Julia: From multicore to GPU parallelism

presented by Steffen Haug

What is Julia?

(Briefly)

1. High level programming language

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2. Dynamically typed

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   (Central on CPU and GPU)

Untyped AST specialized at runtime

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2. Dynamically typed
3. For HPC
4. **Novel compilation infrastructure**
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Untyped AST specialized at runtime

"Looks like Python – runs like Fortran"

Example

```julia
function square!(xs)
  for i in eachindex(xs)
    xs[i] ^= 2
  end
end

V = rand(10000);
@code_native syntax=:intel square(V)
```

Function that squares (mutates) a vector.

Example

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  for i in eachindex(xs)
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end

V = rand(10000);
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```

Not a type in sight!

Example

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```

When invoked with `V`, `square!` is specialized to **`Vector{Float64}`**.

Example

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function square!(xs)
  for i in eachindex(xs)
    xs[i] ^= 2
  end
end

V = rand(10000);
@code_native syntax=:intel square(V)
```

`@code_native` is a "macro" that allows us to inspect code generated for a particular specialization.

Example

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function square!(xs)
  for i in eachindex(xs)
    xs[i] ^= 2
  end
end

V = rand(10000);
@code_native syntax=:intel square(V)
```

Simple function – surely the assembly code is reasonably simple? 

```
  .text
  .file  "square"
  .globl  julia_square_86
  .p2align  4, 0x90
  .type  julia_square_86,@function
julia_square_86:
; ┌ @ REPL[1]:1 within `square`
  .cfi_startproc
; │ @ REPL[1]:2 within `square`
; │┌ @ abstractarray.jl:285 within `eachindex`
; ││┌ @ abstractarray.jl:116 within `axes1`
; │││┌ @ abstractarray.jl:95 within `axes`
; ││││┌ @ array.jl:151 within `size`
  endbr64
  mov  rax, qword ptr [rdi + 8]
; │└└└└
; │┌ @ range.jl:879 within `iterate`
; ││┌ @ range.jl:654 within `isempty`
; │││┌ @ operators.jl:382 within `>`
; ││││┌ @ int.jl:83 within `<`
  test  rax, rax
; │└└└└
  je  .LBB0_7
  mov  rcx, qword ptr [rdi]
  mov  edx, 1
; │ @ REPL[1]:3 within `square`
; │┌ @ array.jl:924 within `getindex`
  cmp  rax, 16
  jb  .LBB0_5
  mov  rsi, rax
  and  rsi, -16
  lea  rdx, [rsi + 1]
  xor  edi, edi
  .p2align  4, 0x90
.LBB0_3:
  vmovups  xmm0, xmmword ptr [rcx + 8*rdi]
  vmovups  xmm1, xmmword ptr [rcx + 8*rdi + 32]
  vmovups  xmm2, xmmword ptr [rcx + 8*rdi + 64]
  vmovups  xmm3, xmmword ptr [rcx + 8*rdi + 96]
  vinsertf128  ymm0, ymm0, xmmword ptr [rcx + 8*rdi + 16], 1
