University of Illinois at Urbana-Champaign
Dept. of Electrical and Computer Engineering

ECE 408 / CS 483 / CSE 408: Applied Parallel Programming

Generalizing Parallelism

What Will You Learn Today?

- to learn terminology and concepts from the broader high-performance computing community

- to generalize some of the techniques illustrated in class for use with future codes

Speedup Measures the Success of Parallelization

Let's start by defining **parallel speedup** (usually just called speedup).

Let's say that
- when I run my program in parallel
- it finishes **X** times faster
- than when I run it sequentially.

Specifically,
- **X = T(sequential) / T(parallel)**, and
- **X is the speedup** of my parallel code.

Note that speedup assumes a fixed problem size.

Speedup Depends on the Best Sequential Code

We have T(sequential) / T(parallel).

But how do we find T(sequential)?

T(sequential) **should measure** the

- **best algorithm** for a sequential machine (may/may not be the algorithm parallelized),
- **optimized** for a sequential machine, with
- **no parallelism support** remnants (no parallel overhead).

Find (Don't Write) a Competitive Baseline

Sequential code is what we in Engineering call
- the **baseline design**,
- the alternative against which
- we demonstrate improvements.

As Prof. Hwu once pointed out to me,
- **no one will believe** that **you** worked hard
- to **optimize your baseline**…
- even if you did!

If possible, **compare someone else's best work**.

Efficiency Measures Effective Use of Resources

Next is **parallel efficiency**
(or just efficiency).

Efficiency measures how well
a code uses parallel resources.

When executing **on P processors**,

efficiency = speedup on P processors / P.

Efficiency is Often Below 1, But Should Not be Tiny

What value should efficiency have?

According to those paying for the machines, 1.

According to most real applications,
- **something non-negligible, near 1**
- but not 1,
- as other bottlenecks come into play.

Efficiency is Rarely Above 1

Can efficiency be >1?

Rarely—called **superlinear speedup**.

possible causes:

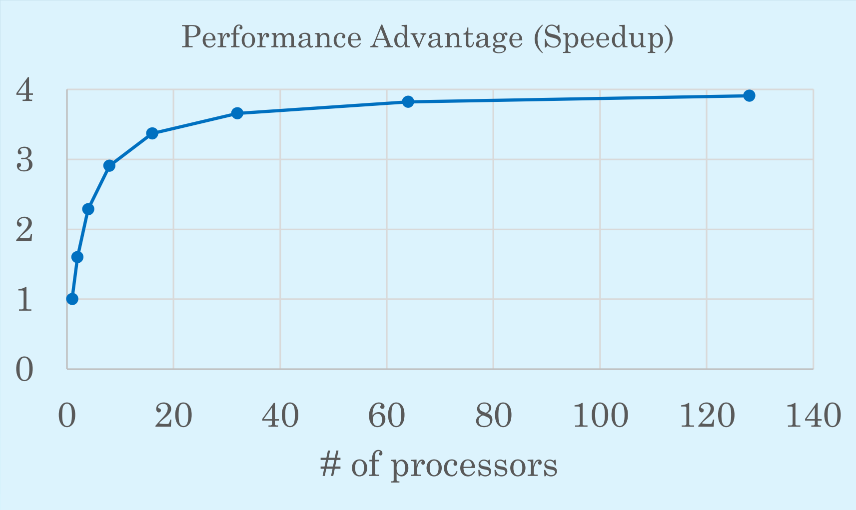
- certain types of extra resources (such as caches)
- luck (parallel search happens to find an answer more quickly).

Scalability Measures Effect of Parallel Overheads

Next, **scalability**:

- **for how many processors is**
- **speedup linear**, or is efficiency flat?

At some **P**, with fixed problem size, speedup will flatten out.

