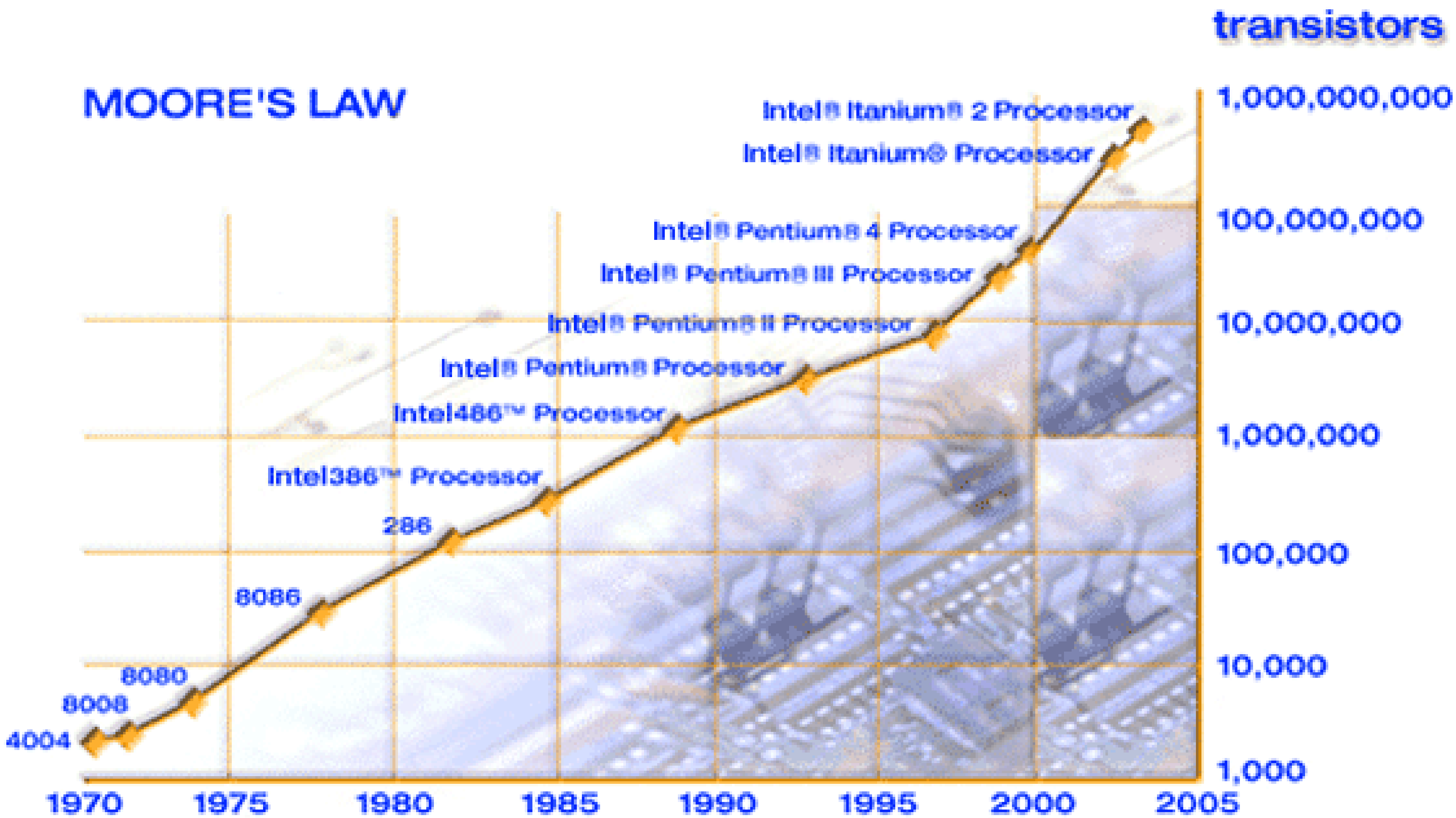
Intel Core Duo in Macs, etc.: 2 x86 processors on same chip

