

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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2. Dynamically typed
3. For HPC



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2. Dynamically typed
3. For HPC
4. **Novel compilation infrastructure**
(Central on CPU and GPU)

Untyped AST specialized at runtime



1. High level programming language
2. Dynamically typed
3. For HPC
4. **Novel compilation infrastructure**
(Central on CPU and GPU)

Untyped AST specialized at runtime

“Looks like Python – runs like Fortran”



EXAMPLE

```
function square!(xs)
  for i in eachindex(xs)
    xs[i]  $\hat{=}$  2
  end
end

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

Function that squares (mutates) a vector.

EXAMPLE

```
function square!(xs)
    for i in eachindex(xs)
        xs[i]  $\hat{=}$  2
    end
end

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

Not a type in sight!

EXAMPLE

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

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

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

EXAMPLE

```
function square!(xs)
  for i in eachindex(xs)
    xs[i]  $\hat{=}$  2
  end
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```

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

EXAMPLE

```
function square!(xs)
    for i in eachindex(xs)
        xs[i]  $\hat{=}$  2
    end
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V = rand(10000);
@code_native syntax=:intel square(V)
```

Simple function – surely the assembly code is reasonably simple?





?

```

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]
    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
    vshlps ymm0, ymm0, ymm0
    vshlps ymm1, ymm1, ymm1
    vshlps ymm2, ymm2, ymm2
    vshlps ymm3, ymm3, ymm3
    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
    cmp rax, rsi
    je .LBB0_7
.LBB0_5:
    dec rdx
.LBB0_6:
    vmovsd xmm0, qword ptr [rcx + 8*rdx]
    vshlps 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]
    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
    vmulpd   ymm0, ymm0, ymm0
    vmulpd   ymm1, ymm1, ymm1
    vmulpd   ymm2, ymm2, ymm2
    vmulpd   ymm3, ymm3, ymm3
    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

```

Julia has **unrolled the loop** and used **SIMD-instructions**!

```

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

```

```

.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, 0xffffffffffffffff80
    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 HUGE 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* 🤖
3. We have no explicit control over memory
(Allocation, copying, ...)

Accidental heap operations can really hurt!

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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, ...)
4. *The whole thing breaks* if Julia can't figure out the types

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

```

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)

```

```

const Δx = 0.1

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Two seemingly quite similar programs...

```

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```

0.010550 seconds
(499.49 k allocations)

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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
```

```
for i in eachindex(xs)  
end
```



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

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

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THE NORMAL CAVEATS APPLY

1. Spawning threads involve some overhead

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3. Possible speedup severely limited by core count

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for i in eachindex(xs)
end
```



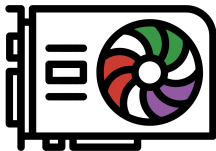
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Similar API to OpenMP: *Just annotate loops with a macro.*

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(100000000)  
accumulate!(max, w, v)
```

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

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```

Block- and gridsizes automatically determined.

“VECTORIZED” ARRAY API

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

```
using CUDA.CUFFT
```

```
 $\omega$  = 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

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```

GPU code generated on the fly using LLVMs PTX/SASS backend...
(Same sort of infrastructure as specializing Julia functions)

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@device_code_sass w *= w.^2 .+ v
```

Enables kernel fusion and global optimization (!)

“VECTORIZED” ARRAY API

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 $\omega$  = fft(v)
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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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```

The `@cuda` macro transforms typed [Julia IR](#) into [GPU code](#)!



JULIA ON THE GPU

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```

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

JULIA ON THE GPU

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Nt = 1024
Nb = ceil{Int}(length(v) / Nt)
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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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`CUDA.jl` composes with `DistributedArrays.jl`

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`CUDA.jl` composes with `DistributedArrays.jl`

`DistributedArrays.jl` : Domain decomposition and distribution algorithms

`CUDA.jl` : Manages device-side buffers and host-device communication

Both understands Julia's abstract concept of an "Array", so they work together.

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`DistributedArrays.jl` : Domain decomposition and distribution algorithms

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Both understands Julia's abstract concept of
an “Array”, so they work together.

Rapid Software Prototyping for Heterogeneous and Distributed Platforms
Besard et. al.

IN SUMMARY

Julia makes bold claims

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It is a truth with a big asterisk.

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If there is *one thing* that is true, it is that you can’t escape

LOCATION, LOCATION, LOCATION

IN SUMMARY

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LOCATION, LOCATION, LOCATION

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

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Julia makes bold claims: “*Only dynamic language to achieve petascale*”

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LOCATION, LOCATION, LOCATION

I spend a lot of time “fighting the abstraction”

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Julia makes bold claims: “*Only dynamic language to achieve petascale*”

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LOCATION, LOCATION, LOCATION

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

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

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

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LOCATION, LOCATION, LOCATION

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

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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What niche does Julia even fill?

Julia won't replace lower-level languages.

IN SUMMARY

That being said...

IN SUMMARY

I quite like Julia

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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



julia`lang.org`