Julia with MPI

Challenges and Best Practices

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Who am I?

And what am I doing here?

- About Me:
 - Lead software engineer on the CliMA project @ Caltech
 - Building a GPU + MPI climate model in Julia
 - Contributor to the Julia language and packages since 2012
 - A primary maintainer of MPI.jl and NVTX.jl
- Why this talk?
 - Julia is great for scientific computing, but...
 - There are some pitfalls which may not be obvious





Overview

- 1. Configuring Julia on a HPC system
- 2. MPI.jl
- 3. Profiling parallel Julia code with Nsight Systems
- 4. Julia + MPI pitfalls

Getting started

Configuring Julia for HPC

Installing Julia The easy part

- Download the binaries from julialang.org
 - Don't build from source, or use distribution-provided binaries
 - Especially don't try to link against existing dependencies on the system
 - Julia includes quite a few patches for some of these (LLVM, libuv)
 - Building from source won't enable any magic optimizations
 - Julia has its own compiler for that
- Plays nice with cluster module files

Some helpful environment variables Getting the most out of your system

- JULIA_DEPOT_PATH
 - Where Julia stores packages, artifacts, precompilation caches, etc
 - Default is ~/.julia
 - Make sure it is on a fast disk (not NFS)
 - Can specify multiple (helpful for caching artifacts across users)
- JULIA_CPU_TARGET (Julia 1.9+)
 - Julia now caches native code: specify the microarchitecture to use
 - Can specify multiple targets (helpful on a heterogeneous cluster)
 - export JULIA_CPU_TARGET='broadwell; skylake'

Configuring packages: the new way Preferences.jl

- Old Pkg.build() scripts are now discouraged
- Preferences: per-package key-value store
 - @load preference(key, default value)
 - @set_preferences! (key => value)
- Stored per project (LocalPreferences.toml or Project.toml)
- Used as part of the precompilation hash
 - Specific to a given project
 - Correctly invalidate the cache on changes
 - Can be used to define constant variables

Configuring binary dependencies Overriding your JLLs

- Julia package manager provides binary dependencies through its artifact system
 - Built using BinaryBuilder.jl cross-compilation framework
 - Windows/Mac/Linux, on x86/ARM/PPC
- Can be used to override JLL binaries
 - Need to be careful: typically you will need to override all downstream dependencies
- Inherited from LOAD_PATH
 - Modify preferences for the current session
 - Can integrate with cluster module files

```
# /config/path/Project.toml
[extras]
HDF5_jll = "0234f1f7-429e-5d53-9886-15a909be8c"
[preferences.HDF5_jll]
libhdf5 path = "libhdf5"
```

```
export JULIA_LOAD_PATH=\
"$JULIA LOAD PATH:/config/path"
```

libhdf5 hl path = "libhdf5 hl"

MPI.jI

Julia interface for MPI

MPI.jl basics

- Automatically determines array datatype and length
- Integration with Julia's exception handling
- Custom structs, strided arrays => generate custom datatypes
- Julia functions => generate custom reduction operators
- Covers most used MPI functions
 - Point-to-point, collectives, one-sided, I/O
 - Easy to add more: please open an issue!
- Supports GPU-aware MPI interfaces
 - Simply pass CuArray/ROCArray as a buffer
- Used by multiple Julia packages

```
# Custom datatype
struct SummaryStat
    mean::Float64
    var::Float64
    n::Float64
end
function SummaryStat(X::AbstractArray)
    m = mean(X)
    v = varm(X,m,corrected=false)
    n = length(X)
    SummaryStat(m, v, n)
end
# Custom reduction operator
# pools the mean, variance, length
# more numerically stable than sum-of-squares
function pool(S1::SummaryStat, S2::SummaryStat)
    n = S1.n + S2.n
    m = (S1.mean*S1.n + S2.mean*S2.n) / n
    v = (S1.n*(S1.var + S1.mean*(S1.mean-m)) +
         S2.n*(S2.var + S2.mean*(S2.mean-m)))/n
    SummaryStat(m, v, n)
end
# Perform reduction
summ = MPI.Reduce(SummaryStat(X), pool, comm)
```

