Growing a Compiler

Getting to machine learning from a general purpose compiler

CGO C4ML 2019

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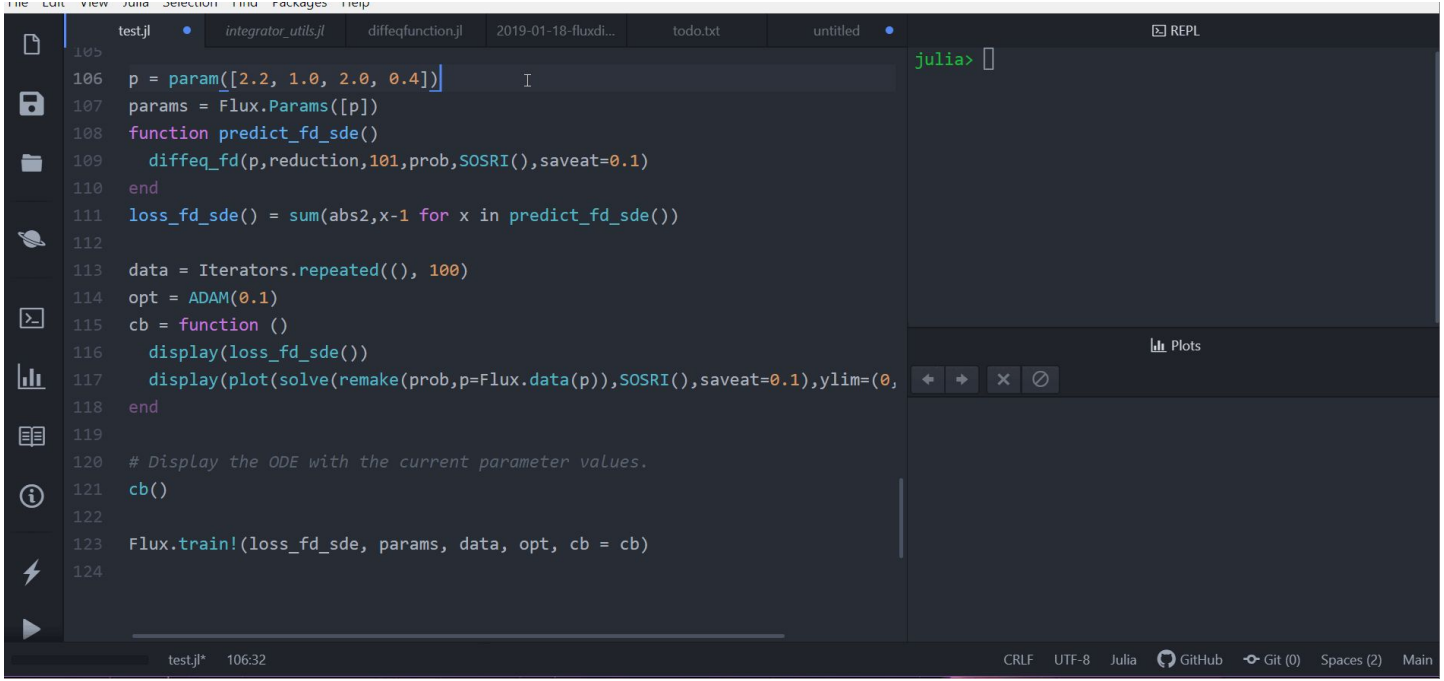
julia

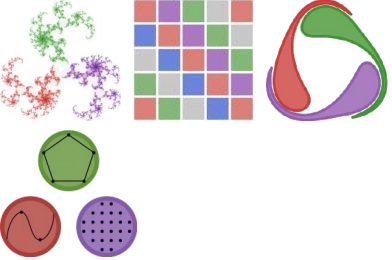
Julia computing

Neural ODEs

Combining ML and Differential Equation libraries



DiffEqFlux.jl — A Julia Library for Neural Differential Equations (arXiv:1902.02376)




Composability of Libraries

- Numbers (Integer, Floating Point, Complex, Quaternion, Rational, Fixed Point, non-standard precision, Intervals, Unitful, Symbolic, Dual, Grassmanian, Log-Domain, Polynomial, ...)
- Arrays (Matrices, Tensors, Offset, Named, Remote, ...)
- Linear Algebra (Factorizations, Arithmetic, Infinite, Finite Fields, ...)
- Differential Equations
- Convex Optimization
- Parallel Computing
- Data Science
- Graphics
- Machine Learning
- Image Processing Libraries

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Composability of Compiler Transforms?

Transforms / Programming Models	Optimizations	Code Generators
Automatic Differentiation SPMD Task Parallelism Data Query Interval Constraint Programming Disciplined Convex Programming Tracing/Profiling/Debugging Verification/Formal Methods . . .	Scalar Tensor Parallel/Distributed Data Layout Data Access (Polyhedral) Relational (Query Compilers) Symbolic . . .	CPU GPU TPU / ML Accelerators Virtual Machines (WebAssembly) FPGA / Silicon Quantum Computers Homomorphic Encryption . . .