XBox360: 3 PowerPC cores

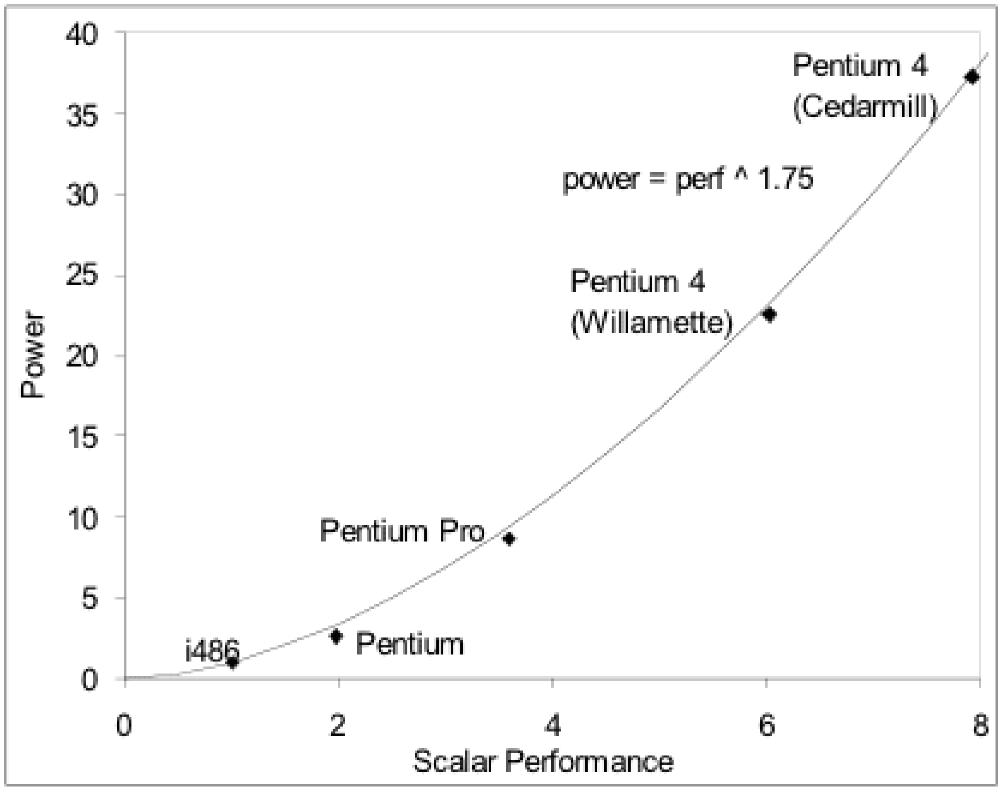
Sony Playstation 3: Cell processor, an asymmetric multi-core with 9 cores (1 general-purpose, 8 special purpose SIMD processors)

Why Multi-cores Now?

