Julia: A competitive high-level choice for performance portability in HPC?

Jim M. R. Teichgräber

5th July, 2022

Outline

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1. Motivation & Background
    - Julia's compilation process

Sources

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- Goal: Speed and convenience
  $\rightarrow$ Just-in-time (JIT) compilation

Julia — Compilation

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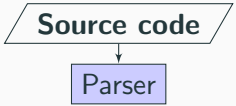

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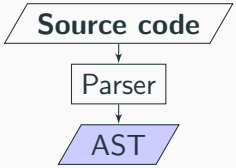

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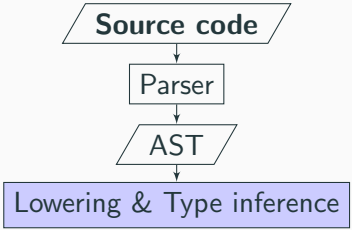

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  - Allows static memory allocation
  - Avoid dynamic multiple dispatch

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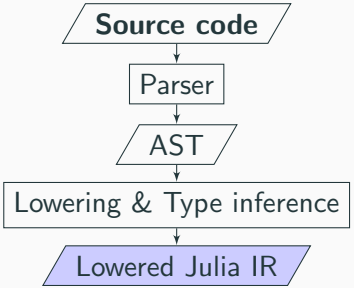

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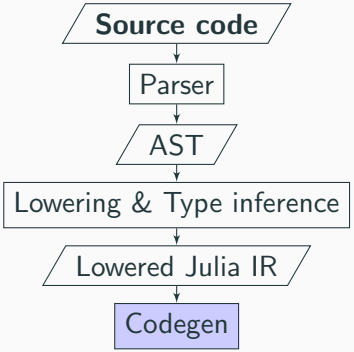

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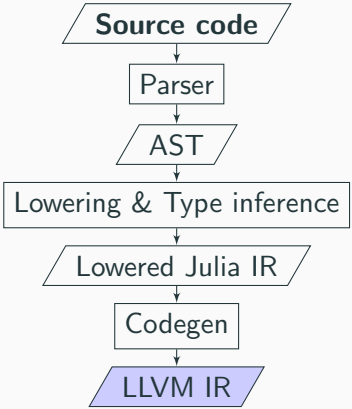

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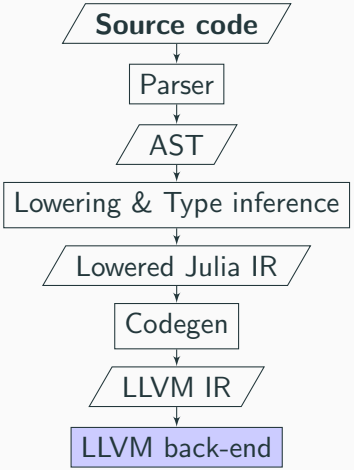

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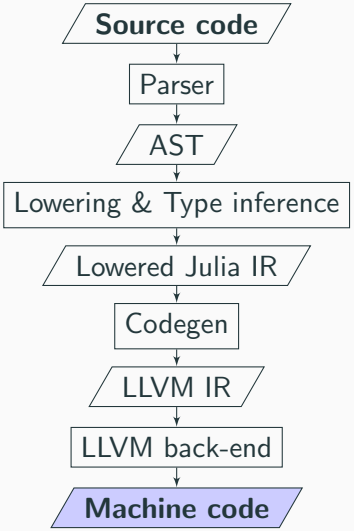

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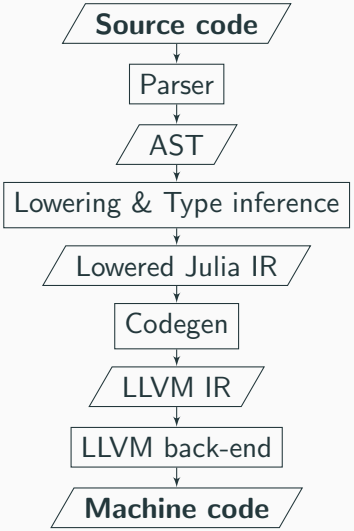