  vinsertf128  ymm1, ymm1, xmmword ptr [rcx + 8*rdi + 48], 1
  vinsertf128  ymm2, ymm2, xmmword ptr [rcx + 8*rdi + 80], 1
  vinsertf128  ymm3, ymm3, xmmword ptr [rcx + 8*rdi + 112], 1
; │└
; │┌ @ intfuncs.jl:321 within `literal_pow`
; ││┌ @ float.jl:385 within `*`
  vmulpd  ymm0, ymm0, ymm0
  vmulpd  ymm1, ymm1, ymm1
  vmulpd  ymm2, ymm2, ymm2
  vmulpd  ymm3, ymm3, ymm3
; │└└
; │┌ @ array.jl:966 within `setindex!`
  vextractf128  xmmword ptr [rcx + 8*rdi + 16], ymm0, 1
  vmovupd  xmmword ptr [rcx + 8*rdi], xmm0
  vextractf128  xmmword ptr [rcx + 8*rdi + 48], ymm1, 1
  vmovupd  xmmword ptr [rcx + 8*rdi + 32], xmm1
  vextractf128  xmmword ptr [rcx + 8*rdi + 80], ymm2, 1
  vmovupd  xmmword ptr [rcx + 8*rdi + 64], xmm2
  vextractf128  xmmword ptr [rcx + 8*rdi + 112], ymm3, 1
  vmovupd  xmmword ptr [rcx + 8*rdi + 96], xmm3
  add  rdi, 16
  cmp  rsi, rdi
  jne  .LBB0_3
; │└
; │ @ REPL[1]:4 within `square`
  cmp  rax, rsi
  je  .LBB0_7
.LBB0_5:
  dec  rdx
  .p2align  4, 0x90
.LBB0_6:
; │ @ REPL[1]:3 within `square`
; │┌ @ array.jl:924 within `getindex`
  vmovsd  xmm0, qword ptr [rcx + 8*rdx]
; │└
; │┌ @ intfuncs.jl:321 within `literal_pow`
; ││┌ @ float.jl:385 within `*`
  vmulsd  xmm0, xmm0, xmm0
; │└└
; │┌ @ array.jl:966 within `setindex!`
  vmovsd  qword ptr [rcx + 8*rdx], xmm0
; │└
; │ @ REPL[1]:4 within `square`
  inc  rdx
  cmp  rdx, rax
  jb  .LBB0_6
.LBB0_7:                                # %L33
  vzeroupper
  ret
.Lfunc_end0:
  .size  julia_square_86, .Lfunc_end0-julia_square_86
  .cfi_endproc
  .section  ".note.GNU-stack","",@progbits
```

```
square:
  mov  rax, qword ptr [rdi + 8]
  test rax, rax
  je  .LBB0_7
  mov  rcx, qword ptr [rdi]
  mov  edx, 1
  cmp  rax, 16
  jb  .LBB0_5
  mov  rsi, rax
  and  rsi, -16
  lea  rdx, [rsi + 1]
  xor  edi, edi
.LBB0_3:
  vmovups  xmm0, xmmword ptr [rcx + 8*rdi]
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  vmovups  xmm2, xmmword ptr [rcx + 8*rdi + 64]
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  vinsertf128  ymm0, ymm0, xmmword ptr [rcx + 8*rdi + 16], 1
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  vextractf128  xmmword ptr [rcx + 8*rdi + 16], ymm0, 1
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  add  rdi, 16
  cmp  rsi, rdi
  jne  .LBB0_3
  cmp  rax, rsi
  je  .LBB0_7
.LBB0_5:
  dec  rdx
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  vmovsd  xmm0, qword ptr [rcx + 8*rdx]
  vmulsd  xmm0, xmm0, xmm0
  vmovsd  qword ptr [rcx + 8*rdx], xmm0
  inc  rdx
  cmp  rdx, rax
  jb  .LBB0_6
.LBB0_7:
  vzeroupper
  ret
```

Remove some comments...

```
.LBB0_3:
  vmovups  xmm0, xmmword ptr [rcx + 8*rdi]
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  vextractf128  xmmword ptr [rcx + 8*rdi + 112], ymm3, 1
  vmovupd  xmmword ptr [rcx + 8*rdi + 96], xmm3
  add  rdi, 16
  cmp  rsi, rdi
  jne  .LBB0_3
```

