



Scientific
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C++ Benchmarking

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Course Outline

- Performance
 - How to get good performance
 - Why benchmarking is important
- Micro-benchmarks
 - Run a tiny snippet of code on real hardware
 - Do it many times & see how long it takes
- Profiling
 - Run the entire code on real hardware, occasionally check what it's doing
 - Non-deterministic statistical sampling of events, but on real hardware
- Simulation
 - Run entire code on a virtual machine & measure every single operation
 - Deterministic measurement of all events, but not real hardware

Performance

Motivation

- We use c++ because we need performance
 - Otherwise we could (should?) use a higher-level language, e.g. Python
- Writing fast code is simple
 - Need to use good **algorithms** for **efficiency** (do less work)
 - Need to use good **data structures** for **speed** (do work faster)
- Writing fast code is difficult
 - Often these two needs are in conflict with each other
 - So the answer to “what is the fastest way to do this?” is “it depends”
- Benchmarking can help
 - With the question “which method is fastest?”
 - With the question “where and why is my code slow?”

Algorithms

- Complexity
 - Count operations required to process N items
 - E.g. $2N + 5N \log(N)$
 - For large N , term with highest power of N dominates
 - “Big-O” algorithmic complexity is the highest power of N
 - E.g. $O(N \log(N))$
- Memory
 - Required memory is also counted and expressed in Big-O notation
- Optimal algorithms
 - For many problems, can prove an algorithm is “optimal”
 - This means it has the same Big-O cost as the best possible algorithm

Algorithm goal: reduce complexity

- Generally we want the most efficient algorithm
 - I.e. the one with the smallest Big-O complexity
- Often there are multiple “optimal” algorithms
 - Different pros and cons depending on your data and your hardware
- Although sometimes a less efficient algorithm can be better
 - if memory is a constraint, and there is a less efficient algorithm that requires less memory
 - if the big-O *coefficient* is much smaller
 - E.g. unless N is very large, $1e9 * \log(N)$ is larger than N
 - if it allows for a much faster implementation on your hardware
 - E.g. more fast operations can be better than a few slow operations
 - if it allows for parallelization over threads / cores / nodes
 - etc

Hardware

- CPU gets some data, operates on it:
- Get the data from
 - L1 cache (32kb): 1 ns
 - L2 cache (256kb): 3 ns
 - L3 cache (32mb): 20 ns
 - RAM (32gb): 100 ns
 - SSD (1tb): 10000 ns
- Do the operation
 - CPU core cycle: 1 ns
 - SIMD: apply same instruction to multiple data in the same operation
 - Multi-core: a CPU typically has several cores
- CPU spends a lot of time idle, waiting for data

Cache

- Cache misses are very expensive
 - L1 cache: 1 ns wait + 1 ns work
 - RAM: 100 ns wait + 1 ns work
- Cache lines
 - Cache data is organised in lines of 64 bytes
 - CPU gets the whole cache line when it asks for an item of data
- SIMD
 - A single CPU instruction can operate on multiple items of data
 - Eg AVX512 instructions can operate on all 64 bytes in a single operation
- Pre-fetching
 - CPU will also try to guess what data will be needed next
 - If you are iterating linearly over contiguous data, will nearly always predict correctly

Hardware goal: avoid cache misses

- Spatial locality of data
 - Store data contiguously, and in the order in which it will be accessed
 - Also known as “Data-oriented design”
 - or old-fashioned C-style arrays of data
 - or SoA (struct-of-arrays) vs AoS (arrays-of-struct)
 - Why? So that it is more likely to already be in the cache
- Temporal locality of algorithms
 - When accessing the same data again, do it sooner rather than later
 - Why? So that it is more likely to still be in the cache

General Performance strategy

- For large problems
 - We care about the efficiency of our **algorithms**
 - We want to do less work
- For small problems
 - We care about cache friendly **data structures**
 - We want to do our work fast
- Sometimes a large problem can also be many small problems
 - Use an **efficient** algorithm to reduce a large problem to many small problems
 - Use a **fast** cache-friendly method to solve each small problem
- Algorithms and data structures are interconnected
 - But helpful to consider their impact separately
 - Helps to understand the tradeoffs you are making with your choices

