A tour of ParallelAccelerator.jl

A Library and Compiler for High-Level, High-Performance Scientific Computing in Julia

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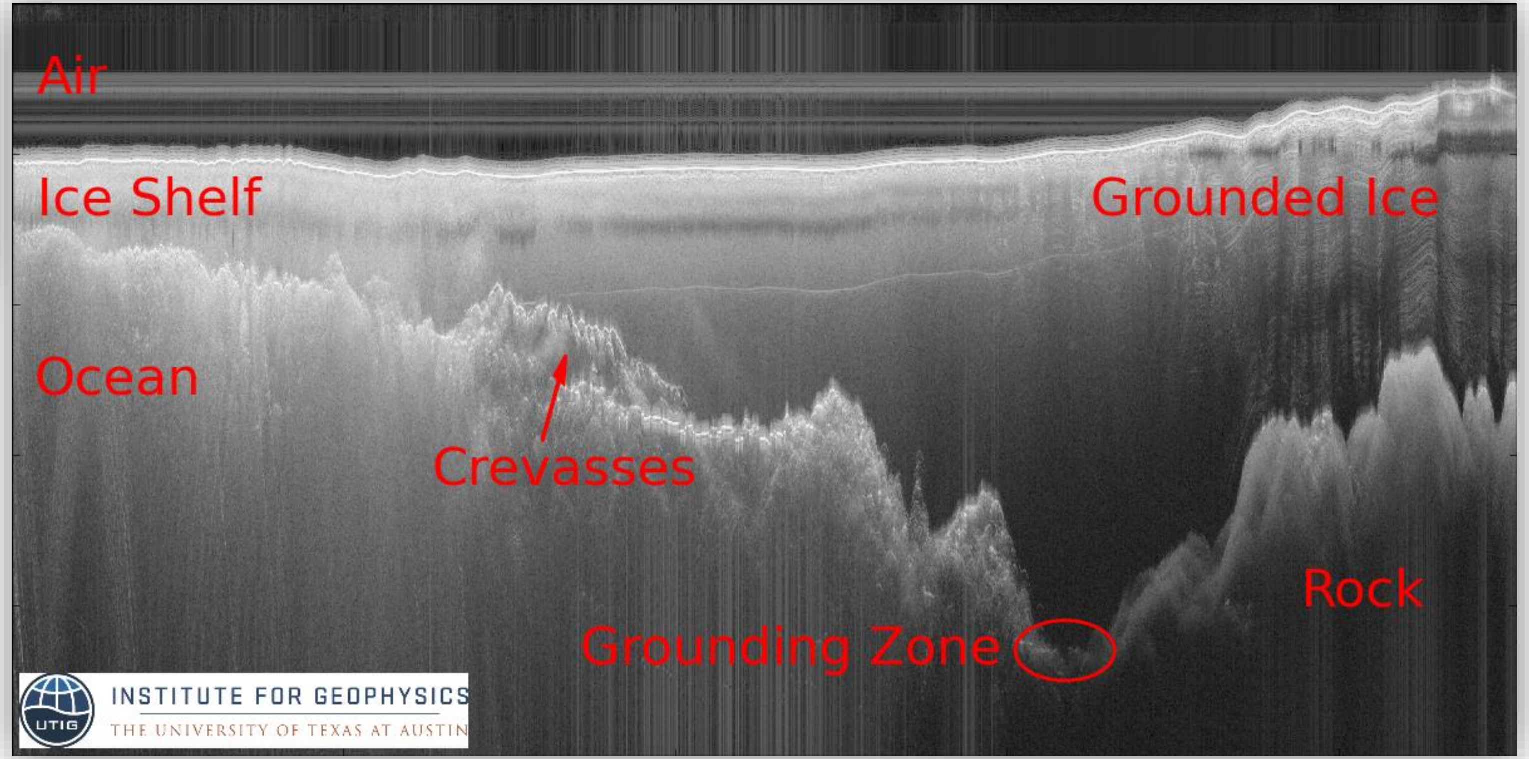
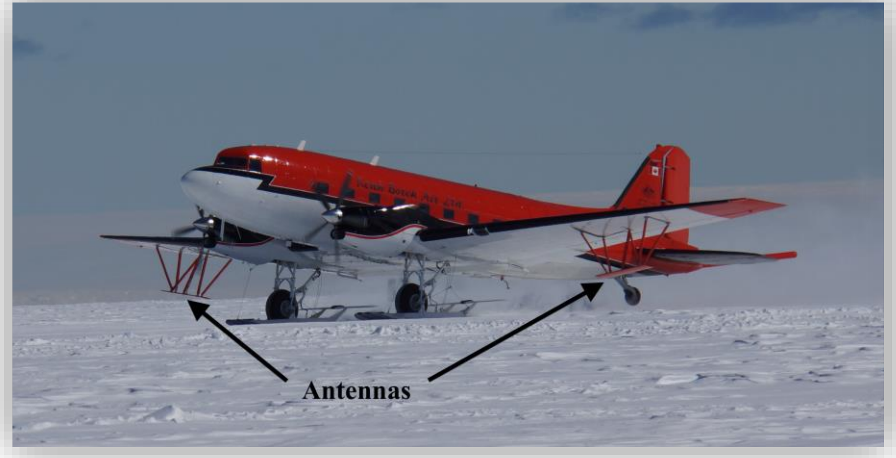