- Number of transistors we can put on a chip growing exponentially…



… and performance growing too…

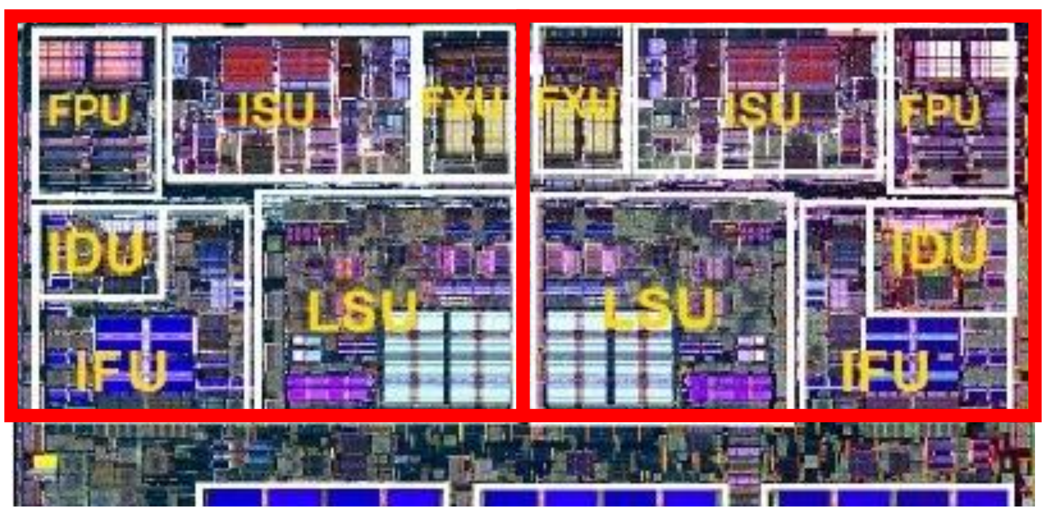


- But power is growing even faster!!
  - Power has become limiting factor in current chips

As programmers, do we care?

- What happens if we run a program on a multi-core?

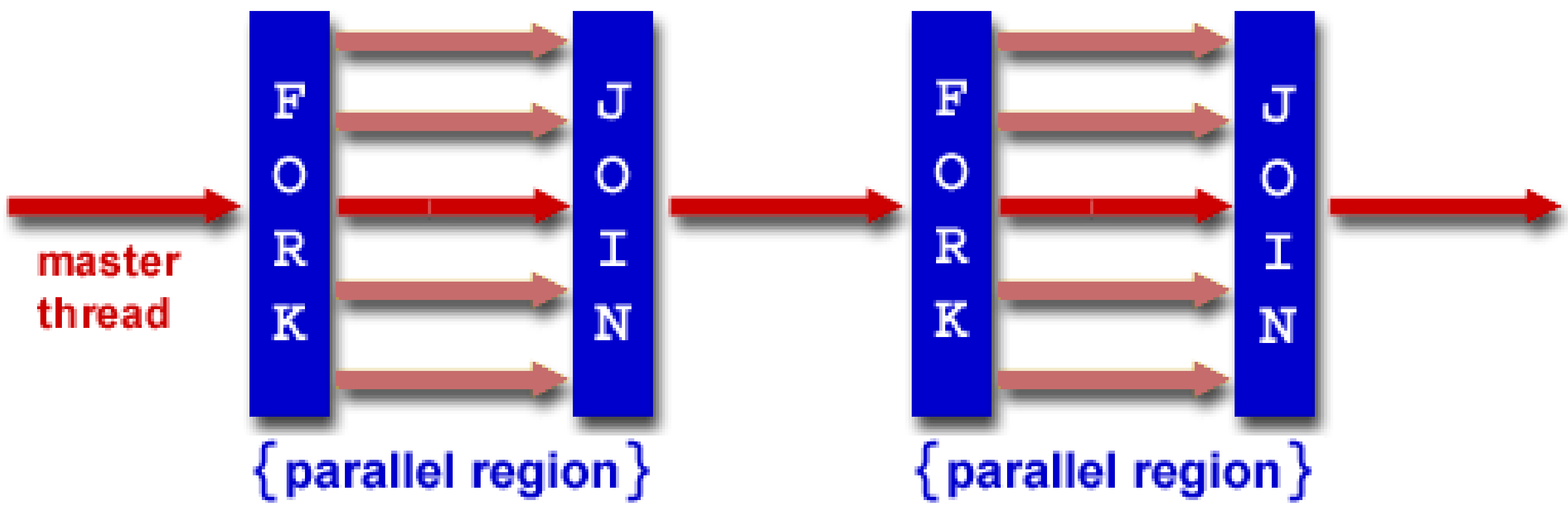
```
void
array_add(int A[], int B[], int C[], int length) {
  int i;
  for (i = 0 ; i < length ; ++i) {
   C[i] = A[i] + B[i];
  }
}
```

#1  #2

What if we want a program to run on both processors?