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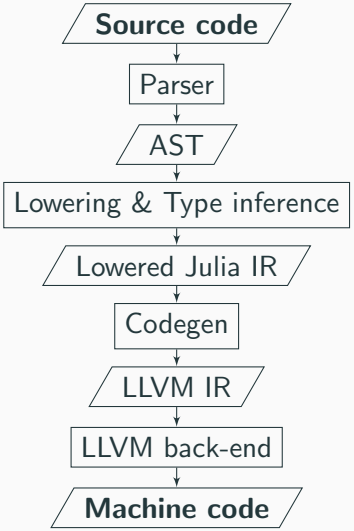

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- Dynamic code where it's convenient
- Speed where it's necessary

Julia — high-level features and idioms

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   `@threads`, `@simd`

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  - Hook into compilation process through extension interfaces (e.g. disallow exceptions)
  - Different LLVM backends to produce GPU code
- API uniformity

Benchmarks

Compute bound — miniBUDE

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Highly compute bound

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    for $i \leftarrow 0, n$ **do**
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Memory-bandwidth bound

Taken from [LM21]

Inter-node communication — ReproMPI

- **Message Passing Interface** (**MPI**): Inter-node communication standard

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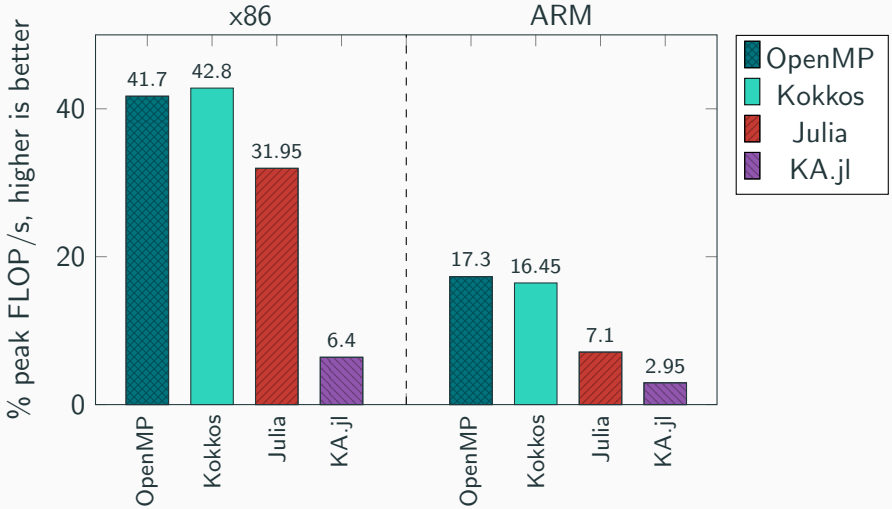
- ReproMPI
- Varying message sizes

Performance Results

Compute bound — miniBUDE: CPU



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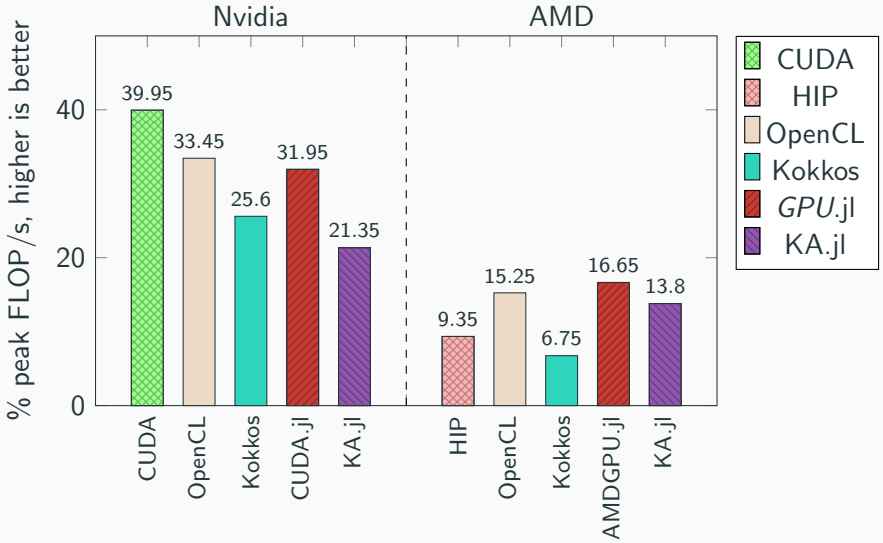