Map implementation performance

- Binary Tree: $O(\log(N))$ to find an item
 - Good algorithmic efficiency
 - Terrible cache locality
 - Use case: large N
- Unsorted Vector: $O(N)$ linear traversal to find an item
 - Terrible algorithmic efficiency
 - Good cache locality
 - Use case: small N
- Hash table: $O(1)$
 - Excellent algorithmic efficiency
 - Although not guaranteed - need a good hash function
 - Cache locality depends on implementation
 - Use case: large N

Micro-benchmarks

Micro-benchmarks

- Run a tiny snippet of code on real hardware
- Do it many times & see how long it takes
- Good to get accurate results for specific functions
- May not be so close to “real world” scenarios
- Have to take care compiler doesn’t optimize away the supposed work!
- Not deterministic: but can repeat many times & measure statistical significance
- Different possible metrics
 - Average time: most common and most relevant for many use cases
 - Median time: less noisy than the average, not affected by outliers
 - Fastest time: e.g. if investigating peak performance
 - Slowest time: e.g. if latency / worst-case scenario is important

Micro-benchmarking tools

- Google benchmark
 - Widely used and actively maintained
 - See also Quick-bench (online version a bit like compiler explorer)
- Celero
 - Actively maintained
- Nonius
 - Older, less/not actively maintained
- Catch2
 - Some integration of nonius to add benchmarks to unit tests
- Do it yourself solution
 - E.g. using `std::chrono::high_resolution_clock`
 - Not recommended

Google benchmark minimal example

```
#include <benchmark/benchmark.h>

static void bench_map(benchmark::State &state) {
    Map map; // initialize data
    for (auto _ : state) {
        map.find(keys[0]); // code to benchmark
    }
}

BENCHMARK(bench_map);

BENCHMARK_MAIN();
```

Live coding time

```
git clone --recursive https://github.com/ssciwr/cpp-benchmarking.git
cd cpp-benchmarking
mkdir build
cd build
cmake -DCMAKE_BUILD_TYPE=Release ..
cmake --build .
ctest
./bench/bench1
```


Benchmark 1

```
for (auto _ : state) {  
    map.find(keys[0]);  
}
```

bench_small_map/1	0.000 ns	0.000 ns	1000000000
bench_small_map/2	0.000 ns	0.000 ns	1000000000
bench_small_map/4	0.000 ns	0.000 ns	1000000000

- Looks bogus: Zero run-time, no N-dependence
- Why? Compiler optimizes away the entire statement

Benchmark 2

```
for (auto _ : state) {  
    benchmark::DoNotOptimize(map.find(keys[0]));  
}
```

bench_small_map/1	0.990 ns	0.990 ns	691986485
bench_small_map/2	1.00 ns	1.00 ns	705385115
bench_small_map/4	0.989 ns	0.989 ns	703257489

- Force compiler to put result into register or memory
- Non-zero runtime, but still no N-dependence
- Why? Always looking for the first key!

Benchmark 3

```
for (auto _ : state) {  
    benchmark::DoNotOptimize(map.find(keys[n/2 + 1]));  
}
```

bench_small_map/1	1.14 ns	1.14 ns	600298793
bench_small_map/2	1.38 ns	1.38 ns	507900144
bench_small_map/4	2.51 ns	2.51 ns	278833095

- Force compiler to put result into register or memory
- Ask for a key roughly in the middle of the vector
- Get reasonable-looking N-dependence