Configuring MPI for Julia

- By default, MPI.jl uses a JLL-built binary
 - MicrosoftMPI_jll on Windows, MPICH_jll everywhere else
 - Many downstream binaries (e.g. HDF5, ADIOS2, PETSc)
- For HPC: typically want to use the binary for that system
 - Support for specific network hardware and libraries
 - Integration with system launcher (srun, aprun)
 - Direct device-device communication (CUDA-aware)
- Problem: MPI application binary interface (ABI) is implementation-defined
 - Handles (e.g. MPI Comm) can be an int or a pointer
 - Constants (e.g. MPI_ANY_SOURCE) values vary
 - May be fixed in MPI 5

MPIPreferences.jl

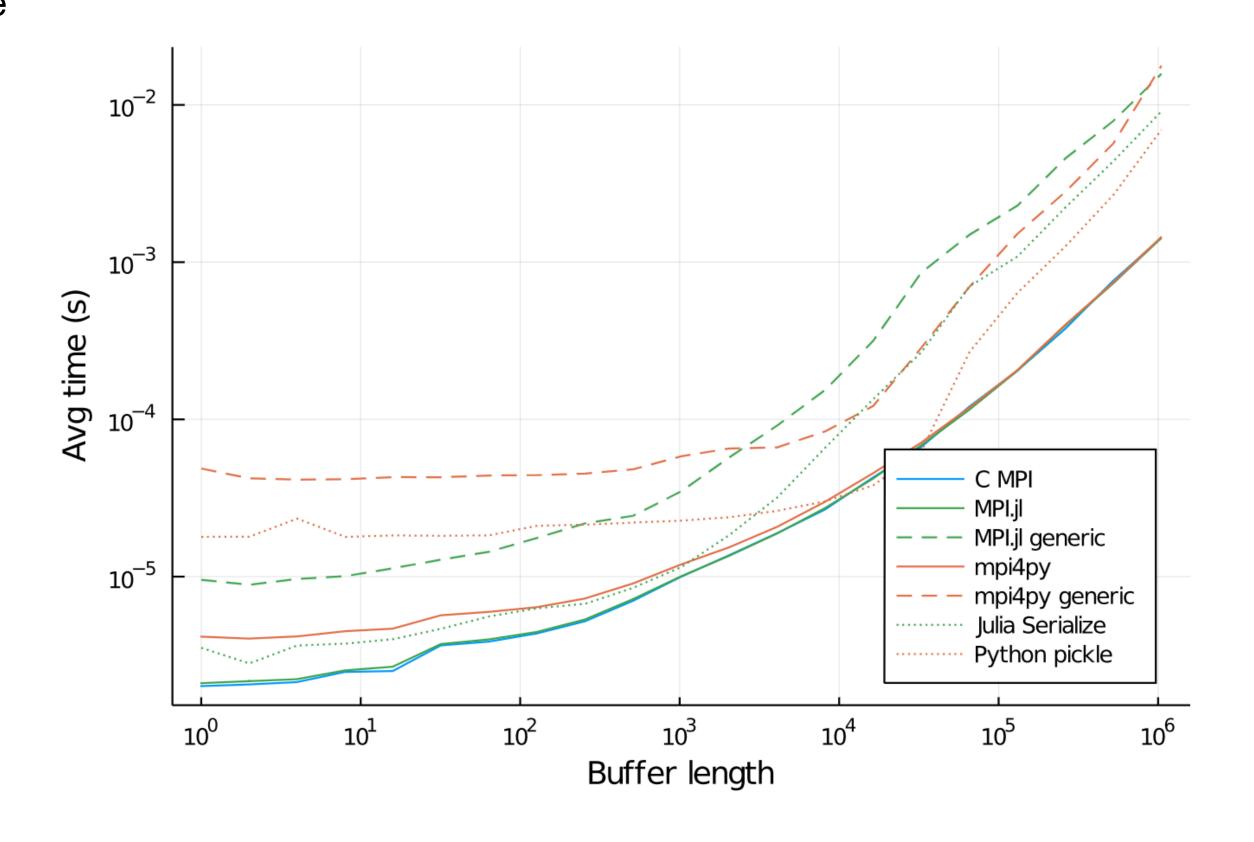
Two options

- MPIPreferences.use system binary()
 - Detects and configures ABI
 - Uses system binary directly
 - Need to override all downstream binaries
- MPIPreferences.use_jll_binary("MPItrampoline")
 - Uses MPItrampoline by Erik Schnetter
 - Requires building a shim (MPIwrapper) around your MPI library
 - Some operations can incur overhead (e.g. MPI Waitall)
 - Downstream JLL binaries "just work"