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Inference Deep Dive

Extracting Information From Dynamic Programs

Extensive Standard Library

```
julia> @which sin(1.0)
sin(x::T) where T<:Union{Float32, Float64} in Base.Math at special/trig.jl:30

julia> using Base.Math: @horner

julia> begin
       # Coefficients in 13th order polynomial approximation on [0; π/4]
       #     sin(x) ≈ x + S1*x³ + S2*x⁵ + S3*x⁷ + S4*x⁹ + S5*x¹¹ + S6*x¹³
       # D for double, S for sin, number is the order of x-1
       const DS1 = -1.6666666666666324348e-01
       const DS2 = 8.333333333322489461 24e-03
       const DS3 = -1.984126982985794931 34e-04
       const DS4 = 2.755731370707006767 89e-06
       const DS5 = -2.505076025340686341 95e-08
       const DS6 = 1.589690995211550102 21e-10
       function sin_kernel_f64(y)
           y² =  y*y
           y⁴ =  y²*y²
           r  =  @horner(y², DS2, DS3, DS4) + y²*y⁴*@horner(y², DS5, DS6)
           y³ =  y²*y
           return y+y³*(DS1+y²*r)
       end
       end;
```

Avoiding “boilerplate” syntax: no types, interfaces, or lifetime constraints mentioned. The polynomial evaluation (Horner’s method) is also concisely and efficiently specified with a macro

Dynamic semantics

+

Static Analysis:

Just-Ahead-of-Time analysis to extract static properties of code

```
julia> code_lowered(sin_kernel_f64)
1 ─      nothing
   @ REPL[29]:12 within `sin_kernel_f64'
      y² = y * y
   @ REPL[29]:13 within `sin_kernel_f64'
      y⁴ = y² * y²
   @ REPL[29]:14 within `sin_kernel_f64'
      t@_3 = y²
   @ base/math.jl:101 within `@horner'
   %5 = t@_3
   %6 = Base.Math.muladd(t@_3, Main.DS4, Main.DS3)
      r@_4 = Base.Math.muladd(%5, %6, Main.DS2)

   %8  = r@_4
   %9  = y²
   %10 = y⁴
      t@_5 = y²
   @ base/math.jl:101 within `@horner'
      r@_6 = Base.Math.muladd(t@_5, Main.DS6, Main.DS5)

   %13 = r@_6
   %14 = %9 * %10 * %13
      r@_9 = %8 + %14
   @ REPL[29]:15 within `sin_kernel_f64'
      y³ = y² * y
   @ REPL[29]:16 within `sin_kernel_f64'
   %17 = y³
   %18 = y² * r@_9
   %19 = Main.DS1 + %18
   %20 = %17 * %19
   %21 = y + %20
      return %21
```

```
julia> methods(Base.Math.muladd)
# 12 methods for generic function "muladd":
[1] muladd(a::Float16, b::Float16, c::Float16)
      in Base at float.jl:406
[2] muladd(x::Float64, y::Float64, z::Float64)
      in Base at float.jl:404
[3] muladd(x::Float32, y::Float32, z::Flo
      in Base at float.jl:403
...
[10] muladd(x::T, y::T, z::T) where T<:Nu
      in Base at promotion.jl:397
[11] muladd(x::Number, y::Number, z::Numb
      in Base at promotion.jl:348
[12] muladd(x, y, z)
      in Base.Math at math.jl:1011

julia> methods(+)
# 161 methods for generic function "+":
[1] +(x::Bool, y::Bool)
      in Base at bool.jl:96
[2] +(a::Float16, b::Float16)
      in Base at float.jl:392
[3] +(x::Float32, y::Float32)
      in Base at float.jl:394
[4] +(x::Float64, y::Float64)
      in Base at float.jl:395
[5] +(c::BigInt, x::BigFloat)
      in Base.MPFR at mpfr.jl:408
[6] +(a::BigInt, b::BigInt, c::BigInt, d::BigInt, e::BigInt)
      in Base.GMP at gmp.jl:436
...
```

Everything is a virtual function call.