Julia has unrolled the loop and used SIMD-instructions!

```c
void square(double *xs, int N) {
  for (int i = 0; i < N; i++) {
    xs[i] *= xs[i];
  }
}
```

```asm
.L1:
  vmovupd ymm0,YMMWORD PTR [rdi+rsi*1]
  vmovupd ymm1,YMMWORD PTR [rdi+rsi*1+0x20]
  vmovupd ymm2,YMMWORD PTR [rdi+rsi*1+0x40]
  vmovupd ymm3,YMMWORD PTR [rdi+rsi*1+0x60]
  vmulpd ymm0,ymm0,ymm0
  vmulpd ymm1,ymm1,ymm1
  vmulpd ymm2,ymm2,ymm2
  vmulpd ymm3,ymm3,ymm3
  vmovupd YMMWORD PTR [rdi+rsi*1],ymm0
  vmovupd YMMWORD PTR [rdi+rsi*1+0x20],ymm1
  vmovupd YMMWORD PTR [rdi+rsi*1+0x40],ymm2
  vmovupd YMMWORD PTR [rdi+rsi*1+0x60],ymm3
  sub    rsi,0xffffffffffffff80
  cmp    rdx,rsi
  jne    .L1
```

This is what Clang does.

(*Slightly* better due to Julia-arrays being strided)

Julia uses LLVM

Julia can do the same optimizations we expect in C/C++

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Julia can do the same optimizations we expect in C/C++

...because it is literally the same optimizer!

But there are some <u>huge</u> caveats

1. There is some *slight* compilation overhead at startup

However: As problem size grows, relative compilation time decreases.

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2. Julia is *garbage-collected* 🤮

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1. There is some *slight* compilation overhead at startup
2. Julia is *garbage-collected* 🤮
3. We have no explicit control over memory
   (Allocation, copying, ...)

Accidental heap operations can really hurt!

But there are some huge caveats

1. There is some *slight* compilation overhead at startup
2. Julia is *garbage-collected* 🤮
3. We have no explicit control over memory
   (Allocation, copying, ...)
4. *The whole thing breaks* if Julia can't figure out the types

There are many ways to shoot yourself in the foot! 🙂

```julia
Δx = 0.1

function riemann!(X, x)
    N = length(x)
    X[0] = 0.0
    for i in 2:N
        X[i] = X[i - 1] + Δx * X[i]
    end
end

v = rand(100000)
V = zeros(100000)
@time riemann!(V, v)
```

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const Δx = 0.1

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Two seemingly quite similar programs...

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0.010550 seconds
(499.49 k allocations)

0.000175 seconds

One is $\sim 60\times$ faster than the other!

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And 500K allocations? 🤯

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`Δx` could be reassigned $\implies$ Julia can't assume its type!

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Leads to runtime type checks and dynamic dispatching...

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...and forces intermediate calculations onto the heap!

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But the *lack of explicit control* requires a lot of attention.

Even more so when we parallelize our programs.

Multicore

```
using .Threads: @threads
```

```julia
for i in eachindex(xs)

end
```

$\longrightarrow$

```julia
@threads for i in eachindex(xs)

end
```

Similar API to OpenMP: *Just annotate loops with a macro.*

```julia
for i in eachindex(xs)

end
```

$\longrightarrow$

```julia
@threads for i in eachindex(xs)

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Similar API to OpenMP: *Just annotate loops with a macro.*

The normal caveats apply

1. Spawning threads involve some overhead

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for i in eachindex(xs)

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THE NORMAL CAVEATS APPLY

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3. Possible speedup severely limited by core count

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for i in eachindex(xs)

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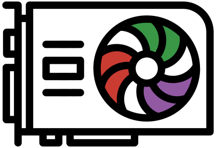
Similar API to OpenMP: *Just annotate loops with a macro.*

The normal caveats apply

1. Spawning threads involve some overhead
2. Memory is shared (Race conditions, deadlocks)
3. Possible speedup severely limited by core count
4. Domain decomposition sometimes necessary to get speedup on simple problems

GPU Parallelism



Level 1: "Vectorized" Array API

(Vectorized in the sense that you only operate on arrays, Numpy style)

“Vectorized” Array API

```
# In-place operations.
v = CUDA.rand(10000000)
v *= 10.0
v ^= 2
v .= sqrt.(v)