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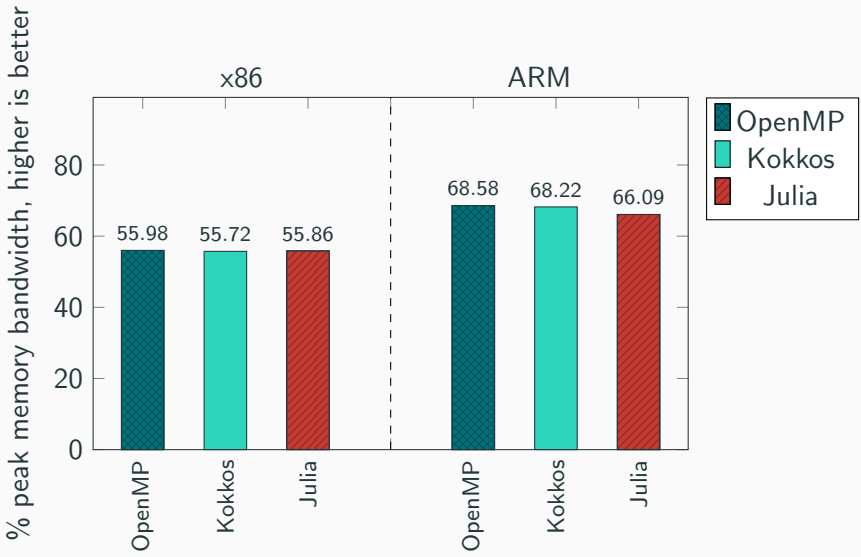
Memory bound — BabelStream: CPU



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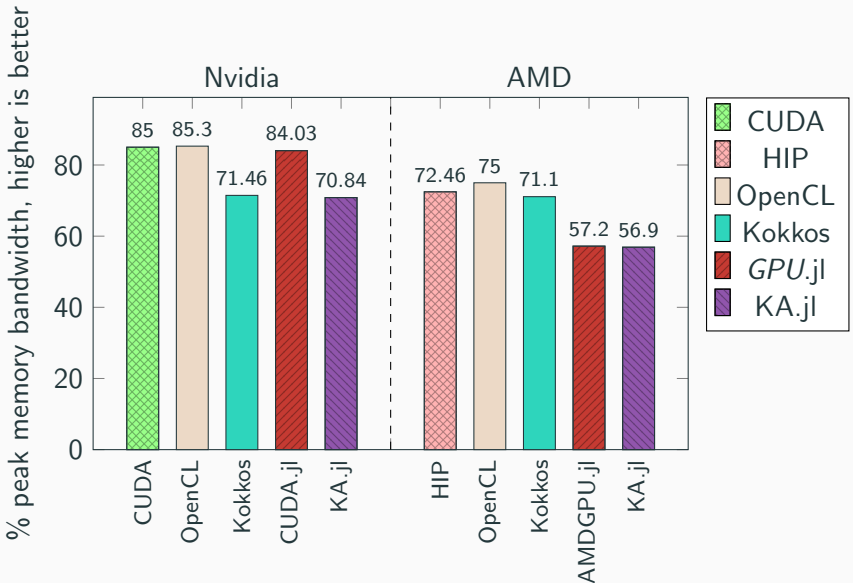

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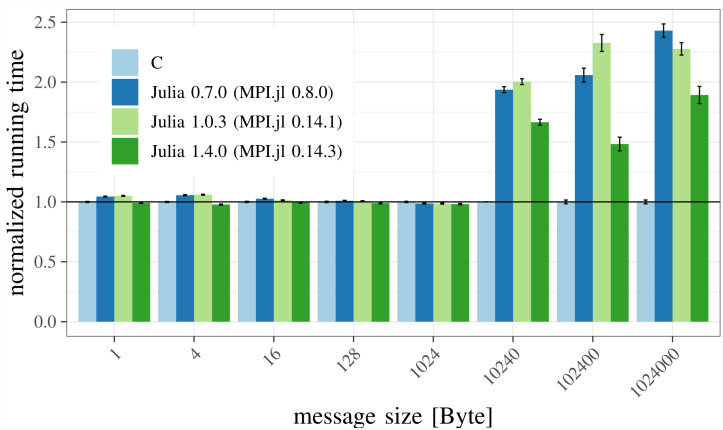