Oh no!

```
julia> code_lowered(sin_kernel_f64)
1 ─       nothing
   @ REPL[29]:12 within `sin_kernel_f64'
         y² = y * y
   @ REPL[29]:13 within `sin_kernel_f64'
         y⁴ = y² * y²
   @ REPL[29]:14 within `sin_kernel_f64'
         t@_3 = y²
   @ base/math.jl:101 within `@horner'
   %5 = t@_3
   %6 = Base.Math.muladd(t@_3, Main.DS4, Main.DS3)
         r@_4 = Base.Math.muladd(%5, %6, Main.DS2)
   %8  = r@_4
   %9  = y²
   %10 = y⁴
         t@_5 = y²
   @ base/math.jl:101 within `@horner'
         r@_6 = Base.Math.muladd(t@_5, Main.DS6, Main.DS5)
   %13 = r@_6
   %14 = %9 * %10 * %13
         r@_9 = %8 + %14
   @ REPL[29]:15 within `sin_kernel_f64'
         y³ = y² * y
   @ REPL[29]:16 within `sin_kernel_f64'
   %17 = y³
   %18 = y² * r@_9
   %19 = Main.DS1 + %18
   %20 = %17 * %19
   %21 = y + %20
         return %21
```

```
julia> @code_warntype sin_kernel_f64(0.3)
Body::Float64
1 ─       nothing
          (y² = y * y)::Float64
          (y⁴ = y² * y²)::Float64
          (t@_3 = y²)::Float64
   %5  = t@_3::Float64
   %6  = Base.Math.muladd(t@_3, Main.DS4, Main.DS3)::Float64
          (r@_4 = Base.Math.muladd(%5, %6, Main.DS2))::Float64
   %8  = r@_4::Float64
   %9  = y²::Float64
   %10 = y⁴::Float64
          (t@_5 = y²)::Float64
          (r@_6 = Base.Math.muladd(t@_5, Main.DS6, Main.DS5))::Float64
   %13 = r@_6::Float64
   %14 = (%9 * %10 * %13)::Float64
          (r@_9 = %8 + %14)::Float64
          (y³ = y² * y)::Float64
   %17 = y³::Float64
   %18 = (y² * r@_9)::Float64
   %19 = (Main.DS1 + %18)::Float64
   %20 = (%17 * %19)::Float64
   %21 = (y + %20)::Float64
         return %21::Float64

Variables
  #self#::Core.Compiler.Const(sin_kernel_f64)
  y::Float64 t@_3::Float64 r@_4::Float64 t@_5::Float64 r@_6::Float64
  y²::Float64 y⁴::Float64 r@_9::Float64 y³::Float64
```

But the compiler can devirtualize and simplify it.

And simple is *fast*.

Simple Auto-Differentiation: Forward Derivatives

```
julia> struct Dual{T<:Real} <: Real
         x::T    # the value
         dx::T   # the derivative at that point
       end;

# Some convenience constructors describing the derivative of a constant
julia> Dual(x) = Dual(x, zero(x));

julia> Dual{T}(x) where {T} = Dual{T}(x, zero(x));

# Compose with existing types of numbers
julia> Base.promote_rule(::Type{Dual{T}}, ::Type{S}) where {T, S} =
            Dual{Base.promote_type(T, S)};

# Define the base cases for arithmetic
julia> Base.:+(a::Dual{T}, b::Dual{T}) where {T} =
            Dual{T}(a.x + b.x, a.dx + b.dx);

julia> Base.:*(a::Dual{T}, b::Dual{T}) where {T} =
            Dual{T}(a.x * b.x, a.x*b.dx + a.dx*b.x);
```

Small abstraction to define a new subtype of real numbers

Simple Auto-Differentiation: Forward Derivatives

```
julia> wrt(x) = Dual(x, typeof(x)(1)) # helper for taking derivative “with-respect-to” this parameter

julia> sin_kernel_f64(wrt(.3)) |> dump # first derivative
Dual{Float64}
  x: Float64 0.29552020666133955
  dx: Float64 0.955336489125606

julia> sin_kernel_f64(wrt(wrt(.3))) |> dump # first and second derivatives
Dual{Dual{Float64}}
  x: Dual{Float64}
    x: Float64 0.29552020666133955
    dx: Float64 0.955336489125606
  dx: Dual{Float64}
    x: Float64 0.955336489125606
    dx: Float64 -0.2955202066613394

julia> sincos(0.3) # ground truth
(0.29552020666133955, 0.955336489125606)
```

And it works!

```
julia> @code_warntype sin_kernel_f64(wrt(0.3))
Body::Dual{Float64}
1 ─       nothing
          (y² = y * y)::Dual{Float64}
          (y⁴ = y² * y²)::Dual{Float64}
          (t@_3 = y²)::Dual{Float64}
    %5  = t@_3::Dual{Float64}
    %6  = Base.Math.muladd(t@_3, Main.DS4, Main.DS3)::Dual{Float64}
    %7  = Base.Math.muladd(%5, %6, Main.DS2)::Dual{Float64}
    %8  = y²::Dual{Float64}
    %9  = y⁴::Dual{Float64}
          (t@_4 = y²)::Dual{Float64}
    %11 = Base.Math.muladd(t@_4, Main.DS6, Main.DS5)::Dual{Float64}
    %12 = (%8 * %9 * %11)::Dual{Float64}
          (r = %7 + %12)::Dual{Float64}
          (y³ = y² * y)::Dual{Float64}
    %15 = y³::Dual{Float64}
    %16 = (y² * r)::Dual{Float64}
    %17 = (Main.DS1 + %16)::Dual{Float64}
    %18 = (%15 * %17)::Dual{Float64}
    %19 = (y + %18)::Dual{Float64}
          return %19::Dual{Float64}
```