# Parallel scan.
w = CUDA.zeros(10000000)
accumulate!(max, w, v)
```

`v`, `w` of type `CuArray` that manages a device-side buffer.

"Vectorized" Array API

```
# In-place operations.
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v *= 10.0
v ^= 2
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# Parallel scan.
w = CUDA.zeros(10000000)
accumulate!(max, w, v)
```

Block- and gridsizes automatically determined.

“Vectorized” Array API

```julia
# FFT (10M-point FFT takes 200ms on 980)
using CUDA.CUFFT
ω = fft(v)

# Kernels get fused
w •= w.^2 .+ v

# Check out what happens on the GPU
@device_code_sass w •= w.^2 .+ v
```

Bindings to CUDA libraries like cuFFT and cuBLAS
(Also cuSPARSE, cuSOLVER, ...)

"Vectorized" Array API

```
# FFT (10M-point FFT takes 200ms on 980)
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```

GPU code generated on the fly using LLVMs PTX/SASS backend...

(Same sort of infrastructure as specializing Julia functions)

"Vectorized" Array API

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# FFT (10M-point FFT takes 200ms on 980)
using CUDA.CUFFT
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```

Enables kernel fusion and global optimization (!)

"Vectorized" Array API

```
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using CUDA.CUFFT
ω = fft(v)

# Kernels get fused
w •= w.^2 .+ v

# Check out what happens on the GPU
@device_code_sass w •= w.^2 .+ v
```

Like with CPU code, you can inspect the generated GPU code.
(SASS/PTX code is too long/ugly to put on a slide)

Level 2: Julia on the GPU

Julia on the GPU

```
function cusquare!(xs)
    i = (blockIdx().x - 1) * blockDim().x + threadIdx().x
    if i < length(xs)
        xs[i] *= xs[i]
    end
    return nothing
end

Nt = 1024
Nb = ceil(Int, length(v) / Nt)
@cuda threads=Nt blocks=Nb cusquare!(v)
```

`cusquare!` is defined *as a regular Julia function*!

(It won't run if you call it; block- and thread-ID is not defined on the CPU)

Julia on the GPU

```
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    i = (blockIdx().x - 1) * blockDim().x + threadIdx().x
    if i < length(xs)
        xs[i] *= xs[i]
    end
    return nothing
end

Nt = 1024
Nb = ceil(Int, length(v) / Nt)
@cuda threads=Nt blocks=Nb cusquare!(v)
```

The `@cuda` macro transforms typed Julia IR into GPU code! 🤯

Julia on the GPU

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Nt = 1024
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```

Basically, almost *any* sensible Julia can just work on the GPU

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```

However, there is no escape hatch: *The code must type check, and can't allocate*

Pitfalls

Pitfalls

`CuArray` controls all memory transfer

Pitfalls

Accidentally reading back to the CPU is really painful!

Level 3: Multi-GPU / Multi-node

Future Outlook

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`DistributedArrays.jl` : Domain decomposition and distribution algorithms

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IN SUMMARY

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It is a truth with a big asterisk.

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Location, location, location

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Julia has *real* potential, but it is *not a free lunch!*
(Especially on the GPU)

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LOCATION, LOCATION, LOCATION

I spend a lot of time "fighting the abstraction"

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Allocation, garbage-collection, copies, CUDA device$\leftrightarrow$host transfers, etc.
are all *implicit!*

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As Julia takes away your control, you have to be careful.

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The abstraction leaks!

IN SUMMARY

What niche does Julia even fill?

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If you *don't understand* the compilation process, Julia is basically unusable.

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Julia wont't replace lower-level languages.

IN SUMMARY

That being said...

IN SUMMARY

I quite like Julia

IN SUMMARY

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In Summary

What niche does Julia even fill?

Julia makes HPC a *first-class citizen* in the "Matlab workflow"

1. Interactive REPL/Notebook-based workflow
2. Good for *fucking around* with data
3. Sensible package manager
4. "Math stuff" is easily accessible
5. **Visualization is made easy**

julialang.org