Source: http://lindzey.github.io/blog/2015/07/27/a-brief-introduction-to-ice-penetrating-radar/

The productivity/performance tradeoff

Productivity languages: Matlab, Python, R, Julia, …

How do you "scale up" a productivity-language prototype? The answer today: Get an expert to port the code to an efficiency language

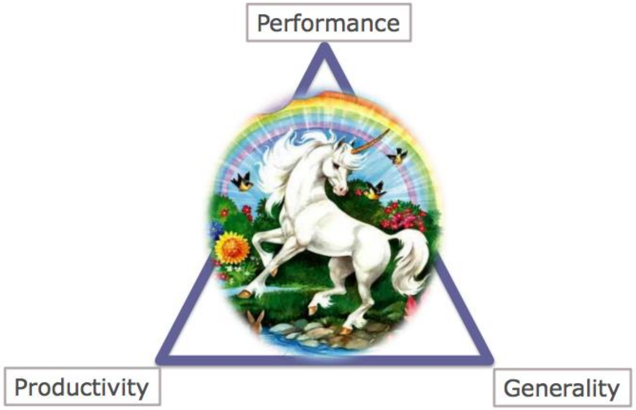
The result is fast…and also brittle, hard to experiment with, and hard to maintain

Can we do better?

How about high-performance EDSLs?

Idea: trade off generality for productivity and performance

Delite (Brown *et al*., 2011),
SEJITS (Catanzaro *et al*., 2009),
…



[Olokutun *et al*., 2012]

Great results! But, two challenges:

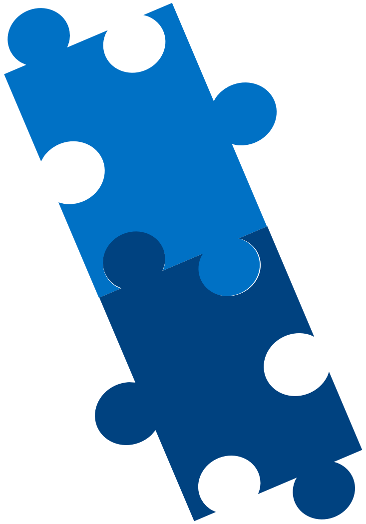
- The learning curve
- The rest of the productivity story…

The rest of the EDSL productivity story

Several dimensions to productivity beyond offering the “right” abstractions for a domain:

- Fast compilation time
- Robust to a wide variety of inputs
- Debuggable using familiar techniques
- Available on the platforms users want to use

ParallelAccelerator



A combination compiler-library solution

- Accelerate existing language constructs:
  - map, reduce, comprehension
- Support additional domain-specific constructs (`runStencil`)
  - …with two implementations: library-only and native

Run in library-only mode during development and debugging

Run in native mode for high performance at deployment

ParallelAccelerator

Implemented as a julia package:

github.com/IntelLabs/ParallelAccelerator.jl

Provides an `@acc` macro to annotate code to be optimized

Under the hood, it's a Julia-to-C++* compiler, written in Julia

Approach:

- Find *implicit data-parallel patterns* in a subset of Julia code
- Compile to explicit parallel for loops
- Minimize run-time overheads

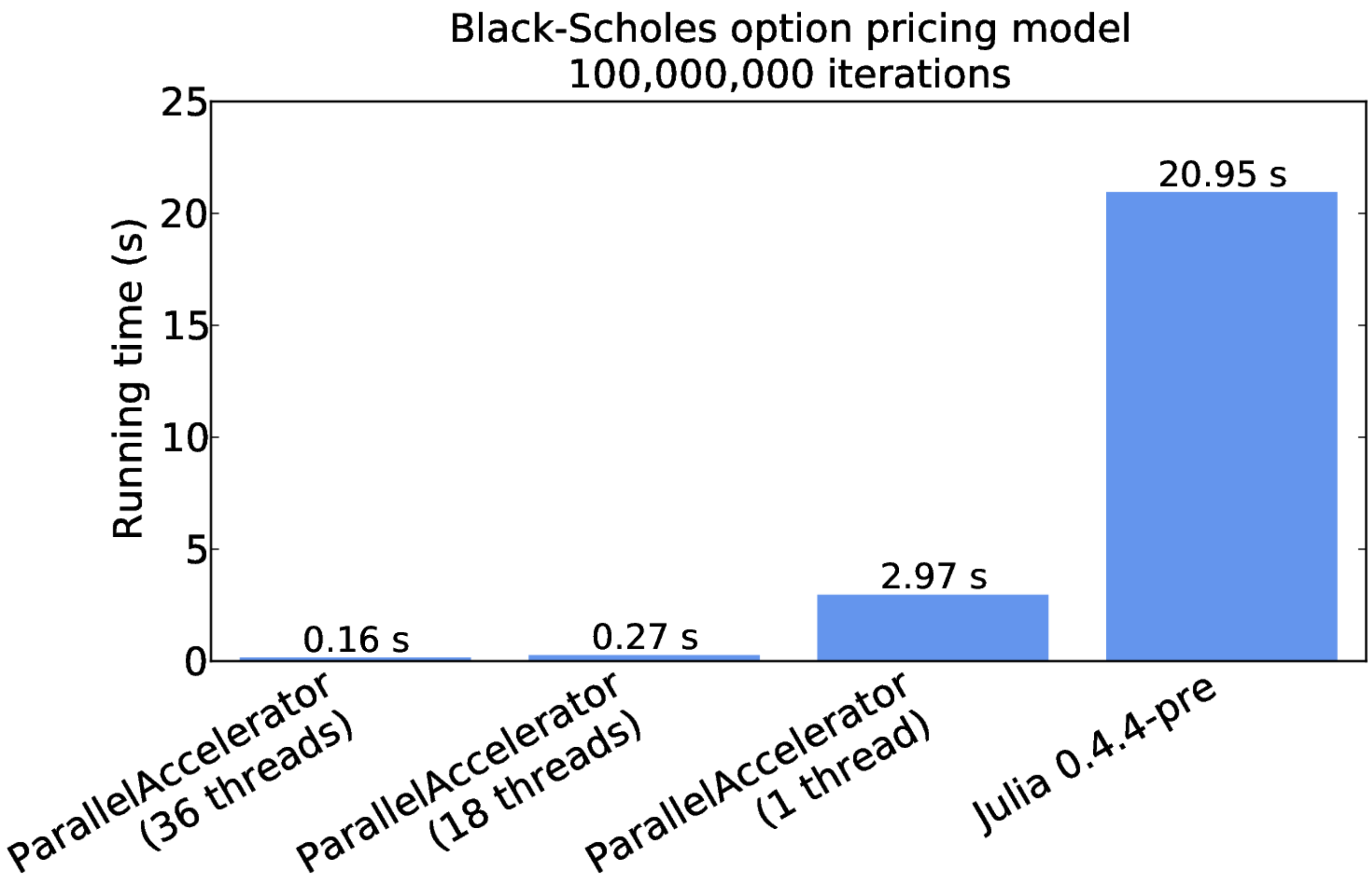
Example: Black-Scholes

```
using ParallelAccelerator

@acc function blackscholes(sptprice::Array{Float64,1},
                           strike::Array{Float64,1},
                           rate::Array{Float64,1},
                           volatility::Array{Float64,1},
                           time::Array{Float64,1})
    logterm = log10(sptprice ./ strike)
    powterm = .5 .* volatility .* volatility
    den = volatility .* sqrt(time)
    d1 = (((rate .+ powterm) .* time) .+ logterm) ./ den
    d2 = d1 .- den
    NofXd1 = cndf2(d1)
    ...
    put = call .- futureValue .+ sptprice
end

put = blackscholes(sptprice, initStrike, rate, volatility, time)
```