Custom user types no different from “builtin” ones:
It’s still inferred fully!

```
julia> @code_native sin_kernel_f64(wrt(wrt(.3)))
        .text
        vmovupd (%rsi), %ymm21
        vmulsd  %xmm21, %xmm21, %xmm1
        vpermilpd      $1, %xmm21
        vmulsd  %xmm9, %xmm21, %x
        vaddsd  %xmm2, %xmm2, %xm
        vextractf32x4  $1, %ymm2
        vmulsd  %xmm11, %xmm21, %
        vpermilpd      $1, %xmm1
        vmulsd  %xmm8, %xmm21, %x
        vmulsd  %xmm11, %xmm9, %x
        vaddsd  %xmm5, %xmm4, %xm
        vaddsd  %xmm3, %xmm3, %xm
        vaddsd  %xmm4, %xmm4, %xm
        vmulsd  %xmm1, %xmm1, %xmm
        vmulsd  %xmm2, %xmm1, %xmm6
        vaddsd  %xmm6, %xmm6, %xmm10
        vmulsd  %xmm3, %xmm1, %xmm6
        vmulsd  %xmm16, %xmm1, %xmm7
        vmulsd  %xmm3, %xmm2, %xmm5
        vaddsd  %xmm7, %xmm5, %xmm5
        vaddsd  %xmm6, %xmm6, %xmm14
        vaddsd  %xmm5, %xmm5, %xmm13
        movabsq $140702207837800, %rax   # imm = 0x7FF7C91E0668
        vmovsd  (%rax), %xmm5            # xmm5 = mem[0],zero
        vmulsd  %xmm5, %xmm1, %xmm15
        vxorpd  %xmm20, %xmm20, %xmm20
        vmulsd  %xmm20, %xmm1, %xmm7
        vmulsd  %xmm5, %xmm2, %xmm4
        vaddsd  %xmm4, %xmm7, %xmm17
        vmulsd  %xmm20, %xmm2, %xmm4
        vaddsd  %xmm4, %xmm7, %xmm18
        vmulsd  %xmm5, %xmm3, %xmm4
```

```
movabsq  $140702207837800, %rax   # imm = 0x7FF7C91E0668
vmovsd   (%rax), %xmm5            # xmm5 = mem[0],zero
vmulsd   %xmm5, %xmm1, %xmm15
vxorpd   %xmm20, %xmm20, %xmm20
vmulsd   %xmm20, %xmm1, %xmm7
vmulsd   %xmm5, %xmm2, %xmm4
vaddsd   %xmm4, %xmm7, %xmm17
```

And it’s fast!

Eliminated runtime overhead of dynamic definition!

```
julia> function mysum(a)
           s = zero(eltype(a))
           for x in a
               s += x
           end
           return s
       end;
```

Just a “simple” for-loop

```
Variables
  #self#::Core.Compiler.Const(mysum)
  a::UnitRange{Int64}
  s::Int64
  @_4::Union{Nothing, Tuple{Int64,Int64}}
  x::Int64
```

But dynamic, like what

```
julia> @code_warntype mysum(1:10)
Body::Int64
    @ REPL[86]:2 within `mysum'
1 ─ %1  = Main.eltype(a)::Core.Compiler.Const(Int64)
│         (s = Main.zero(%1))::Int64
    @ REPL[86]:3 within `mysum'
    %3  = a::UnitRange{Int64}
          (@_4 = Base.iterate(%3))::Union{Nothing, Tuple{Int64,Int64}}
    %5  = (@_4 === nothing)::Bool
    %6  = Base.not_int(%5)::Bool
└──       goto #4 if not %6
2 ┄ %8  = @_4::Tuple{Int64,Int64}::Tuple{Int64,Int64}
│         (x = Core.getfield(%8, 1))::Int64
    %10 = Core.getfield(%8, 2)::Int64
    @ REPL[86]:4 within `mysum'
          (s = s + x)::Int64
          (@_4 = Base.iterate(%3, %10))::Union{Nothing, Tuple{Int64,Int64}}
    %13 = (@_4 === nothing)::Bool
    %14 = Base.not_int(%13)::Bool
└──       goto #4 if not %14
3 ─       goto #2
    @ REPL[86]:6 within `mysum'
4 ┄       return s::Int64
```

```
julia> sigma(n) = mysum(1:n);
julia> @code_llvm sigma(10)
define i64 @julia_sigma_12697(i64) {
top:
  %1 = icmp sgt i64 %0, 0
  br i1 %1, label %L7.L12_crit_edge, label %L29

L7.L12_crit_edge:                                 ; preds = %top
  %2 = shl nuw i64 %0, 1
  %3 = add nsw i64 %0, -1
  %4 = zext i64 %3 to i65
  %5 = add nsw i64 %0, -2
  %6 = zext i64 %5 to i65
  %7 = mul i65 %4, %6
  %8 = lshr i65 %7, 1
  %9 = trunc i65 %8 to i64
  %10 = add i64 %2, %9
  %11 = add i64 %10, -1
  br label %L29

L29:                                              ; preds = %L7.L12_crit_edge, %top
  %value_phi9 = phi i64 [ 0, %top ], [ %11, %L7.L12_crit_edge ]
  ret i64 %value_phi9
}

julia> f() = sigma(10);
julia> @code_llvm f()
define i64 @julia_f_12704() {
top:
  ret i64 55
}
```

Not even a loop, like woah!