Benchmark 4

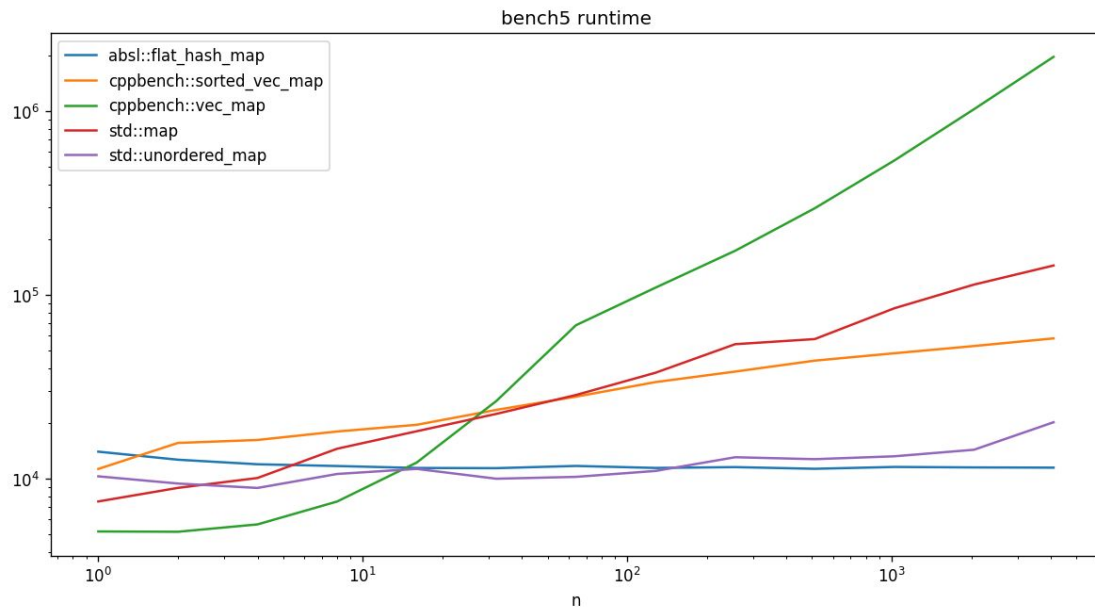
```
for (auto _ : state){  
    for (auto key : keys) {  
        benchmark::DoNotOptimize(map.find(key));  
    }  
}
```

bench_small_map/1	1.34 ns	1.34 ns	495155683
bench_small_map/2	3.21 ns	3.21 ns	218922642
bench_small_map/4	6.53 ns	6.53 ns	105903854

- Force compiler to put result into register or memory
- Loop over all keys: now doing N finds per benchmark iteration
- Get average performance over all inputs