MPI.jl tips

How to use it efficiently

- Use uppercase functions (MPI.Send/MPI.Recv) where possible
 - Requires both sender & receiver to know datatype & length
 - Minimal overhead vs C
- Lowercase functions (MPI.send/MPI.recv) serialize & deserialize
 - More flexible (e.g. strings, mutable objects), but slower
- Pre-allocate output arrays
 - Use MPI.Reduce! instead of MPI.Reduce
- Define MPI.Buffer(array) wrapper outside loop/function
 - Important when using custom datatypes (e.g. SubArrays)
- Learn how to make your launcher output ranks to individual files
 - Interleaved error stacks are difficult!
- Profile, profile



Parallel profiling of Julia code

Nsight Systems + NVTX.jl

- Nsight Systems is an instrumenting profiler from Nvidia
 - Profiler supports Linux & Windows
 - Viewer for Linux, Windows and MacOS
 - Supports multithreading and MPI
 - Does not require a GPU (can be used for CPU-only code)
- NVTX.jl package for instrumenting Julia code
 - Annotate Julia code with macros which the profiler can then access
 - Options to instrument the Julia garbage collector
 - Safe to include as a package dependency (becomes a no-op if not using the profiler)

NVTX.jl basics

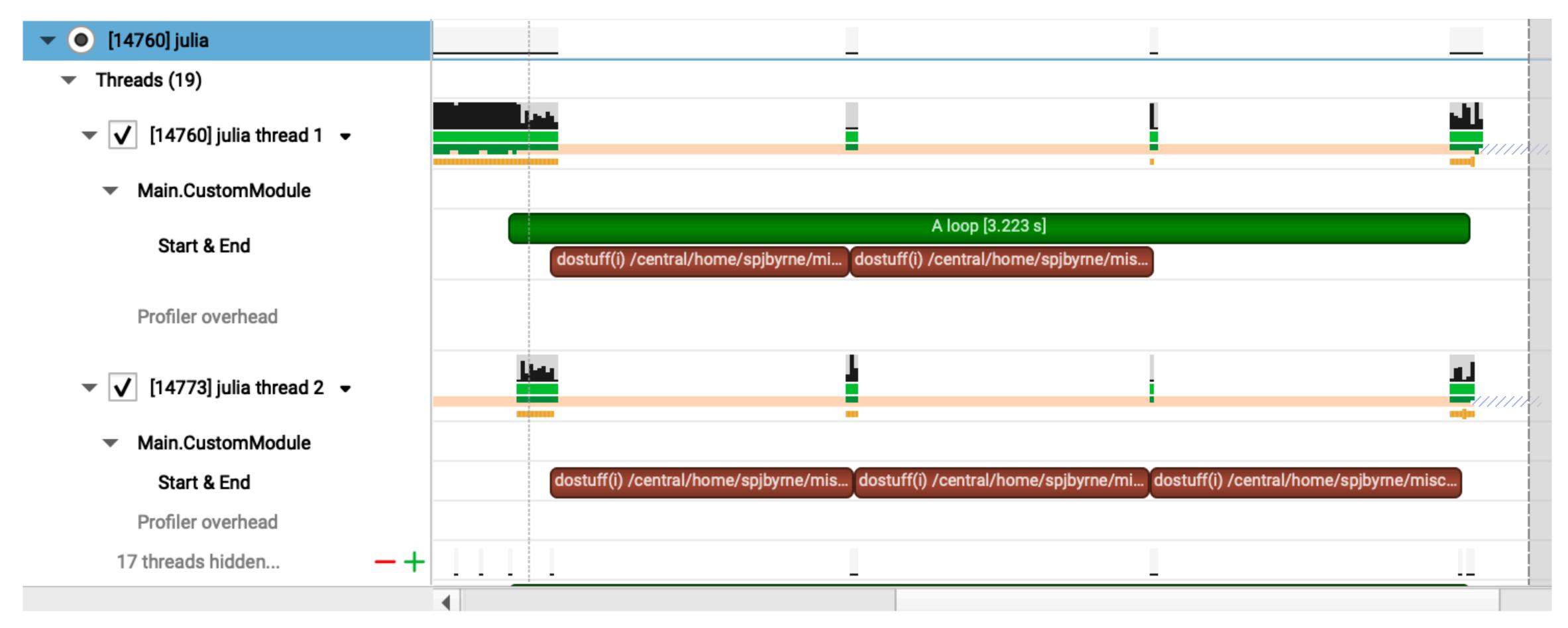
Annotating Julia code

- Basic macros
 - NVTX.@mark: Instruments an instantaneous event
 - NVTX.@range expr: Instruments a code block with a range
 - NVTX.@annotate function ... end: Instruments a function definition with a range
- Can attach metadata to each of these
 - domain (default: current Julia module)
 - message (default: [function name] file:lineno)
 - color: (default: generate unique)
 - payload: a single integer or float value
 - category: enum value

```
module CustomModule
using NVTX
NVTX.@annotate function dostuff(i)
    sleep(1)
end
NVTX.@range "A loop" begin
    Threads. @threads for i = 1:5
        dostuff(i)
    end
end
end
```

Simple example

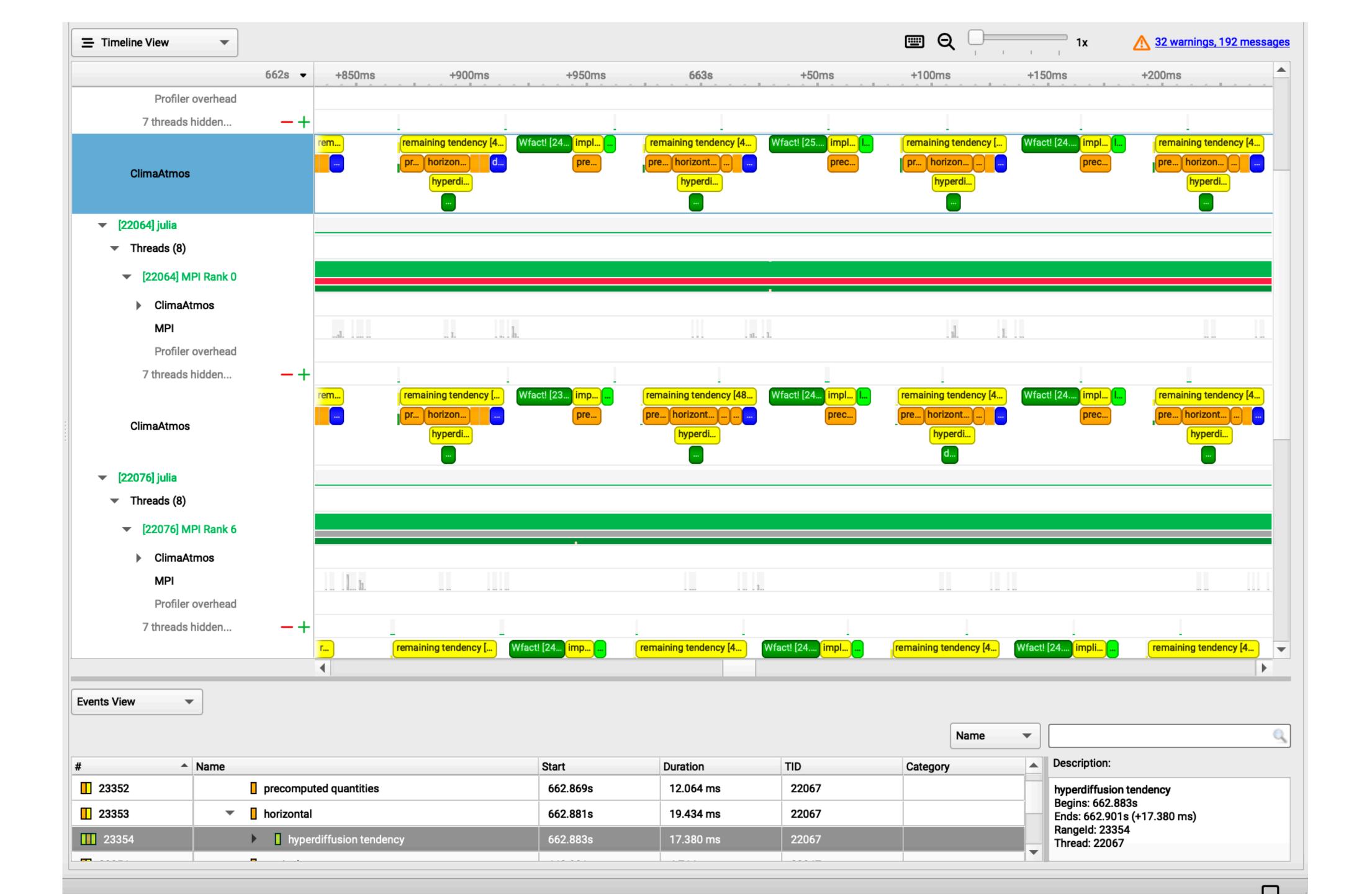
nsys profile --trace=nvtx julia example.jl