Gone, all gone!

~~Machine Learning~~
Differentiable Programming

Fashionable Modelling with Flux (arXiv:1811.01457)

Building a Language and Compiler for Machine Learning (julialang:ml-language-compiler)

Zygote.jl - AD is a compiler problem

```
function foo(W, Y, x)
    Z = W * Y
    a = Z * x
    b = Y * x
    c = tanh.(b)
    r = a + c
    return r
end
```


```
function ∇foo(W, Y, x)
    Z = W * Y
    a = Z * x
    b = Y * x
    c, 𝒥tanh = ∇tanh.(b)
    a + c, function (Δr)
        Δc = Δr, Δa = Δr
        (Δtanh, Δb) = 𝒥tanh(Δc)
        (ΔY, Δx) = (Δb * x', Y' * Δb)
        (ΔZ = Δa * x', Δx += Z' * Δa)
        (ΔW = ΔZ * Y', ΔY = W' * ΔZ)
        (nothing, ΔW, ΔY, Δx)
    end
end
```

Note: Simplified to assume *,+ are compiler primitives (Not the case in the original implementation)

Note: Reverse-AD model (actual implementation uses mixed)

Don't Unroll Adjoint: Differentiating SSA-Form Programs (arXiv:1810.07951)

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    c = tanh.(b)
    r = a + c
    return r
end
```


```
function ∇foo(W, Y, x)
    Z = W * Y
    a = Z * x
    b = Y * x
    c, 𝒥tanh = ∇tanh.(b)
    a + c, function (Δr)
        Δc = Δr, Δa = Δr
        (Δtanh, Δb) = 𝒥tanh(Δc)
        (ΔY, Δx) = (Δb * x', Y' * Δb)
        (ΔZ = Δa * x', Δx += Z' * Δa)
        (ΔW = ΔZ * Y', ΔY = W' * ΔZ')
        (nothing, ΔW, ΔY, Δx)
    end
end
```

In the backwards pass

- Inputs become Outputs
- Outputs become Inputs

Zygote.jl - AD is a compiler problem

```
function foo(W, Y, x)
    Z = W * Y
    a = Z * x
    b = Y * x
    c = tanh.(b)
    r = a + c
    return r
end
```


```
function ∇foo(W, Y, x)
    Z = W * Y
    a = Z * x
    b = Y * x
    c, 𝒥tanh = ∇tanh.(b)
    a + c, function (Δr)
        Δc = Δr, Δa = Δr
        (Δtanh, Δb) = 𝒥tanh(Δc)
        (ΔY, Δx) = (Δb * x', Y' * Δb)
        (ΔZ = Δa * x', Δx += Z' * Δa)
        (ΔW = ΔZ * Y', ΔY = W' * ΔZ')
        (nothing, ΔW, ΔY, Δx)
    end
end
```

The compiler builds the “tape” for us

Zygote.jl - AD is a compiler problem

```
struct 𝒥_foo
    W
    Y
    x
    Z
    𝒥tanh
end

(::𝒥_foo)(Δr) = ....

function ∇foo(W, Y, x)
    Z = W * Y
    a = Z * x
    b = Y * x
    c, 𝒥thanh = ∇tanh.(b)
    r = a + c
    (r, 𝒥_foo(W, Y, x, Z, 𝒥thanh))
end
```

Closure conversion

```
function ∇foo(W, Y, x)
    Z = W * Y
    a = Z * x
    b = Y * x
    c, 𝒥tanh = ∇tanh.(b)
    a + c, function (Δr)
        Δc = Δr, Δa = Δr
        (Δtanh, Δb) = 𝒥tanh(Δc)
        (ΔY, Δx) = (Δb * x', Y' * Δb)
        (ΔZ = Δa * x', Δx += Z' * Δa)
        (ΔW = ΔZ * Y', ΔY = W' * ΔZ')
        (nothing, ΔW, ΔY, Δx)
    end
end
```

AD as a compiler problem

Simple (Syntactic) - but requires optimizing compiler for performance

Partial Specialization (/DCE) => Partial Gradients

Better Compiler Optimizations ⇔ Faster AD

Nested AD for free

Even Control Flow!