Black-Scholes performance results



Data from 01/31/2016
2 Intel(R) Xeon(R) CPU E5-2699 v3 @ 2.3GHz processors, 18 cores each (36 cores total)
128 GB RAM

Data-parallel patterns

- Map: Translate pointwise array operations like `.+`, `.-`, `.*`, and `./` to data-parallel map operations
- Reduce: Translate `minimum`, `maximum`, `sum`, `prod`, `any`, and `all` to data-parallel reduce operations
- Array comprehensions: Translate to in-place map operations

```
avg(x) =
[ 0.25*x[i-1] + 0.5*x[i] + 0.25*x[i+1] for i = 2:length (x)-1 ]
```

- Special `runStencil` form for stencil computations

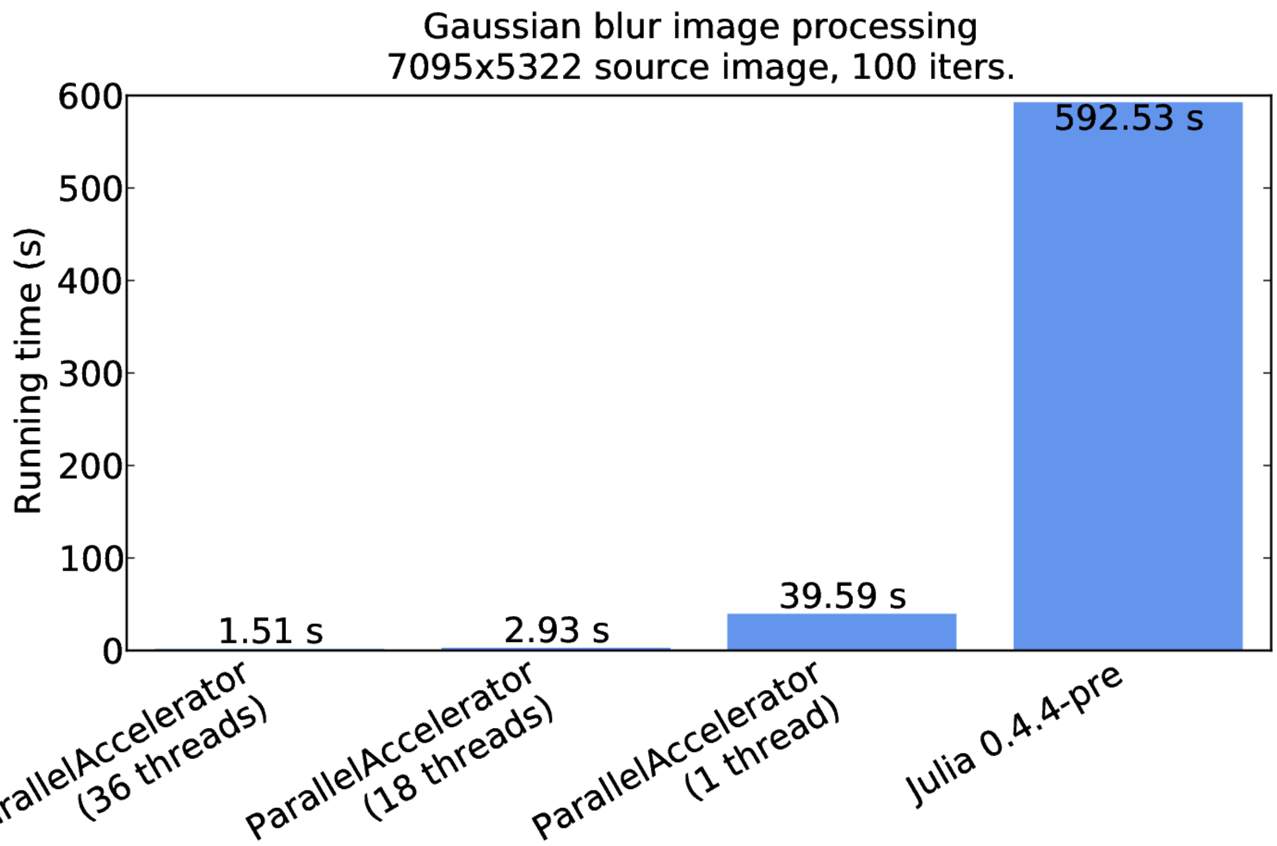
runStencil example: Gaussian blur

```
using ParallelAccelerator

@acc function blur(img::Array{Float32,2}, iterations::Int)
    buf = Array(Float32, size(img)...)
    runStencil(buf, img, iterations, :oob_skip) do b, a
       b[0,0] =
            (a[-2,-2] * 0.003  + a[-1,-2] * 0.0133 + a[0,-2] * ...
             a[-2,-1] * 0.0133 + a[-1,-1] * 0.0596 + a[0,-1] * ...
             a[-2, 0] * 0.0219 + a[-1, 0] * 0.0983 + a[0, 0] * ...
             a[-2, 1] * 0.0133 + a[-1, 1] * 0.0596 + a[0, 1] * ...
             a[-2, 2] * 0.003  + a[-1, 2] * 0.0133 + a[0, 2] * ...
       return a, b
    end
    return img
end

img = blur(img, iterations)
```