Can also be invoked from the Julia REPL

Nsight + MPI Profiling parallel Julia code

- Instruments common MPI operations using MPI profiling interface
- Can be used in two ways
 - profiler launcher program
 - nsys profile <nsys-args> mpiexec <mpi-args> julia ...
 - Generates single profile
 - Only works if all processes are on the same node
 - launcher profiler program
 - mpiexec <mpi-args> nsys profile <nsys-args> julia ...
 - Generates a profile per rank
 - Can be opened as a "multi-profile view"
- Profiler itself has overhead
 - Recommend allocating additional CPU core per profiler instance + launch with core binding



More on profiling

- Alternatives:
 - Score-P/ScoreP.jl (https://github.com/JuliaPerf/ScoreP.jl) by Carsten Bauer
 - Intel VTune/IntelITT.jl (https://github.com/JuliaPerf/IntelITT.jl) by Valentin Churavy
- Recent effort at instrumenting the Julia runtime
 - Compilation, task switching, etc.
 - Requires a custom build of Julia
 - Currently supports Tracy & Intel ITT
- Future work
 - Develop a common instrumentation API

Julia + MPI Pitfalls

My Julia HPC gripes

1. MPI library quirks

Every MPI implementation is weird in its own way

- MPI libraries do lots of weird things
 - Intercept signals, malloc, dynamic libraries
 - GPU-aware interfaces make everything worse
- Julia is good at triggering these issues
 - ccall uses dlopen, multithreaded runtime
- Can often be worked around (e.g. with environment variables)
 - See https://juliaparallel.org/MPI.jl/stable/knownissues/
- MPI launchers have poor support for interactivity
 - No parallel Julia REPL 🐷

2. Shared file system woes

Performance issues

- User home directories are mounted via NFS: set your depot to be on a fast disk
- DDOS-ing your parallel file system metadata server: system images, containers, scratch partitions

Incompatibilities

- Typically don't allow memory mapping (mmap): JLD2.jl, use jldopen (...; iotype=IOStream)
- Race conditions: multiple processes/multiple jobs trying to write at the same time
 - e.g. Pkg operations, precompilation, artifact downloading
 - Recommend Pkg.instantiate() on a singleton process
 - Use a clean depot on top (see DepotCompactor.jl)
- Disk usage: on systems with low limits
 - Use a shared depot of Julia artifacts

3. Compilation complaints

- JIT for HPC is extremely powerful
 - Benefits: generating specialized code for your particular problem (especially for GPU)
 - Downside: compiling specialized code for your particular problem
- Much recent work compiler work on reducing latency
 - Time-to-first-X (TTFX)
- Critical to avoid method invalidations
 - SnoopCompile.jl and related tools
- Native code caching (system images, pkgimages on Julia 1.9)
 - Complicated on a heterogeneous cluster
 - Caching for GPU kernels a work-in-progress