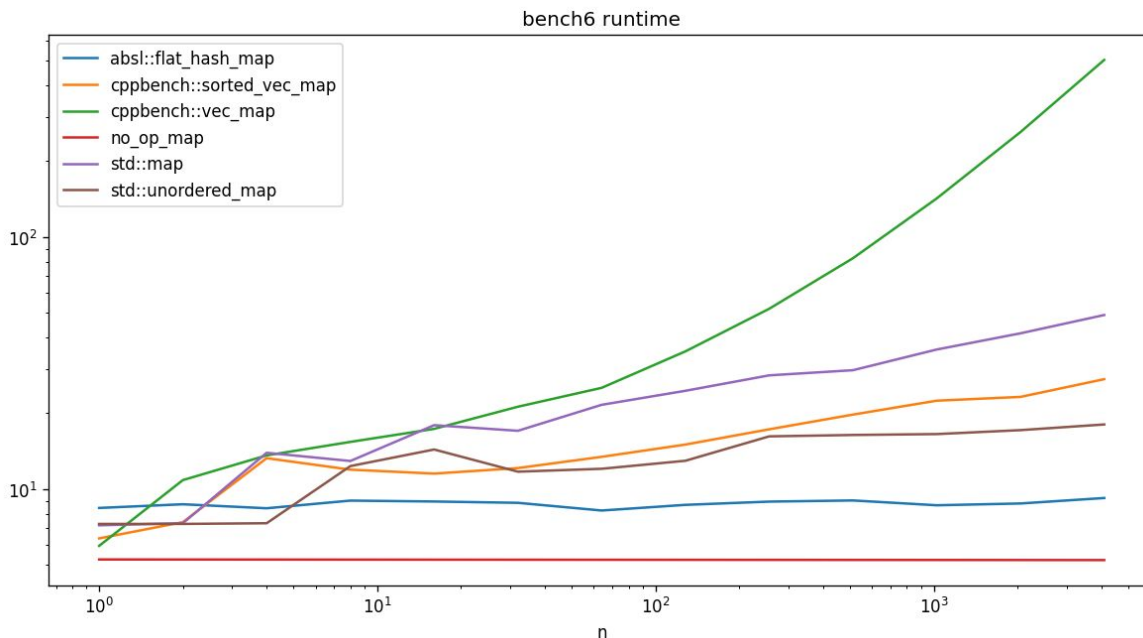
Benchmark 5

- Compare with `std::map`, `std::unordered_map` implementations
- Do the same number of find operations per benchmark iteration



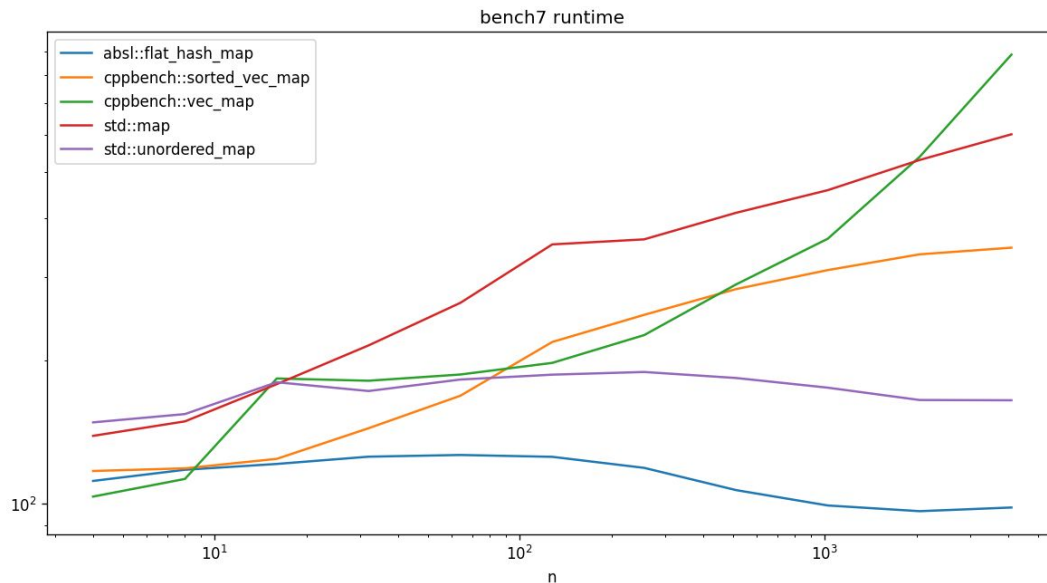
Benchmark 6

- Pick a random key at each iteration (more realistic, but adds overhead)
- Add a “no-op” Map to measure this overhead



Benchmark 7

- Try to simulate a “cold cache scenario”
 - Generate millions of identical maps (a few gig of RAM)
 - Pick a random map (probably not already in cache) for each benchmark iteration



Micro-benchmarking tips

- Compile in release mode
- Reduce the noise
 - Disable CPU turbo-boost / frequency scaling
 - Avoid running anything else at the same time
 - Repeat benchmarks to estimate noise, statistical significance of differences
- Try to be sure you're measuring what you intend to
 - Check the inputs and outputs are correct
 - Check the compiler is not optimizing away the work
 - Try to use or generate representative realistic input data
 - Compare timings with a no-op version of your operation / function
 - Look at the scaling as you vary the size of the input data
 - Try varying the order of the input data
 - Cold cache or hot cache scenario