Taken from [HS20]

Discussion

Performance

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- Communication performance for inter-node workloads basically identical, except for the `MPI_Allreduce` anomaly

Lines of code

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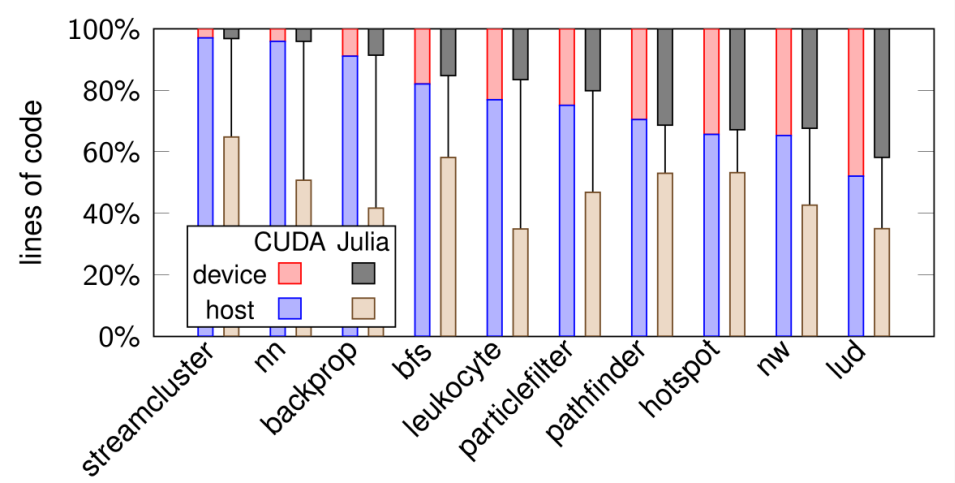

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- Single-source portability on GPUs constrained to the individual GPU packages
- Manual porting between GPU packages relatively easy, often simple API call substitutions

Conclusion

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- JIT, LLVM, and compiler extensions mean speed, portability, code reuse
- Convenience through dynamic code and high-level idioms
- Julia is competitive in HPC, but porting still requires some manual effort
- Performance itself is quite good across architectures and nodes

References i

[Bez+12] Jeff Bezanson et al. “Julia: A fast dynamic language for technical computing”. In: arXiv preprint (2012). DOI: 10.48550/ARXIV.1209.5145.

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GPU Kernel API Cross-Refrence i

	CUDA.jl	AMDGPU.jl
Global size	`blockDim().x * gridDim().x`	`gridDim().x`
Group count	`gridDim().x`	`gridDimWG().x`
Group size	`blockDim()`	`workgroupDim().x`

Adapted from [LM21]

GPU Kernel API Cross-Refrence ii

	CUDA.jl	AMDGPU.jl	oneAPI.jl	KernelAbstractions.jl
Global size	`blockDim().x*gridDim().x`	`gridDim().x`	`get_global_size(0)`	(Not exposed)
Group count	`gridDim().x`	`gridDimWG().x`	`get_num_groups(0)`	(Not exposed)
Group size	`blockDim().x`	`workgroupDim().x`	`get_local_size(0)`	`@groupsize()[1]`
Index (global)	`(blockIdx().x - 1) * blockDim().x + threadIdx().x`	`(workgroupIdx().x - 1) * workgroupDim().x + workitemIdx().x`	`get_global_id(0)`	`@index(Global)`
Index (group)	`blockIdx().x`	`workgroupIdx().x`	`get_group_id(0)`	`@index(Group)`
Index (local)	`threadIdx().x`	`workitemIdx().x`	`get_local_id(0)`	`@index(Local)`
Synchronise	`sync_threads()`	`sync_workgroup()`	`barrier()`	`@synchronize`
Memory (register) size=N, type=T	`data = MArray{Tuple{N},T}`	`data = MArray{Tuple{N},T}`	`data = MArray{Tuple{N},T}`	`data = MArray{Tuple{N},T}`
Memory (private) size=N, type=T	`data = @cuStaticSharedMem(T, N)`	`data = ROCDeviceArray((N,), alloc_local(:data,T, N))`	`data = @LocalMemory(T, (N,))`	`data = @localmem T N`