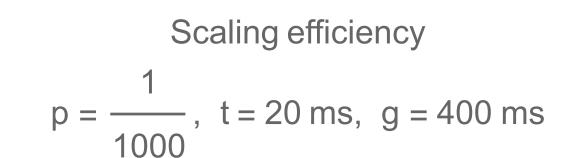
4. MPI + GC

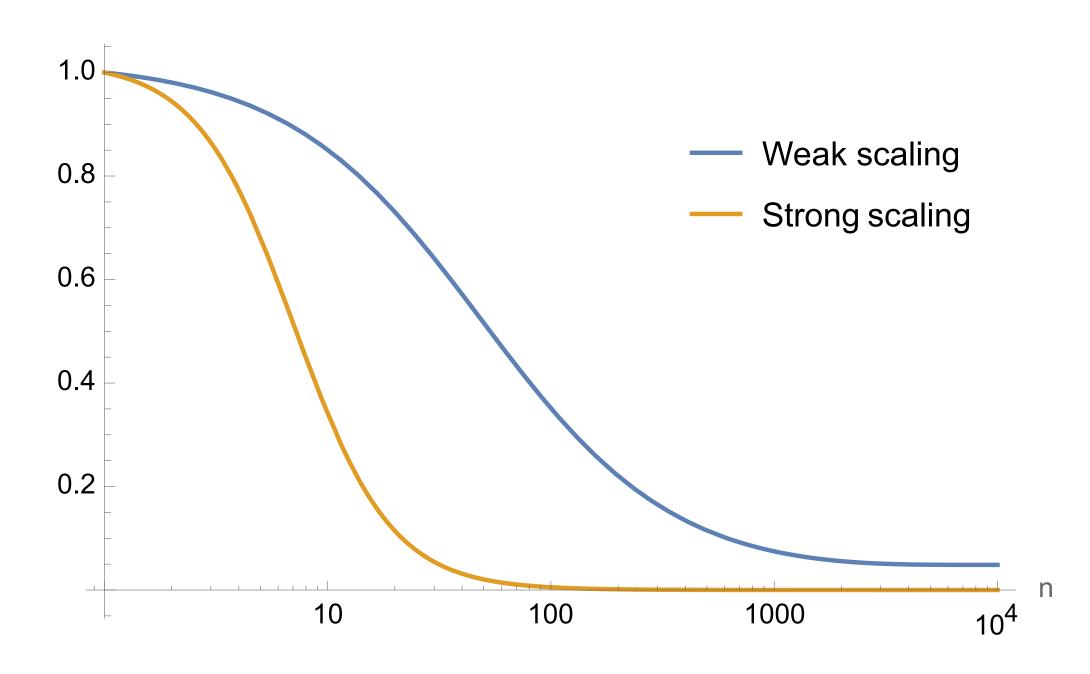
- All other processes stuck waiting on a process calling the GC
 - More MPI ranks => higher probability of a rank invoking GC
- Consider an iteration of compute + all-to-all communication
 - *t* = time per iteration without GC (assume perfect scaling)
 - g = time per GC pause
 - p = probability of GC invocation per iteration on each processor
 - Assuming each processor independent
 - n = number of processes
- Average time per iteration