Profiling

Profiling

- Run real production code on real hardware
- Occasionally check what it's doing
 - Not too often to avoid interfering with execution / slowing it down!
- Good to get an overview of real-world bottlenecks
- Not deterministic
- Only sample a tiny fraction of events
 - But likely to find hotspots this way

Profiling Tools

- Perf
 - No special instrumentation or re-compilation of code required
 - Relatively simple to use, pre-installed on most linux distributions
 - But linux only, and need sudo permissions:
<https://www.kernel.org/doc/html/latest/admin-guide/perf-security.html>
- [Gperftools](#)
- [Intel VTune](#)
- [Likwid](#)
- [Tracy](#)
- [and many more...](#)

Compiling for profiling

- Generally want to compile in Release mode
 - Goal is to run your code exactly as in real-world setting
- Additional flags to improve profile output at minimal cost:
 - `-g` : include debugging symbols (e.g. function names)
 - `CMAKE_BUILD_TYPE = RelWithDebInfo`
 - `-fno-omit-frame-pointer` : don't omit frame pointers (i.e. better stack traces)
- Any additional requirements for your profiler
 - Link to their library?
 - Include their header?
 - Annotate your code?
 - Set environment variables?

Perf stat

- `perf stat ./app`
 - default performance counters
- `perf list`
 - show all available counters
- `perf stat -e L1-dcache-load-misses,L1-dcache-load ./app`
 - how often do we have a L1 data cache miss
- `perf stat -e branches,branch-misses ./app`
 - how often do we have a branch prediction miss

Perf stat example

```
perf stat -e L1-dcache-load-misses,L1-dcache-load \  
./bench/bench6 \  
--benchmark_filter=".*:vec_map.*\/16\$" \  
--benchmark_min_time=2
```

- First line: Measure cache misses using perf stat
- Others: run n=16 vec_map benchmark from bench6 for at least 2 secs

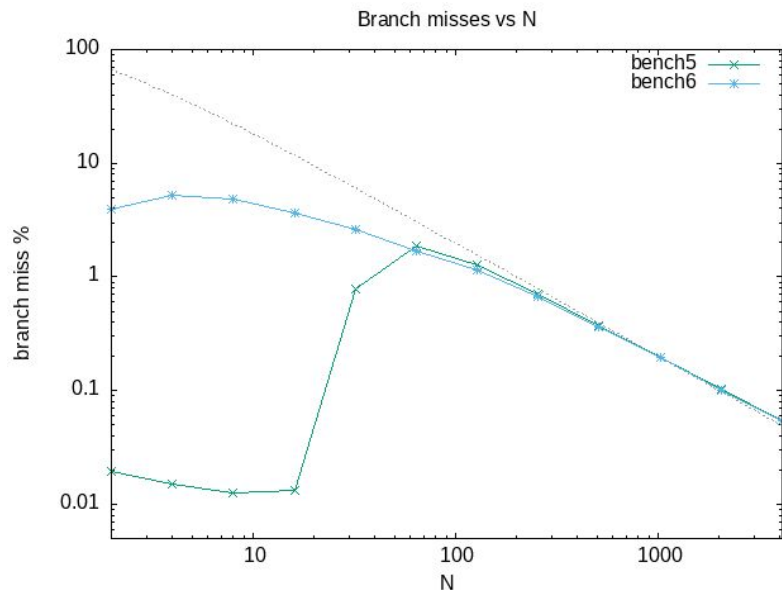
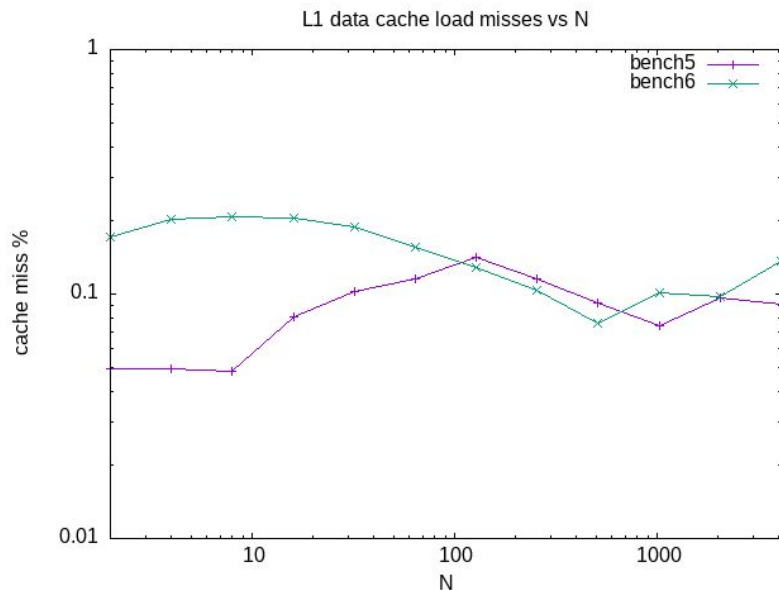
627,014	L1-dcache-load-misses	#	0.01% of all L1-dcache accesses
8,377,940,732	L1-dcache-load		