```
function lstm(model, input, output)
    hidden = initial(model)
    total_loss = 0.
    for sample in take(zip(input, output), 50)
        (hidden, predicted) = model(sample, hidden)
        total_loss += loss(output, predicted)
    end
    total_loss
end
```

```
function ∇lstm(model, input, output)
    stack = Stack()
    hidden, 𝒥initial = ∇initial(model)
    total_loss = 0.
    for sample in take(zip(input, output), 50)
        (hidden, predicted), 𝒥model = ∇model(sample, hidden)
        (total_loss +), 𝒥loss = loss(output, predicted)
        push!(stack, (𝒥model, 𝒥loss))
    end
    total_loss, function(Δ)
        Δmodel_total = zero(typeof(model))
        Δhidden = nothing
        for (𝒥model, 𝒥loss) in reverse(stack)
            (Δloss, Δoutput, Δpredicted) = 𝒥loss(Δ)
            (Δmodel_it, Δsample, Δhidden) = 𝒥model(Δhidden, Δpredicted)
            Δmodel += Δmodel_it
            # (... For input and output, but let's
            # ignore those for simplicity)
        end
        Δmodel_total += 𝒥initial(Δhidden)
        (Δmodel_total, ...)
    end
end
```

~~Machine Learning~~
Compiler Backends

Fashionable Modelling with Flux (arXiv:1811.01457)

Building a Language and Compiler for Machine Learning (julialang:ml-language-compiler)

CUDAnative.jl - low level GPU Programming

```
function vadd(gpu, a, b, c)
  i = threadIdx().x + blockDim().x *
       ((blockIdx().x-1) + (gpu-1) * gridDim().x)
  @inbounds c[i] = a[i] + b[i]
  return
end

a, b, c = (CuArray(...) for _ in 1:3)
@cuda threads=length(a) vadd(1, a, b, c)
```

Provides:

- CUDA intrinsics
- SPMD Programming model
- GPU memory management

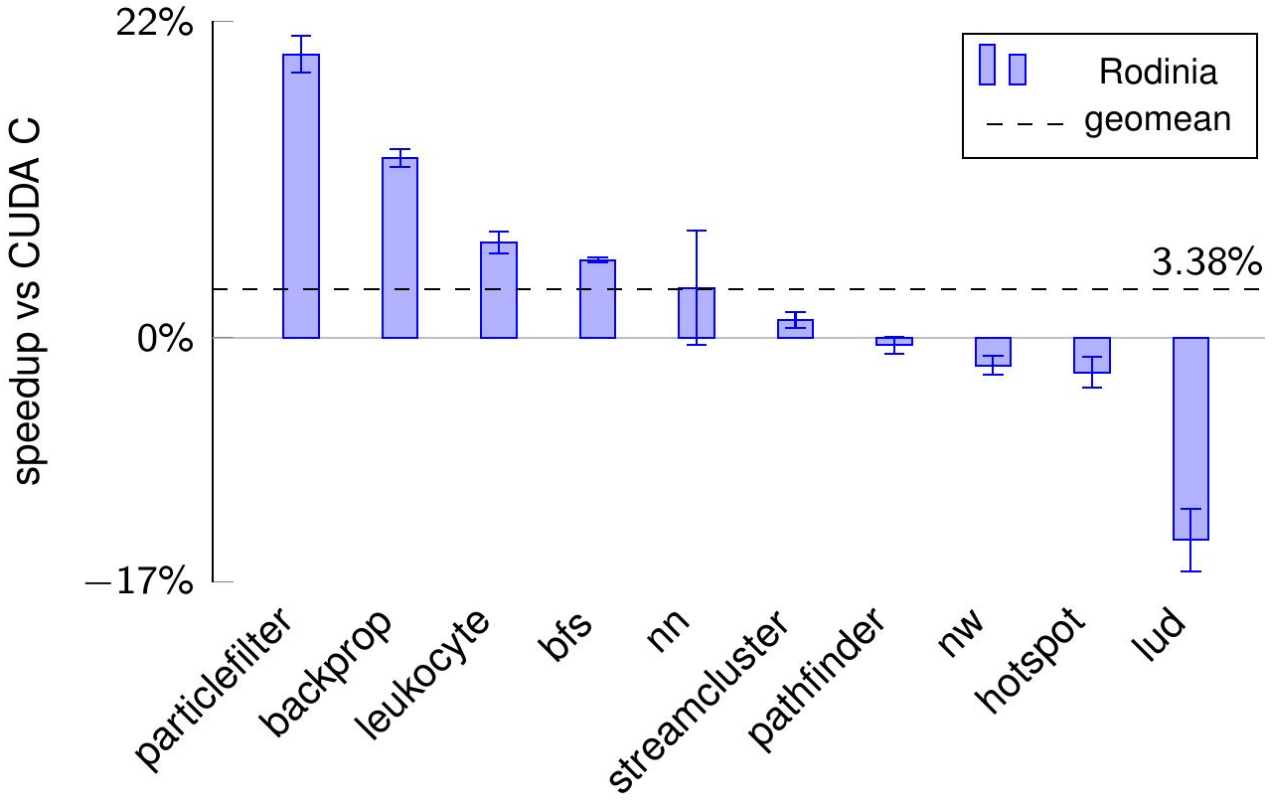
...

Effective Extensible Programming: Unleashing Julia on GPUs (arXiv:1712.03112)

