ECE459: Programming for Performance Winter 2019

Lecture 5 — Concurrency and Parallelism

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Concurrency and Parallelism

Concurrency and parallelism both give up the total ordering between instructions in a sequential program, for different purposes.

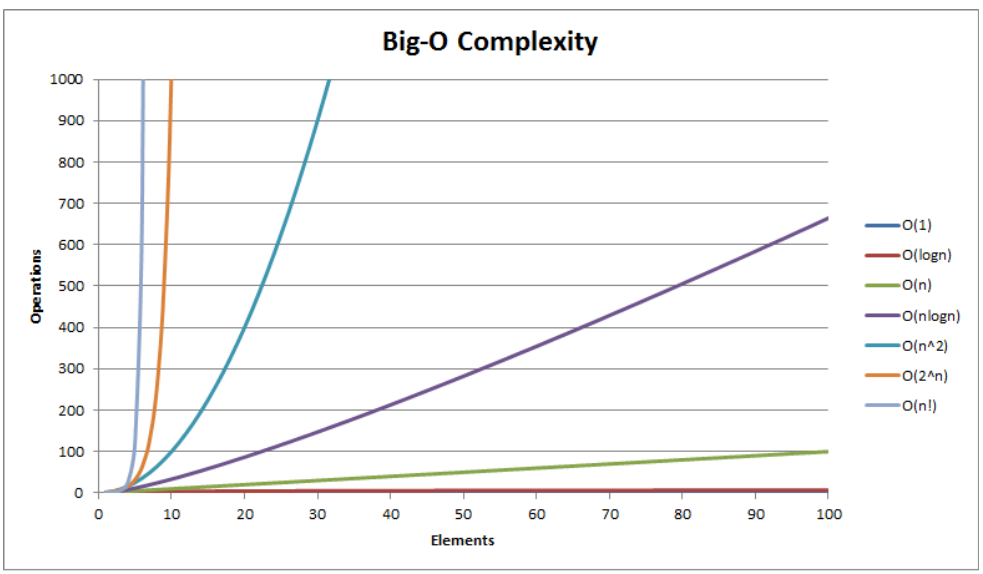
Concurrency. We'll refer to the use of threads for structuring programs as concurrency. Here, we're not aiming for increased performance. Instead, we're trying to write the program in a natural way. Concurrency makes sense as a model for distributed systems, or systems where multiple components interact, with no ordering between these components, like graphical user interfaces.

Parallelism. We're studying parallelism in this class, where we try to do multiple things at the same time in an attempt to increase throughput. Concurrent programs may be easier to parallelize.

Limits to parallelization

I mentioned briefly in Lecture 1 that programs often have a sequential part and a parallel part. We'll quantify this observation today and discuss its consequences.

Scalable Algorithms. Remember from ECE 250/CS 138 that we often care about the worst case run-time performance of the algorithm. An algorithm that's $O(n^3)$ scales so much worse than one that's $O(n)$ that it's not even funny. Trying to do an insertion sort on a small array is fine (actually... recommended); doing it on a huge array is madness. Choosing a good algorithm is very important if we want it to scale.



Big-O Complexity comparison from [R+15]

Amdahl's Law. One classic model of parallel execution is Amdahl's Law. In 1967, Gene Amdahl argued that improvements in processor design for single processors would be more effective than designing multi-processor systems. Here's the argument. Let's say that you are trying to run a task which has a serial part, taking fraction

S, and a parallelizable part, taking fraction $P = 1 - S$. Define T_s to be the total amount of time needed on a single-processor system. Now, moving to a parallel system with N processors, the parallel time T_p is instead:

$$T_p = T_s \cdot (S + \frac{P}{N}).$$

As N increases, T_p is dominated by S, limiting potential speedup.

We can restate this law in terms of speedup, which is the original time T_s divided by the sped-up time T_p:

$$\text{speedup} = \frac{T_s}{T_p} = \frac{1}{S + P/N}.$$

Replacing S with $(1 - P)$, we get:

$$\text{speedup} = \frac{1}{(1-P) + P/N},$$

and

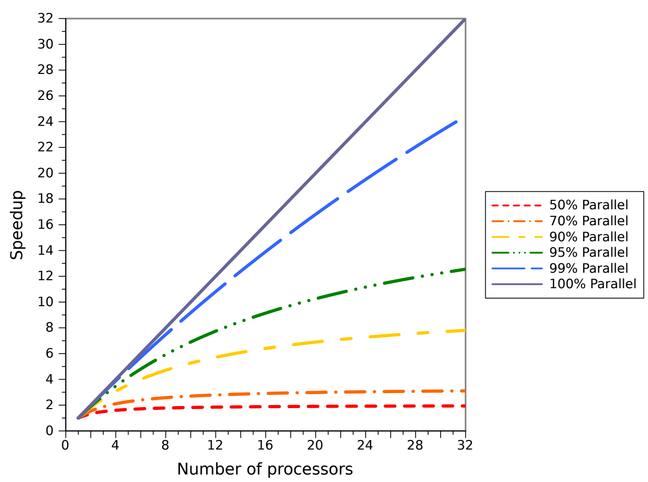
$$\text{max speedup} = \frac{1}{(1-P)},$$

since $\frac{P}{N} \to 0$.