- We have to explicitly tell the machine exactly how to do this
  - This is called parallel programming or concurrent programming

- There are many parallel/concurrent programming models
  - We will look at a relatively simple one: **fork-join parallelism**
  - In CSE 303, you saw a little about threads and explicit synchronization

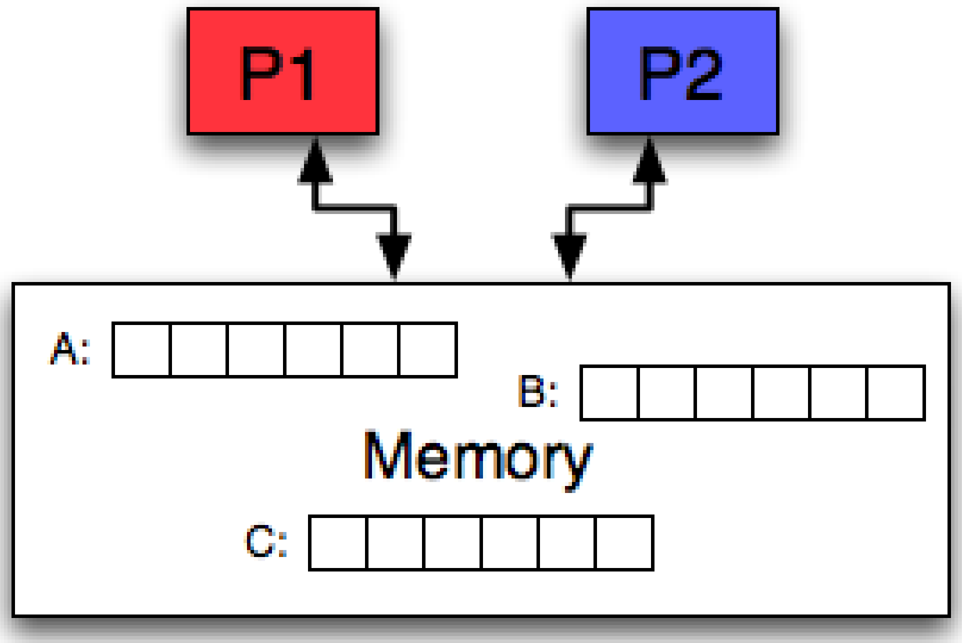


Fork/Join Logical Example

1. Fork N-1 threads
2. Break work into N pieces (and do it)
3. Join (N-1) threads

```
void
array_add(int A[], int B[], int C[], int length) {
   cpu_num = fork(N-1);
   int i;
   for (i = cpu_num ; i < length ; i += N) {
     C[i] = A[i] + B[i];
   }
   join();
}
```

How good is this with caches?