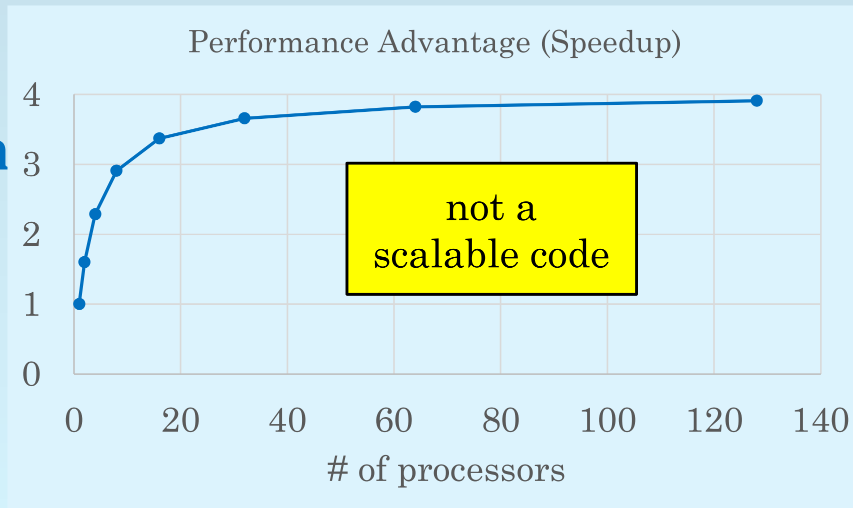


Good Scalability Requires Minimal Parallel Overhead

For larger values of **P**, speedup starts to drop (unless one leaves processors idle).

Good scalability means

- **no falloff** on your machine
- **for maximum** measurable **value of P**.



Efficiency Not So Meaningful When Cores Vary Widely

But what is P for a single GPU?

1?

Number of SMs?

Number of PEs (total)?

We can still measure speedup,
- but for a single GPU,
- we **estimate efficiency**
- **by comparing** resource **use**
- **with** the GPU's **peak values**.

(As we've done in our class already.)

Speedup Measures Improvement for an Input Set

Again, **speedup assumes** a **fixed problem size**.

- For many applications, that's reasonable.
- Users care about their input sets, not about hypothetical inputs.

But that's **not always the best assumption**.

For Other Situations, We Need Different Metrics

Sometimes we care about throughput:
- frames per second for video / game quality,
- transactions per second for databases, or
- user operations per second for datacenters.

And **sometimes input size**
- **is limited** by memory
- or by feasible runtime,
- as in many supercomputing applications.

Scaling Problem Size with P Good for Science Apps

Other **variants of speedup on P processors**:*

scaled speedup:

- problem size is linear in **P**
- (good scaled speedup is **1**)

memory-constrained speedup:

- biggest problem that fits in memory (which scales with **P**)
- only works for **O(N)** algorithms

*J. P. Singh, J. L. Hennessy, A. Gupta, "Scaling Parallel Programs for Multiprocessors: Methodology and Examples," *IEEE Computer*, 26(7):42-50, July 1993.

Problem Size Sometimes Chosen Through Practical Means

Other **variants of speedup on P processors**:*

time-constrained speedup:

- biggest problem that finishes by the time I return from lunch
- sometimes reasonable…
- …but we could wait overnight for a grand challenge application?

*J. P. Singh, J. L. Hennessy, A. Gupta, "Scaling Parallel Programs for Multiprocessors: Methodology and Examples," *IEEE Computer*, 26(7):42-50, July 1993.

Parallel Grain Size is the Work Done per Thread

Parallel grain size is work per thread (task).

- Remember discussing what to parallelize?
- Output elements, input elements, …

Each source of parallelism
has **a natural grain size**:

- loop body,
- objects in a container,
- rows/columns/blocks/elements in a matrix,
- graph nodes/connected components.

Consider Different Sources of Parallelism

Some sources exhibit higher work variance (and branch divergence) than others

- conditionals/inner loops in loop body
- complex per-object methods
- rows in upper/lower diagonal matrix
- matrix elements usually roughly constant
- degree of nodes, size of connected components.