Gaussian blur performance results



Data from 03/02/2016
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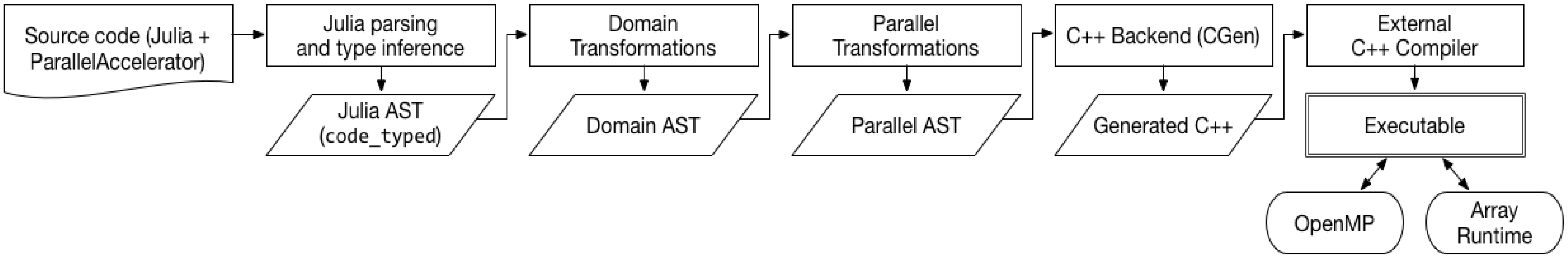
128 GB RAM

ParallelAccelerator compiler pipeline



Domain Transformations: replaces some Julia AST nodes with new “domain nodes” for map, reduce, comprehension, and stencil

Parallel Transformations: replaces domain nodes with “parfor” nodes representing parallel for loops

CGen: converts parfor nodes into OpenMP loops

Why Julia?

Open source

Faster than many scientific computing languages

Good support for array-style programming

Under active development, strong community

A Julia compiler written in Julia is feasible! :D

ParallelAccelerator caveats

Package load time

- Can be mitigated using `ParallelAccelerator.embed()`

Compiler limitations

- Only a subset of Julia is accelerated
- Compiler tries to transitively compile the whole call chain
- If anything fails to compile, fall back to standard Julia
- **These problems should go away with the forthcoming native threading backend**

To learn more…

The Julia blog:

julialang.org/blog/2016/03/parallelaccelerator

Our GitHub repo:

github.com/IntelLabs/ParallelAccelerator.jl

Thanks!

@lindsey

lkuper