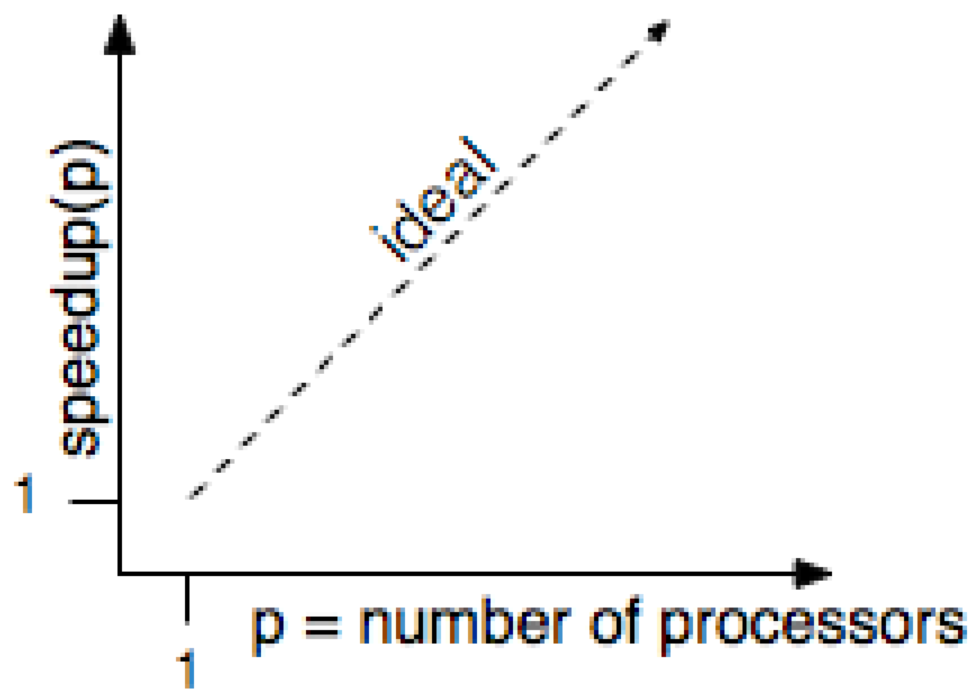


How does this help performance?

- Parallel **speedup** measures improvement from parallelization:

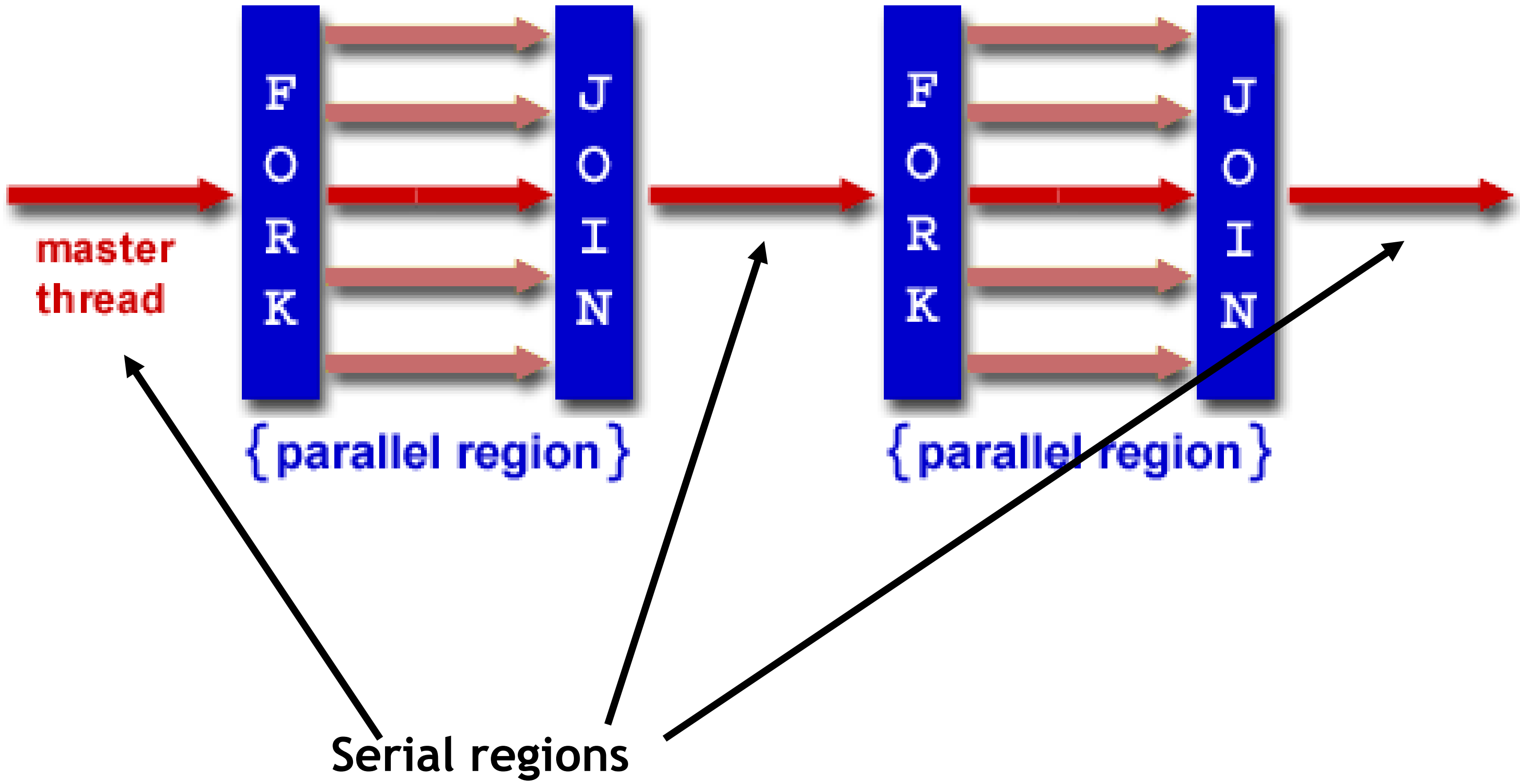
$$\text{speedup}(\mathbf{p}) \quad = \quad \frac{\text{time for best serial version}}{\text{time for version with } \mathbf{p} \text{ processors}}$$