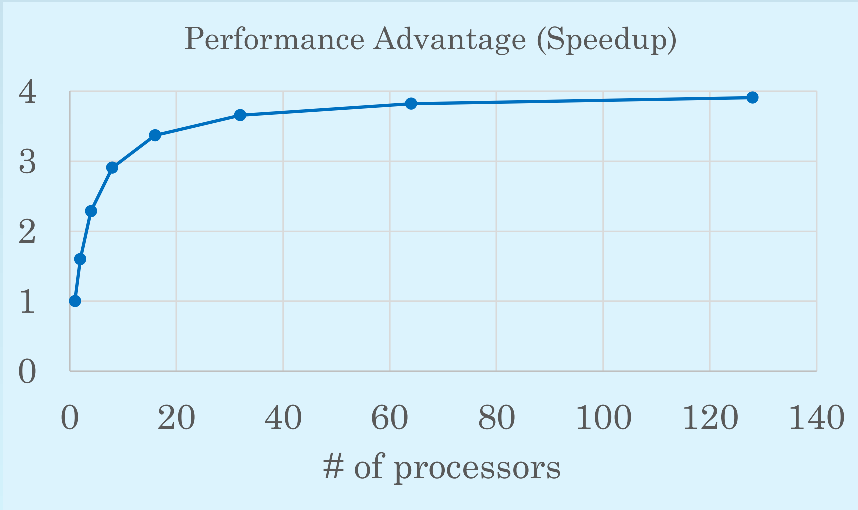
Be sure to consider the alternatives!

Amdahl's Law Helps Set Expectations

Amdahl's Law says

- **speedup** is **bounded** above
- **by 1 / (sequential fraction)**.

For example, if you parallelize code that takes 75% of the time, you can't get more than 4× speedup.



Evaluate Your Work Intelligently and Meaningfully

But, again, for fixed input.

There are other ‘laws’ as well
that view the problem differently.

So what matters most?

- Some apps today are missing/simplified due to resource limits.
- Some apps become possible/more useful with bigger problem sizes.

Fit evaluation of utility to your app, not your app to an evaluation metric.

A Few Useful Concepts

Now, I'd like to go over a few useful ideas from high-performance computing.

Most you've seen before, so I'll tie them in to what you've seen and done in our class.

Bulk Synchronous Execution Dominates Fast Computing

The **bulk synchronous** style
- dominates HPC and CUDA applications.
- **Barriers separate** temporal **regions of code**
  - usually O(100) lines long
  - interleaving / data **sharing occurs only within regions** (called phases).

Why?
- Simpler to debug regions than whole programs.
- (similar to Stroustrup's view of classes' value).

Bulk synchronous execution **does tend to correlate resource usage**, which is bad.

Necessary/Good Sources of Parallel Overhead

Good ways to waste time in parallel;

- push bits around (**communicate**)—a necessary overhead in most parallel codes
- **do some extra work** (to avoid communicating)
  - for example, do pooling after convolution in a CNN kernel to reduce shared-to-global memory traffic
  - another: do extra adds to reduce the number of barriers, as in a Kogge-Stone scan
- bicker about priority (**contend for shared resources**)

Bad Sources of Parallel Overhead

Bad ways to waste time in parallel;

- twiddle your thumbs (**wait for long-latency events**)
- **watch others work**
  - example: branch divergence in a GPU
  - example: poor scheduling decisions
- line up single file (**unnecessary serialization**)
  - example: coarse synchronization, lack of privatization
  - example: temporally correlated accesses to shared hardware resource
  - example: use one CUDA stream

Dynamic Load Balancing Sometimes Needed

In our class, we have generally
- assigned fixed work per thread.
- Usually, this is the simplest approach
- but may lead to load imbalance.

One common solution—**load balancing**:
- dynamic mapping of work to threads using
- one or more queues of work
  - pull chunk of work from a queue, do it, repeat
  - start with bigger chunks, later grab smaller
  - if queue is empty, **steal work** from another.

CUDA Scheduling May Need to Become More Expressive

One last question: kernel/block scheduling.

Most OS schedulers use **time-sharing**:
try to be fair to all of the running programs.

But if you have many processors,
why pay parallel overhead?

Use **space-sharing** instead!

Lots of supercomputers and datacenters do.

How are thread blocks within
CUDA kernels scheduled?