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Here is an example, written using a fictional SIMD C

Suppose we have a get_proc() function ("get processor number") that returns the index of the processor:

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int me;
me = get_proc();
...
```

This allows us to distinguish between processors; the value of me is different on each processor

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v[me] = (v[me - 1] + v[me + 1])/2.0;

So what does this code do?

```
int me, n;
me = get_proc();
if (me > 512) {
    n = 1;
}
else {
    n = -1;
}
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But a SIMD machine executes the same code in all processors, so how can it execute the n = 1 assignment on some and the n = -1 assignment on others?

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This is how we get different code paths on different processors

We must modify our description of SIMD machines:

Each processor either executes the same instruction as the others; or does nothing at all

Returning to the code

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if (me > 512) {
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This is executed as follows:

- All processors execute the test in the if
- In those processors for which the test fails, the inhibit flag is set
- All processors move to the n = 1; the inhibited processors do nothing while the others execute the assignment

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Both branches of an if always taken by all processors!

Proc 0 1 2 ... 513 514 515 ... inhibit F F F F F F F F and after $-1 -1 -1 \dots 1 + 1 + 1 + \dots$

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Exercise Think this through for yourself!

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```
if (me > 512) foo();
else bar();
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```
if (me > 512) foo();
else bar();
```

is not good code: all of foo must be executed before bar can start, so there is a large amount of inhibition

Inhibition applies to all conditional code, like loops:

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Note no processor starts executing after the loop until *all* processors have exited

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Similarly for all conditional constructs: if there is a choice all processors will take all the choices, but some are appropriately inhibited

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We shall return to SIMD programming with CUDA, later, when we talk about parallel languages

End of Architectures

We have seen a variety of machine architectures, but primarily people use:

- shared memory
- distributed memory
- SIMD

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It is time to move from the machines to the code running on them

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The second will be a couple of specific algorithms, such as a parallel sort

Divide and Conquer

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And it works best if the parts are independent of each other: less communication

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- each processor sums its chunk (process in parallel)
- return the results to the main processor and add the values together (merge)
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Too large, thus fewer chunks, and we might not get the parallelism we want



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A big problem in programming parallelism is deciding on the choice of granularity of a sub-problem, for exactly the reasons given above

Computing a single sum is a small grain; while averaging a row of a large matrix is a big grain

The former you might not want to parallelise; the latter you would

Granularity

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Some may admit a fine grain, but should we split it up into small grains?

Fine: more parallelism, more communications

Coarse: less parallelism, less communications

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On everything, but particularly the ratio of computation time to communications speed on the particular hardware we have

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Often, the best way of working it out is just to try some test programs and measure the result