- What can we realistically expect?



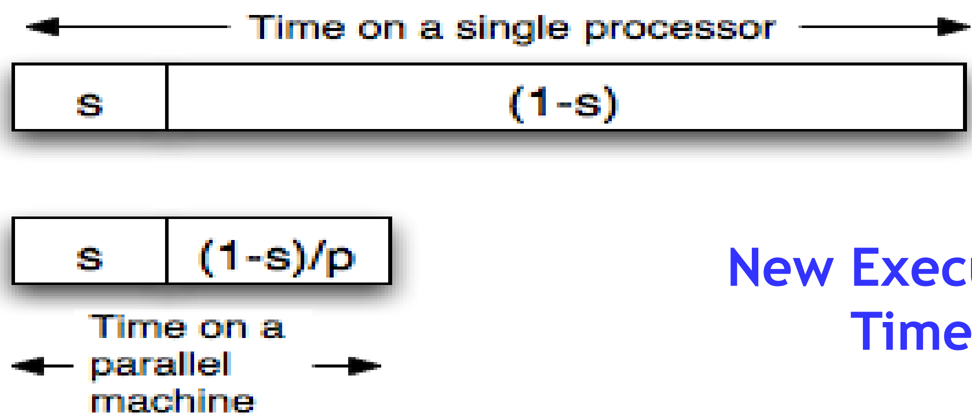
Reason #1: Amdahl's Law

- In general, the whole computation is not (easily) parallelizable



Reason #1: Amdahl's Law

- Suppose a program takes 1 unit of time to execute serially
- A fraction of the program, **s**, is inherently serial (unparallelizable)



$$\text{New Execution Time} = \frac{1-s}{p} + s$$

- For example, consider a program that, when executing on one processor, spends 10% of its time in a non-parallelizable region. How much faster will this program run on a 3-processor system?

$$\textbf{New Execution Time} = \frac{.9T}{3} + .1T =$$

Speedup =

- What is the maximum speedup from parallelization?