Plugging in numbers. If $P = 1$, then we can indeed get good scaling; running on an N-processor machine will give you a speedup of N. Unfortunately, usually $P < 1$. Let's see what happens.

P	speedup ($N = 18$)
1	18
0.99	~ 15
0.95	~ 10
0.5	~ 2

Graphically, we have something like this:



Amdahl's Law tells you how many cores you can hope to leverage in an execution given a fixed problem size, if you can estimate P.

Let us consider an example from [HZMG15]: Suppose we have a task that can be executed in 5 s and this task contains a loop that can be parallelized. Let us also say initialization and recombination code in this routine requires 400 ms. So with one processor executing, it would take about 4.6 s to execute the loop. If we split it up and execute on two processors it will take about 2.3 s to execute the loop. Add to that the setup and cleanup time of 0.4 s and we get a total time of 2.7 s. Completing the task in 2.7 s rather than 5 s represents a speedup of about 46%. Applying the formula, we get the following run times:

Processors	**Run Time (s)**
1	5
2	2.7
4	1.55
8	0.975
16	0.6875
32	0.54375
64	0.471875
128	0.4359375

Empirically estimating parallel speedup P. Assuming that you know things that are actually really hard to know, here's a formula for estimating speedup. You don't have to commit it to memory:

$$P_{\text{estimated}} = \frac{\frac{1}{\mathit{speedup}} - 1}{\frac{1}{N} - 1}.$$

It's just an estimation, but you can use it to guess the fraction of parallel code, given N and the speedup. You can then use $P_{\text{estimated}}$ to predict speedup for a different number of processors.

Consequences of Amdahl's Law. For over 30 years, most performance gains did indeed come from increasing single-processor performance. The main reason that we're here today is that, as we saw last time, single-processor performance gains have hit the wall.

By the way, note that we didn't talk about the cost of synchronization between threads here. That can drag the performance down even more.

Amdahl's Assumptions. Despite Amdahl's pessimism, we still all have multicore computers today. Why is that? Amdahl's Law assumes that:

- problem size is fixed (read on);
- the program, or the underlying implementation, behaves the same on 1 processor as on N processors; and
- that we can accurately measure runtimes—i.e. that overheads don't matter.

A more optimistic point of view

In 1988, John Gustafson pointed out[1] that Amdahl's Law only applies to fixed-size problems, but that the point of computers is to deal with bigger and bigger problems.

In particular, you might vary the input size, or the grid resolution, number of timesteps, etc. When running the software, then, you might need to hold the running time constant, not the problem size: you're willing to wait, say, 10 hours for your task to finish, but not 500 hours. So you can change the question to: how big a problem can you run in 10 hours?

According to Gustafson, scaling up the problem tends to increase the amount of work in the parallel part of the code, while leaving the serial part alone. As long as the algorithm is linear, it is possible to handle linearly larger problems with a linearly larger number of processors.

Of course, Gustafson's Law works when there is some "problem-size" knob you can crank up. As a practical example, observe Google, which deals with huge datasets.

[1] `http://www.scl.ameslab.gov/Publications/Gus/AmdahlsLaw/Amdahls.html`

Software Design Issues

Locking. Think back to a concurrency course and the discussion of locking. We'll be coming back to this subject before too long. But for now, suffice it to say, that the more locks and locking we need, the less scalable the code is going to be. You may think of the lock as a resource and the more threads or processes that are looking to acquire that lock, the more "resource contention" we have, and the more waiting and coordination are going to be necessary.

Memory Allocators. Assuming we're not working with an embedded system where all memory is statically allocated in advance, there will be dynamic memory allocation. The memory allocator is often centralized and may support only one thread allocating or deallocating at a time. This means it does not necessarily scale very well. There are, however, some techniques for dynamic memory allocation that allow these things to work in parallel.