```
julia> @device_code_ptx @cuda vadd(1, a, a, a)
//
// Generated by LLVM NVPTX Back-End
//

.visible .entry ptxcall_vadd_23(
        .param .u64 ptxcall_vadd_23_param_0,
        .param .align 8 .b8 ptxcall_vadd_23_param_1[16],
        .param .align 8 .b8 ptxcall_vadd_23_param_2[16],
        .param .align 8 .b8 ptxcall_vadd_23_param_3[16]
)
{
        mov.u32     %r1, %tid.x;
        mov.u32     %r2, %ntid.x;
        mov.u32     %r3, %ctaid.x;
        ...
}
```

Performance



Julia all the way down

```
function vadd(a, b, c)
    i = threadIdx().x
    c[i] = a[i] + b[i]
    return
end
```

```
W = randn(2, 10)
b = randn(2)

f(x) = softmax(W * x .+ b)
```

```
model = Chain(
  Dense(10, 5, σ),
  Dense(5, 2),
  softmax)
```

Scaling Up

2017

Cataloging the Visible Universe through Bayesian Inference at Petascale

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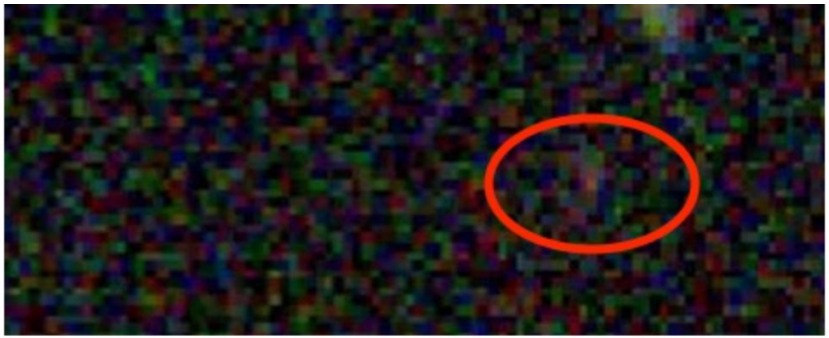


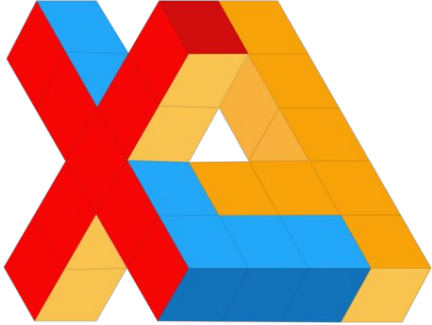
Most light sources are near the detection limit.

2019

Scaling GANs to ExaScale$_{16}$ on GPUs

(Work in Progress)

XLA.jl



```
struct XRTArray{T, Dims, N} <: AbstractArray{T, N}
        # ...
end
XRTScalar{T} = XRTArray{T, (), 0}

function +(a::XRTScalar{T},
           b::XRTScalar{T}) where T
    GenericHloOp{:add}(T, ())(a, b)
End

+(a::XRTScalar, b::XRTScalar) =
    +(promote(a, b)...)
```

Shape information represented in the type system

Declare primitives using multiple dispatch

Re-use vast amount of existing julia code (e.g. promotion, array abstractions, broadcast machinery)

Automatic Full Compilation of Julia Programs and ML Models to Cloud TPUs (arXiv:1810.09868)

Generic Code makes retargeting easy

In Julia Standard Library

```
function mapreduce(f, op, A; dims=:)
    ...
end

add_sum(x, y) = x + y
sum(f, a) = mapreduce(f, add_sum, a)
sum(a) = sum(identity, a)
```

Coverage of a large number of functions from a couple generic abstractions

Existing Julia array primitives map well to XLA primitives

In XLA.jl

```
function Base.mapreduce(f, op, A::XRTArray; dims=:)
   dt = dims_tuple(A, dims)
   res = HloReduce{Core.Typeof(op)}(dt)(op,
       HloMap{Core.Typeof(f)}()(f, A),
       XRTArray(zero(eltype(A)))
   )
   if dims != (:)
       # Put back the dimensions that HloReduce dropped;
       # Julia semantics require this.
       res = HloReshape(
             reduced_dimensions_collapes(size(A), dims))(res)
   end
   return res
end
```

Essentially: An embedding of HLO in Julia IR

dense(W, x, b) = W * x .+ b

Before Julia-level optimization