Reason #2: Overhead

```
void
array_add(int A[], int B[], int C[], int length) {
    cpu_num = fork(N-1);
   int i;
   for (i = cpu_num ; i < length ; i += N) {
     C[i] = A[i] + B[i];
   }
    join();
}
```

- Forking and joining is not instantaneous
  - Involves communicating between processors
  - May involve calls into the operating system
    - Depends on the implementation

$$\text{New Execution Time} = \frac{1-s}{P} + s + \text{overhead}(P)$$

Programming Explicit Thread-level Parallelism

- As noted previously, the programmer must specify how to parallelize
- But, want path of least effort

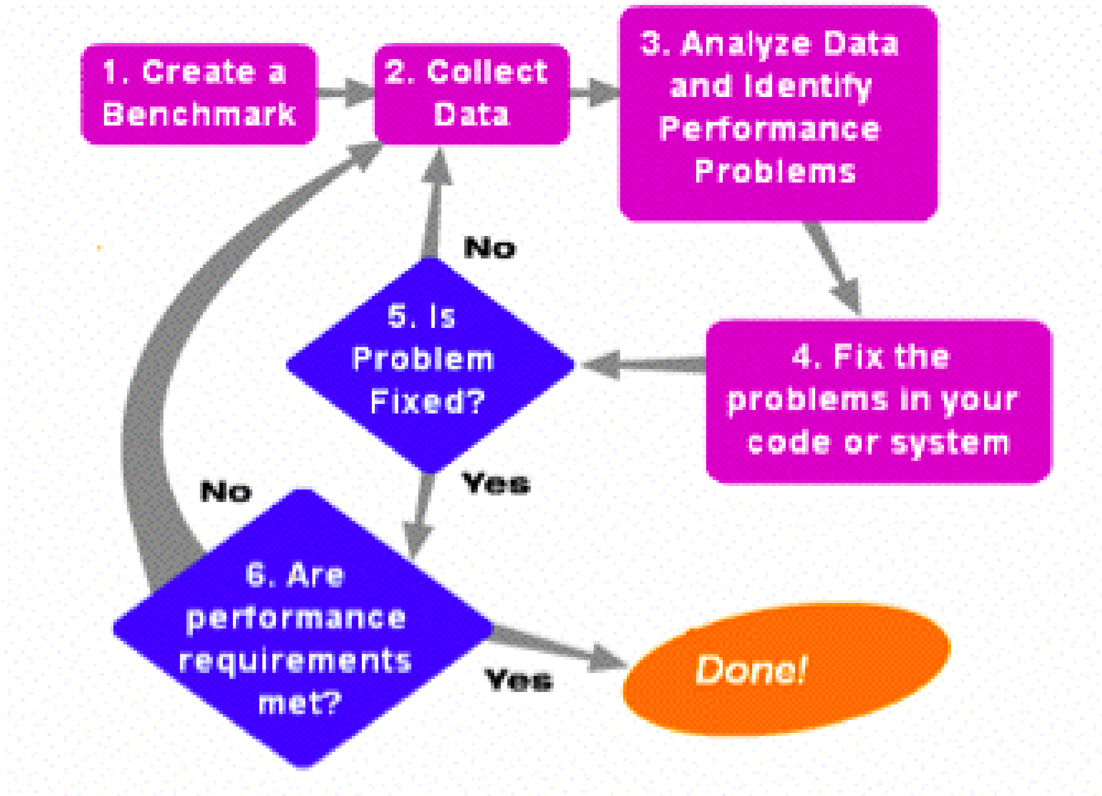
- Division of labor between the **Human** and the **Compiler**
  - **Humans: good at expressing parallelism**, bad at bookkeeping
  - **Compilers:** bad at finding parallelism, **good at bookkeeping**

- Want a way to take serial code and say “Do this in parallel!” without:
  - Having to manage the synchronization between processors
  - Having to know a priori how many processors the system has
  - Deciding exactly which processor does what
  - Replicate the private state of each thread

- OpenMP: an industry standard set of compiler extensions
  - Works very well for programs with structured parallelism.