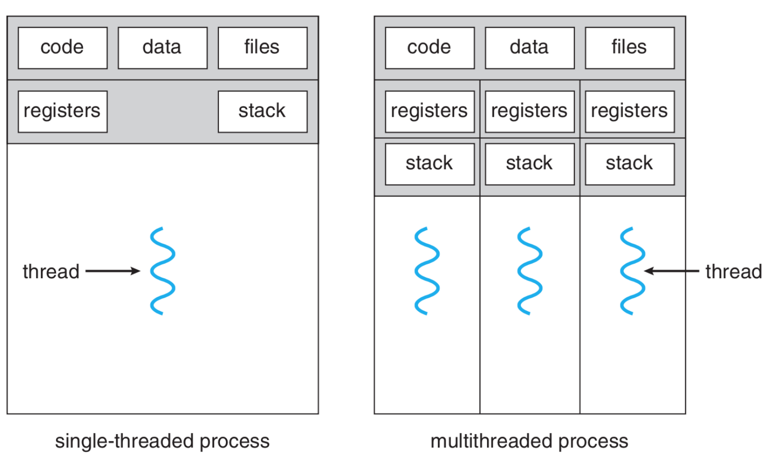
Pools of Worker Threads. We'll talk about threads shortly. At first, one might imagine manually starting the necessary threads. But that's not the only way. We can have a pool of workers. Then the application just submits units of work, and then on the other side these units of work are allocated to workers. The number of workers will scale based on the available hardware. This is neat as a programming practice: as the application developer we don't care quite so much about the underlying hardware. Let the operating system decide how many workers there should be, to figure out the optimal way to process the units of work.

Processes and Threads

Let's review the difference between a process and a thread. A *process* is an instance of a computer program that contains program code and its own address space, stack, registers, and resources (file handles, etc). A *thread* usually belongs to a process. The most important point is that it shares an address space with its parent process, hence variables and code as well as resources. Each thread has its own [Sta14]:

1. Thread execution state (like process state: running, ready, blocked...).
2. Saved thread context when not running.
3. Execution stack.
4. Local variables.
5. Access to the memory and resources of the process (shared with all threads in that process).

Or, to represent this visually:



A single threaded and a multithreaded process compared side-by-side [SGG13].

All the threads of a process share the state and resources of the process. If one thread opens a file, other threads in that process can also access that file.

The way programs are written now, there are few, if any, that are not in some way multithreaded. One common way of dividing up the program into threads is to separate the user interface from a time-consuming action.

Consider a file-transfer program. If the user interface and upload method share a thread, once a file upload has started, the user will not be able to use the UI anymore (and Windows will put the dreaded "(Not Responding)" at the end of its dialog title), even to click the button that cancels the upload. For some reason, users hate that.

We have two options for how to alleviate this problem: when an upload is ready to start, we can call `fork` and create a new process to do the upload, or we can spawn a new thread. In either case, the newly created entity will handle the upload of the file. The UI remains responsive, because the UI thread is not waiting for the upload method to complete.

Motivation for Threads

Why choose threads rather than creating a new process? The primary, but not sole, motivation is performance:

1. Creating a new thread is much faster than creating a new process. In fact, thread creation is on the order of ten times faster [TRG$^+$87].
2. Terminating and cleaning up a thread is faster than terminating and cleaning up a process.
3. It takes less time to switch between two threads within the same process (because less data needs to be stored/restored). In Solaris, for example, switching between processes is about five times slower than switching between threads [SGG13].
4. Because threads share the same memory space, for two threads to communicate, they do not have to use any of the IPC mechanisms; they can just communicate directly.
5. As in the file transfer program, use of threads allows the program to be responsive even when a part of the program is blocked.

This last advantage, background work, is one of four common examples of the uses of threads in a general purpose operating system [Let88]:

1. **Foreground and Background Work:** as already examined, the ability to run something in the background to keep the program responsive.
2. **Asynchronous processing**: for example, to protect against power failure or a crash, a word processor may write the document data in main memory to disk periodically. This can be done as a background task so it does not disrupt the user's workflow.
3. **Speed of Execution:** a multithreaded program can get more done in the same amount of time. Just as the OS can run a different program when the executing program gets blocked (say, on a disk read), if one thread is blocked, another thread may execute.
4. **Modular Structure:** a program that does several different things may be given structure through threads.

There are some drawbacks, however: there is no protection between threads in the same process. So, one thread can easily mess with the memory being used by another thread. This once again brings us to the subject of co-ordination, which will follow the discussion of threads.

Also, if any thread encounters an error (such as a division by zero or Segmentation Fault), the whole process might be terminated by the operating system. If the program has multiple processes for different parts, then the other processes will not be affected. But, if the program has multiple threads and they all share the same process, then any thread encountering an error might bring all of them to a halt. (That's why Google Chrome chose to use separate processes for each tab.)

You can find another explanation of processes versus threads here:

`https://www.purplealienplanet.com/node/50`

Threads and CPUs. In your operating systems class, you've seen implementations of threads ("lightweight processes"). We'll call these threads *software threads*, and we'll program with them throughout the class. Each software thread corresponds to a stream of instructions that the processor executes. On a old-school single-core, single-processor machine, the operating system multiplexes the CPU resources to execute multiple threads concurrently; however, only one thread runs at a time on the single CPU.