```
@code_typed_xla opt=false dense(W, x, b)
 %1 = Base.Broadcast.materialize::Const(
        materialize, false)
 %2 = Base.Broadcast.broadcasted::Const(
        broadcasted, false)
 %3 = (W * x)::XRTArray{Float32,(10,),1}
 %4 = (%2)(Main.:+, %3, b)::Broadcasted{
        XRTArrayStyle{1},Nothing,typeof(+),
        Tuple{XRTArray{Float32,(10,),1},
        XRTArray{Float32,(10,),1}}}
 %5 = (%1)(%4)::XRTArray{Float32,(10,),1}
      return %5
```

After Julia-level optimization

```
@code_typed_xla opt=true dense(W, x, b)
 %1 = invoke HloDot(XLA.DimNums{1,1,0,0}(
    (1,), (0,), (), ()))(_2, _3)::XRTArray
        Float32,(10,),1}
 %2 = invoke HloMap{typeof(+)}(+)(
    %1, _4)::XRTArray{Float32,(10,),1}
      return %2
```

Statements correspond 1:1 to HLO

Trivial to convert to HLO .pb from here

XLA.jl

Compilation

Full Julia Semantics (over XLA primitives)

Control Flow

Takes the place of LLVM

Re-use Inference/Julia Optimizer / AD

~1000 LOC

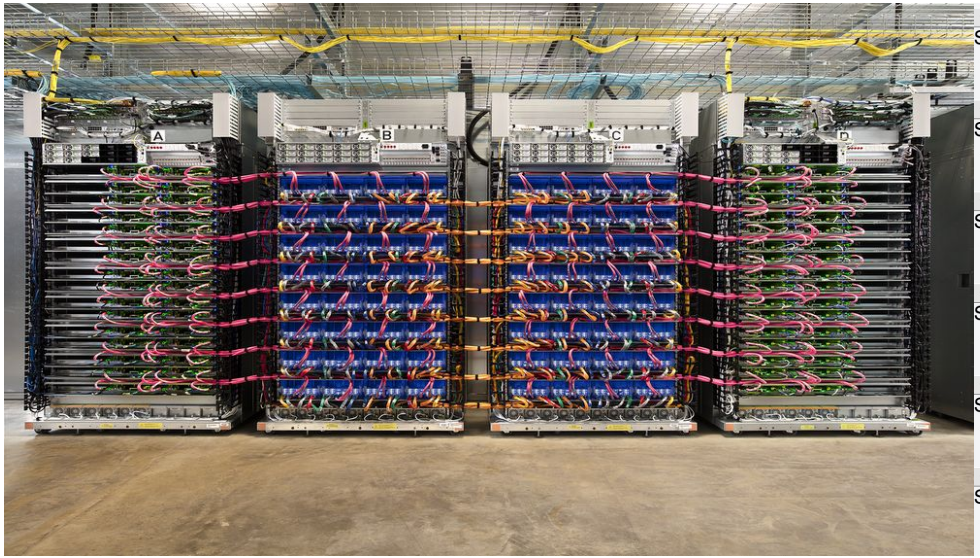
No XLA-specific changes to core julia

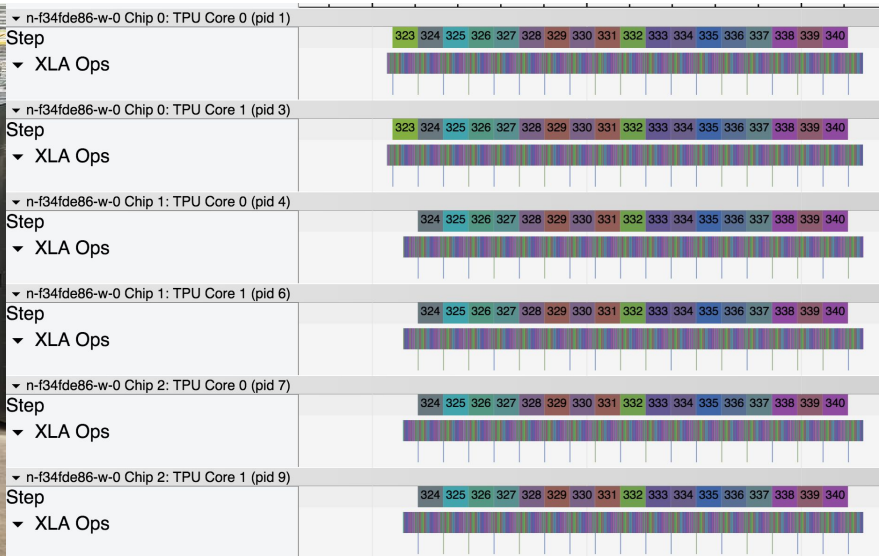
Template for Julia as a frontend to future/experimental IRs/Backends

Runs Well on TPU

Performance on par with TF

Scales to pods (512 TPU cores - 4.3 PF_{16}/s on ResNet50)





This leads me to claim that, from now on, a main goal in designing a language should be to plan for growth. The language must start small, and the language must grow as the set of users grows.

Guy Steele, “Growing a language”, 1998

Growing a language
(youtube:_ahvzDzKdB0)

www.cs.virginia.edu/~evans/cs655/readings/steele.pdf