Branch prediction

- CPU constructs a pipeline of instructions
 - Often “out of order” i.e. not evaluated in the order you wrote them
 - E.g. part of iteration $n+1$ in a loop may be calculated in iteration n
 - You need to know what instructions are coming next to be able to do this
- At every branch (e.g. if statement) in the code
 - CPU doesn’t know where execution will jump to next until condition is evaluated
 - This stalls the pipeline
- So it tries to guess the most likely outcome (branch prediction)
 - Constructs the pipeline based on guessing where the branch will jump to
- Sometimes it guesses wrong
 - This is called a “branch miss” (similar to a cache miss)
 - CPU has to throw away / undo a lot of potentially incorrect operations
 - Then find and execute the correct instructions from the correct branch
 - This is expensive (also similar to a cache miss)

Perf branch prediction

- Branch predictor is outsmarting our benchmark in bench5



Perf record

- perf record ./app && perf report
 - see annotated assembly with % of time for each line
 - h: show shortcuts
 - H: go to hotspot
 - Enter: go to function / follow jump

```

51.47 1d0:  cmp    %ecx,(%rbx,%rsi,4)
0.16   ↑ je    1a0
2.94   inc    %rsi
0.01   cmp    %rsi,%rax
41.29  ↑ jne   1d0
        ↑ jmp   1a7

```

```
./bench/bench5 --benchmark_filter=".*:vec_map.* /1024\$" --benchmark_min_time=2
```

Perf visualization

- Raw assembly can be overwhelming
- Can be easier to interpret a call graph, flame graph, etc
- Options (all inconvenient in different ways)
 - <https://github.com/KDAB/hotspot>
 - Works directly on perf.data, but output seems incomplete / wrong
 - <https://github.com/brendangregg/FlameGraph>
 - Use supplied perl script to convert trace data first
 - <https://github.com/google/pprof>
 - But also need https://github.com/google/perf_data_converter
 - <https://www.eclipse.org/tracecompass>
 - But you need to re-compile perf with CTF support

Profiling tips

- Reduce the noise
 - Disable CPU turbo-boost / frequency scaling
 - Avoid running anything else at the same time
- First step: look at cache misses
 - If there are a lot of these, nothing else matters much
- Look at branch misses
 - Sometimes Profile Guided Optimization (PGO) can help
 - Very rarely you can improve them by hand (`__builtin_expect`, `[[likely]]`, etc)
 - But hard to do better than the CPU (and easy to make things worse!)
- Look at hotspots
 - Lines of code that are called a lot and/or slow
- Profile your benchmarks
 - Can help understand if they are testing what you want them to