On the other hand, a modern chip contains a number of *hardware threads*, which correspond to the virtual CPUs. These are sometimes known as *strands*. The operating system still needs to multiplex the software threads onto the hardware threads, but now has more than one hardware thread to schedule work onto.

Implementing (or Simulating) Hardware Threads. There are a number of ways to implement multiple software threads; for instance, the simplest possible implementation, **kernel-level threading** (or 1:1 model) dedicates one core to each thread. The kernel schedules threads on different processors. (Note that kernel involvement will always be required to take advantage of a multicore system). This model is used by Win32, as well as POSIX threads for Windows and Linux. The 1:1 model allows concurrency and parallelism.

Alternately, we could make one core execute multiple threads. In the **user-level threading**, or N:1, model, the single core would keep multiple contexts and could 1) switch every 100 cycles; 2) switch every cycle; 3) fetch one instruction from each thread each cycle; or 4) switch every time the current thread hits a long-latency event (cache miss, etc.) This model allows for quick context switches, but does not leverage multiple processors. (Why would you use these?) The N:1 model is used by GNU Portable Threads.

Finally, it's possible to both use multiple cores and put multiple threads onto one core, in a **hybrid threading**, or M:N, model. Here, we map M application threads to N kernel threads. This is a compromise between the previous two models, which both allows quick context switches and the use of multiple processors. However, it requires increased complexity; the library provides scheduling services, which may not coordinate well with kernel, and increases likelihood of priority inversion (which you've seen in Operating Systems). This method is used by modern Windows threads.

Choose Your Pain

The first design decision that you need to solve when parallelizing programs is whether you should use threads or processes.

- Threads are basically light-weight processes which piggy-back on processes' address space.

Traditionally (pre-Linux 2.6) you had to use `fork` (for processes) and `clone` (for threads). But `clone` is not POSIX compliant, and its man page says that it's Linux-specific—FreeBSD uses `rfork()`. (POSIX is the standard for Unix-like operating systems).

When processes are better. `fork` is safer and more secure than threads.

1. Each process has its own virtual address space:
    - Memory pages are not copied, they are copy-on-write. Therefore, processes use less memory than you would expect.

2. Buffer overruns or other security holes do not expose other processes.
3. If a process crashes, the others can continue.

Example: In the Chrome browser, each tab is a separate process. Scott McCloud explained this: `http://www.scottmccloud.com/googlechrome/`.

When threads are better. Threads are easier and faster.

1. Interprocess communication (IPC) is more complicated and slower than interthread communication; must use operating system utilities (pipes, semaphores, shared memory, etc) instead of thread library (or just memory reads and writes).
2. Processes have much higher startup, shutdown, and synchronization costs than threads.
3. pthreads fix the issues of `clone` and provide a uniform interface for most systems. (You'll work with them in Assignment 1.)

How to choose? If your application is like this:

- mostly independent tasks, with little or no communication;
- task startup and shutdown costs are negligible compared to overall runtime; and
- want to be safer against bugs and security holes,

then processes are the way to go. If it's the opposite of this, then use threads.

For performance reasons, along with ease and consistency across systems, we'll use threads. We will describe both pthreads and C++ 11 threads, in particular.

Overhead of Processes vs Threads. The common wisdom is that processes are expensive, threads are cheap. Let's verify this with a benchmark on a laptop (included in the live-coding directory on GitHub) which creates and destroys 50,000 threads:

```
jon@riker examples master % time ./create_fork
0.18s user 4.14s system 34% cpu 12.484 total
jon@riker examples master % time ./create_pthread
0.73s user 1.29s system 107% cpu 1.887 total
```

Clearly pthreads incur much lower overhead than `fork`. pthreads offer a speedup of 6.5 over processes in terms of startup and teardown costs.

References

[HZMG15] Douglas Wilhelm Harder, Jeff Zarnett, Vajih Montaghami, and Allyson Giannikouris. *A Practical Introduction to Real-Time Systems for Undergraduate Engineering*. 2015. Online; version 0.15.08.17.

[Let88] Gordon Letwin. *Inside OS/2*. Microsoft Press, 1988.

[R$^+$15] Eric Rowell et al. Know thy complexities!, 2015. Online; accessed 14-November-2015. URL: `http://bigocheatsheet.com/`.

[SGG13] Abraham Silberschatz, Peter Baer Galvin, and Greg Gagne. *Operating System Concepts (9th Edition)*. John Wiley & Sons, 2013.

[Sta14] William Stallings. *Operating Systems Internals and Design Principles (8th Edition)*. Prentice Hall, 2014.

[TRG+87] Avadis Tevanian, Richard F. Rashid, David B. Golub, David L. Black, Eric Cooper, and Michael W. Young. Mach threads and the UNIX kernel: The battle for control. In *Proceedings, Summer 1987 USENIX Conference*, 1987.