Performance Optimization

- Until you are an expert, first write a working version of the program
- Then, and only then, begin tuning, first collecting data, and iterate
  - Otherwise, you will likely optimize what doesn't matter



"We should forget about small efficiencies, say about 97% of the time: premature optimization is the root of all evil." -- *Sir Tony Hoare*

Using tools to do instrumentation

- Two GNU tools integrated into the GCC C compiler

- Gprof: The GNU profiler
  - Compile with the `-pg` flag
    - This flag causes gcc to keep track of which pieces of source code correspond to which chunks of object code and links in a profiling signal handler.
  - Run as normal; program requests the operating system to periodically send it signals; the signal handler records what instruction was executing when the signal was received in a file called `gmon.out`

  - Display results using gprof command
    - Shows how much time is being spent in each function.
    - Shows the calling context (the path of function calls) to the hot spot.

Example gprof output

```
Each sample counts as 0.01 seconds.
  %   cumulative   self              self     total
 time   seconds   seconds    calls   s/call   s/call  name
 81.89      4.16     4.16 37913758     0.00     0.00  cache_access
 16.14      4.98     0.82        1     0.82     5.08  sim_main
  1.38      5.05     0.07  6254582     0.00     0.00  update_way_list
  0.59      5.08     0.03  1428644     0.00     0.00  dl1_access_fn
  0.00      5.08     0.00   711226     0.00     0.00  dl2_access_fn
  0.00      5.08     0.00   256830     0.00     0.00  yylex
```

Over 80% of time spent in one function

Provides calling context (`main` calls `sim_main` calls `cache_access`) of hot spot

```
index % time    self  children    called            name
                0.82    4.26       1/1             main [2]
[1]    100.0    0.82    4.26       1               sim_main [1]
                4.18    0.07 36418454/36484188     cache_access <cycle 1> [4]
                0.00    0.01      10/10            sys_syscall [9]
                0.00    0.00    2935/2967          mem_translate [16]
                0.00    0.00    2794/2824          mem_newpage [18]
```

Using tools for instrumentation (cont.)

- Gprof didn't give us information on where in the function we were spending time. (`cache_access` is a big function; still needle in haystack)
- Gcov: the GNU coverage tool
  - Compile/link with the `-fprofile-arcs -ftest-coverage` options
    - Adds code during compilation to add counters to every control flow edge (much like our by hand instrumentation) to compute how frequently each block of code gets executed.
  - Run as normal
  - For each `xyz.c` file an `xyz.gdna` and `xyz.gcno` file are generated
  - Post-process with gcov xyz.c
    - Computes execution frequency of each line of code
    - Marks with ##### any lines not executed
      - Useful for making sure that you tested your whole program

Example gcov output

Code never executed

```
 14282656:  540:  if (cp->hsize) {
    #####:  541:      int hindex = CACHE_HASH(cp, tag);
        -:  542:
    #####:  543:      for (blk=cp->sets[set].hash[hindex];
        -:  544:           blk;
        -:  545:           blk=blk->hash_next)
        -:  546:          {
    #####:  547:              if (blk->tag == tag && (blk->status & CACHE_BLK_VALID))
    #####:  548:                  goto cache_hit;
        -:  549:      }
        -:  550:  } else {
        -:  551:      /* linear search the way list */
753030193:  552:      for (blk=cp->sets[set].way_head;
        -:  553:           blk;
        -:  554:           blk=blk->way_next)      {
751950759:  555:              if (blk->tag == tag && (blk->status & CACHE_BLK_VALID))
738747537:  556:                  goto cache_hit;
        -:  557:      }
        -:  558:  }
```

Loop executed over 50 interations on average (751950759/14282656)

Summary

- Multi-core is having more than one processor on the same chip.
  - Soon most PCs/servers and game consoles will be multi-core
  - Results from Moore's law and power constraint

- Exploiting multi-core requires parallel programming
  - Automatically extracting parallelism too hard for compiler, in general.
  - But, can have compiler do much of the bookkeeping for us
  - OpenMP

- Fork-Join model of parallelism
  - At parallel region, fork a bunch of threads, do the work in parallel, and then join, continuing with just one thread
  - Expect a speedup of less than P on P processors
    - Amdahl's Law: speedup limited by serial portion of program
    - Overhead: forking and joining are not free