Simulation

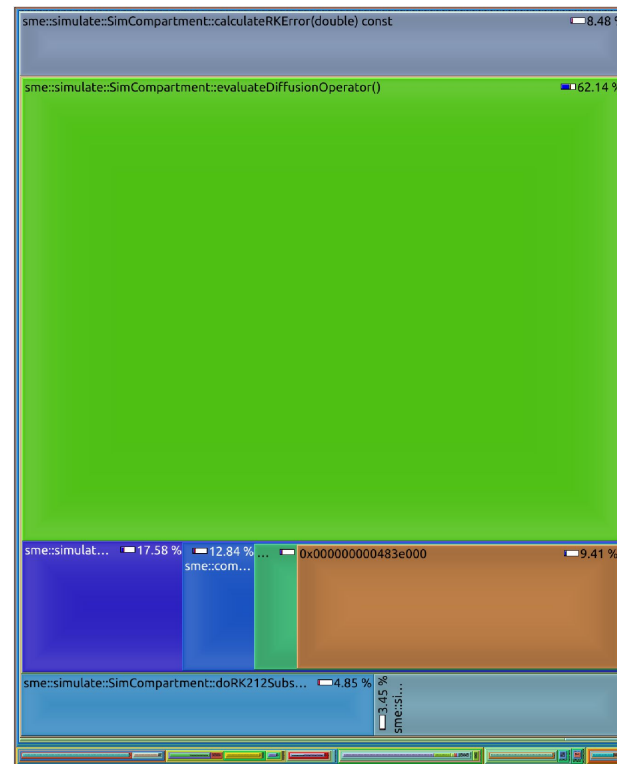
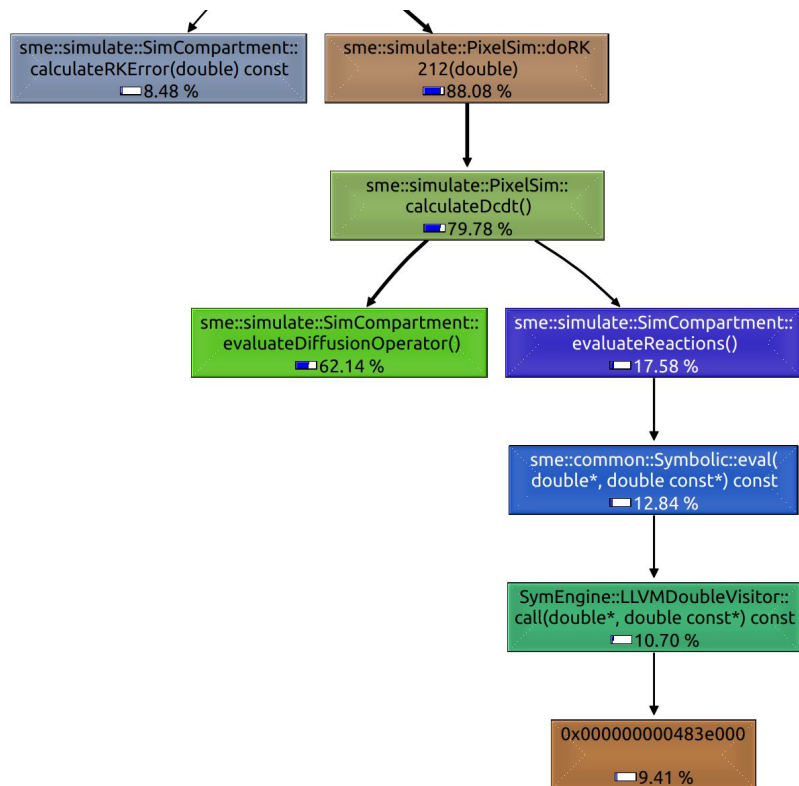
Simulation

- Run real production code on a virtual machine
 - Simulated CPU, simulated cache
- Record every cpu operation, every cache read, etc
 - Doesn't affect (simulated) speed of operations
- Deterministic
 - No statistical variation, not affected by other running processes
- But: not real hardware
 - No guarantee performance implications are the same
- Also: typically vastly slower than real-time (e.g. 50x slower)
 - Can be inconvenient / impractical for certain applications