• Single process:
$$t + gp$$

• Weak scaling regime:
$$t + g(1 - (1 - p)^n)$$

• Strong scaling regime:
$$\frac{t}{n} + g(1 - (1 - p)^n)$$

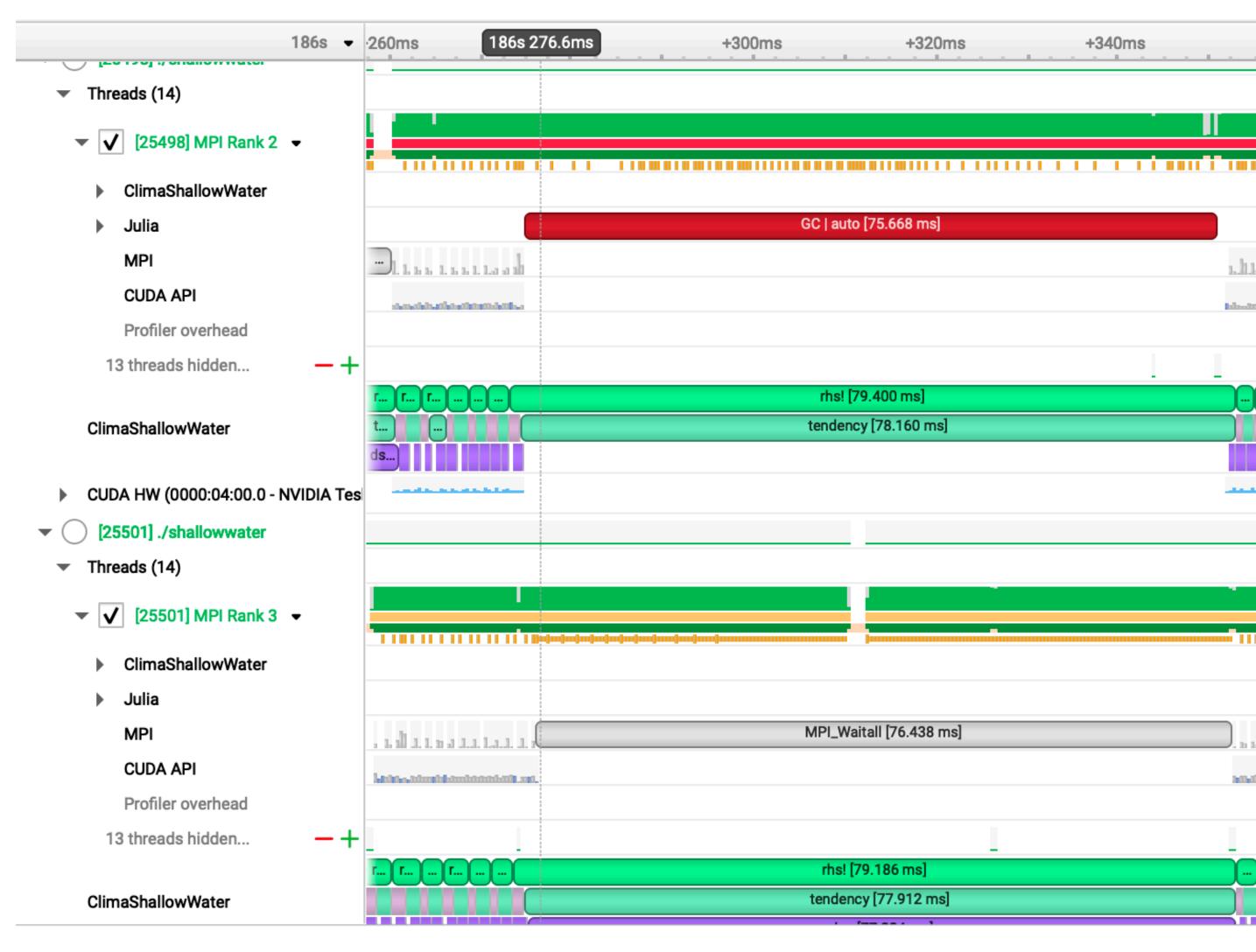




Identifying the problem

Profiling the Julia Garbage Collector

- Load NVTX.jl, set
 JULIA_NVTX_CALLBACKS=gc
 - Activates a hook into the Julia garbage collector
- Look for ranks blocking on MPI operations



What can be done?

- 1. Reduce memory allocations wherever possible
 - A good idea anyway!
 - See Julia docs on memory allocation profiling
 - Not always possible to eliminate entirely: many small memory allocations
 - e.g. CUDA kernel launches, saving output, log printing
- 2. Disable the garbage collector: GC.enable(false)
 - Feasible once allocations are sufficiently small
- 3. Synchronize calling GC on all processes
 - Manually call GC.gc() at set intervals
 - Requires tuning heuristics for a particular workload

Summary

Summary

- Julia is a very powerful language for scientific computing
 - Fast, expressive, multithreading, cross-platform, excellent GPU support
 - Easy-to-use MPI support
- But you need to develop a good understanding of the runtime
- You can only optimize what you can measure
 - Profiling is essential
- Julia HPC has a great community
 - Slack
 - Discourse
 - JuliaHPC monthly call