Kernel launch & Mem. allocation Groups=GN, Blocks=BN, size=N, type=T	`data = CuArray{T}(undef, N)`
	`@cuda`
	`  blocks=N÷GN`
	`  threads=GN`
	`  kernel(data)`
		`data = ROCArray{T}(undef, N)`
		`@roc`
		`  groupsize=GN`
		`  gridsize=GN*BN`
		`  kernel(data)`
			`data = oneArray{T}(undef, N)`
			`@oneapi`
			`  items=GN`
			`  groups=BN`
			`  kernel(data)`
				`device= # one of :`
				`  # CPU()`
				`  # CUDADevice()`
				`  # ROCDevice()`
				`data= # one of :`
				`  # Array{T}`
				`  # CuArray{T}`
				`  # ROCArray{T}`
				`kernel(device, GN)(`
				`  data, ndrange=N)`

Taken from [LM21]

All BabelStream Kernels

procedure $\mathrm{COPY}(A[n], C[n], n)$
  for $i \leftarrow 0, n$ **do**
    $C[i] \leftarrow A[i]$

procedure $\mathrm{ADD}(A[n], B[n], C[n], n)$
  for $i \leftarrow 0, n$ **do**
    $C[i] \leftarrow A[i] + B[i]$

procedure $\mathrm{TRIAD}(A[n], B[n], C[n], scalar, n)$
  for $i \leftarrow 0, n$ **do**
    $C[i] \leftarrow A[i] + (scalar * B[i])$

procedure $\mathrm{MUL}(A[n], C[n], scalar, n)$
  for $i \leftarrow 0, n$ **do**
    $C[i] \leftarrow scalar * A[i]$

procedure $\mathrm{DOT}(A[n], B[n], scalar, n)$
  for $i \leftarrow 0, n$ **do**
    $R \leftarrow R + (A[i] * B[i])$
  return R

Taken from [LM21]

ReproMPI

- `MPI_Bcast`: Push data into network from one source (rooted)
- `MPI_Allreduce`: Reduce data from all sources into one result (non-rooted collective)
- `MPI_Alltoall`: All processes exchange data with all other processes (non-rooted collective)

Platform details

Vendor	Name	Architecture	Abbreviation	Device Type	Theoretical Peak Mem. Bandwidth (GB/s)	Theoretical Peak FP32 FLOP/s (GFLOP/s)
Intel	Xeon Gold 6230	Cascade Lake	Xeon	HPC CPU (20C*2, 2S)	281.6	4096
AMD	EPYC 7742	Zen2 (Rome)	EPYC	HPC CPU (64C*2, 2S)	409.6	9216
Marvell	ThunderX2	Vulcan	TX2	HPC CPU (32C*2, 2S)	288	2560
Fujitsu	A64FX	(Custom ARMv8)	A64FX	HPC CPU (48C*2, 2S)	1024	5530
NVIDIA	Tesla A100 (SXM 80GB)	Ampere	A100	HPC GPU	2039	19490
NVIDIA	Tesla V100 (PCIe 16GB)	Volta	V100	HPC GPU	900	14130
NVIDIA	RTX2080Ti	Turing	2080Ti	Consumer GPU	616	13800
AMD	Instinct MI100	CDNA	MI100	HPC GPU	1228	23100
AMD	Instinct MI50	GCN (Vega 20GL)	MI50	HPC GPU	1024	13300
AMD	Radeon VII	GCN (Vega 20)	RadeonVII	Consumer GPU	1024	13800
Intel	UHD P630 (Xeon E2176G)	Gen9.5	UHD	Server iGPU	42.6	460
Intel	IrisPro 580 (i7 6670HQ)	Gen9	IrisPro	Consumer iGPU	34	1094
Apple	M1	Firestorm+Icestorm	M1	Consumer CPU(4+4, 1S)	68.25	673

Taken from [LM21]

`@threads` vs. OpenMP

```
xs = Vector{Float32}(undef, N)
ys = fill(42f0, N)
Threads.@threads for i = 1:N
  @inbounds xs[i] = ys[i]
end
```

```
std::vector<float> xs(N, 0);
std::vector<float> ys(N, 42.f);
#pragma omp parallel for
for (int i = 0; i < N; i++)
  xs[i] = ys[i];
```

Taken from [LM21]