Callgrind/cachegrind

- Part of valgrind set of tools
 - Default tool is memcheck, but there are others!
- `valgrind --tool=cachegrind ./app`
 - Command line output of simulated cache hits/misses
- `valgrind --tool=callgrind --simulate-cache=yes ./app`
 - Generates call-graph data and cache hits/misses
- `kcachegrind`
 - GUI to visualize above data

Example call graph (cycles)



Perf report for same code

```

61.55% spatial-cli spatial-cli [.] sme::simulate::SimCompartment::evaluateDiffusionOperator
 8.83% spatial-cli spatial-cli [.] sme::simulate::SimCompartment::calculateRKError
 4.98% spatial-cli spatial-cli [.] sme::simulate::SimCompartment::evaluateReactions
 4.36% spatial-cli spatial-cli [.] sme::simulate::SimCompartment::doRK212Substep2
 3.51% spatial-cli spatial-cli [.] sme::simulate::SimCompartment::doRK212Substep1
 2.11% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef69035
 1.59% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef69004
 1.52% spatial-cli spatial-cli [.] SymEngine::LLVMDoubleVisitor::call
 1.37% spatial-cli spatial-cli [.] sme::common::Symbolic::eval
 1.00% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef6904b
 0.78% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef6901b
 0.55% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef6900c
 0.52% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef69031
 0.44% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef69047
 0.41% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef6901f
 0.29% spatial-cli libc.so.6 [.] __GI___strtod_l_internal
 0.29% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef69039
 0.26% spatial-cli [JIT] tid 263317 [.] 0x00007fe92ef69023
 0.22% spatial-cli spatial-cli [.] sme::simulate::SimCompartment::undoRKStep

```


Simulation tips

- Ignore the noise!
 - CPU turbo-boost, other running processes not relevant
- Otherwise, same tips as profiling
 - First step: look at cache misses
 - If there are a lot of these, nothing else matters much
 - Look at branch misses
 - Sometimes Profile Guided Optimization (PGO) can help
 - Very rarely you can improve them by hand (`__builtin_expect`, `[[likely]]`, etc)
 - But hard to do better than the CPU (and easy to make things worse!)
 - Look at hotspots
 - Lines of code that are called a lot and/or slow
 - Profile your benchmarks
 - Can help understand if they are testing what you want them to
- Remember it's a simulation - compare results with actual profiling data

Summary

Summary

- Benchmarking is vital but also difficult to do reliably
- Important not to blindly take one metric or benchmark as the “truth”
- We covered three complementary approaches
 - Micro-benchmarking
 - Profiling
 - Simulation
- Each have their own strengths and weaknesses
- Together they allow you to **understand** the performance of your code
- Also where and how to **improve** the performance of your code

Recommended resources

Benchmarking

- Chandler Carruth talks on benchmarking/performance
 - [Tuning C++: Benchmarks, and CPUs, and Compilers! Oh My!](#)
 - [Efficiency with Algorithms, Performance with Data Structures](#)
 - [Going Nowhere Faster](#)
- Fedor Pikus talk on branchless programming
 - [Branchless Programming in C++](#)

Recommended resources

Performance

- Mike Acton talk on data oriented design
 - [Data-Oriented Design and C++](#)
- Ulrich Drepper paper on memory and cache
 - [What Every Programmer Should Know About Memory](#)
 - Not for “every programmer” but excellent info on RAM / cache / performance
 - From 2007 but still very relevant
- A curated list of c++ performance-related resources
 - [AwesomePerfCpp](#)

More recommended resources

Hash maps

- Malte Skarupke talk on hash map implementations and performance
 - [You Can Do Better than std::unordered_map](#)
- Matt Kulukundis talks on Google's hash map
 - [Designing a Fast, Efficient, Cache-friendly Hash Table, Step by Step](#)
 - [Abseil's Open Source Hashtables: 2 Years In](#)