Julia: A Fresh approach to parallel computing

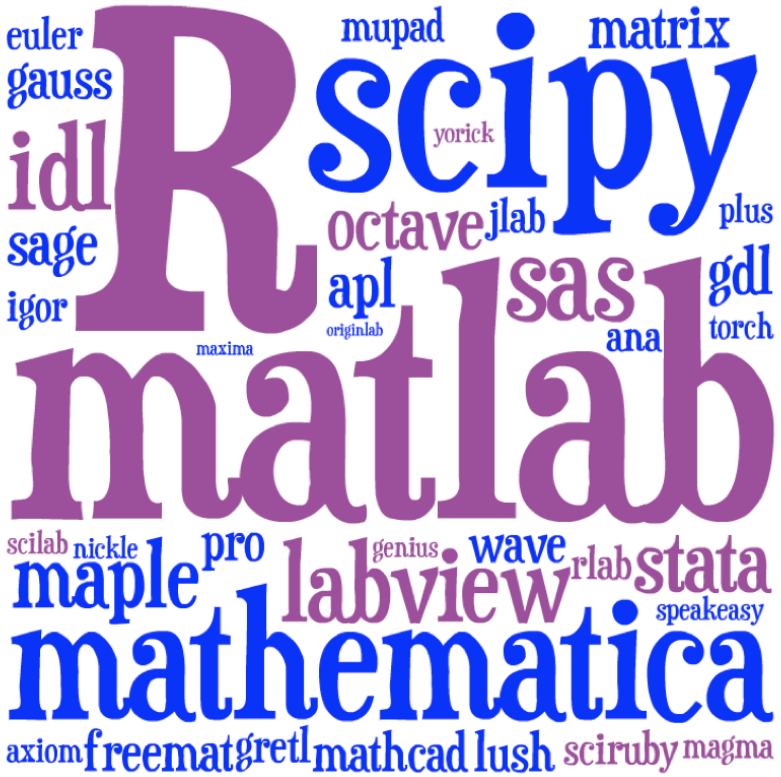
Dr. Viral B. Shah

Intel HPC Devcon, Salt Lake City

Nov 2016

Opportunity: Modernize data science

The last 25 years…



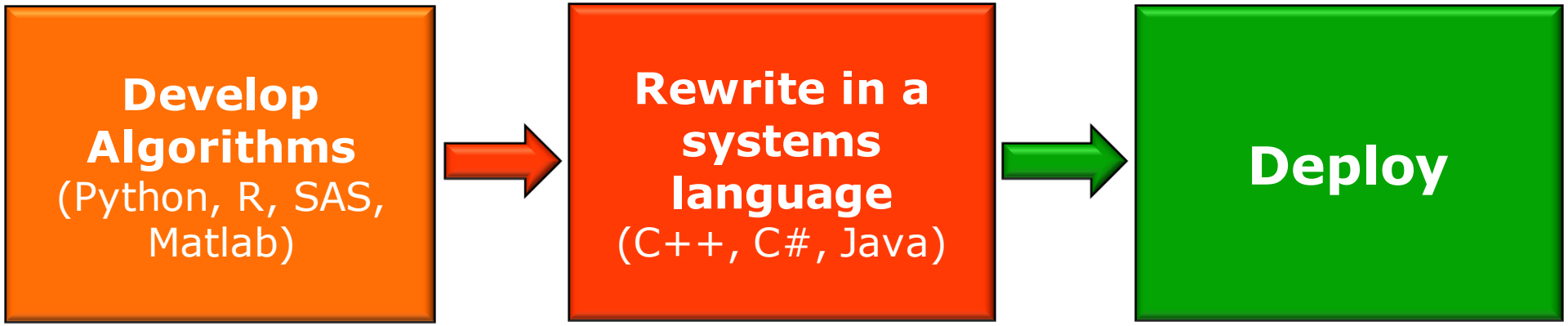
Today's computing landscape:

- Develop new learning algorithms
- Run them in parallel on large datasets
- Leverage accelerators like GPUs, Xeon Phis
- Embed into intelligent products

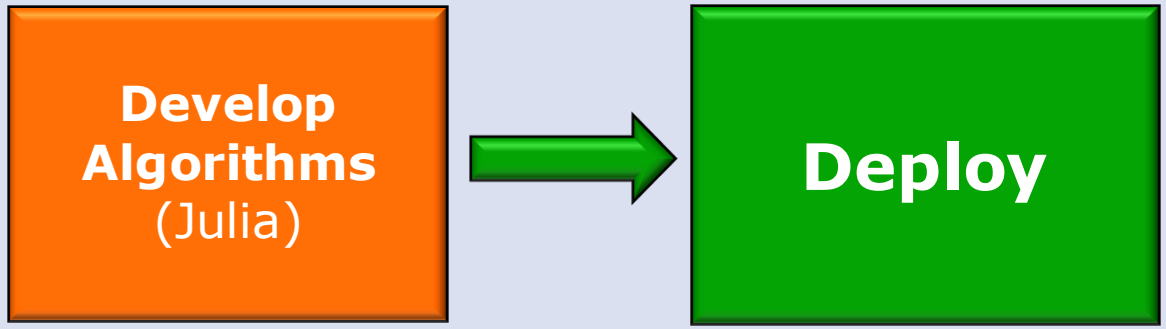
"Business as usual" will simply not do!

Those who convert ideas to products fastest will win

Typical Workflow in the last 25 years



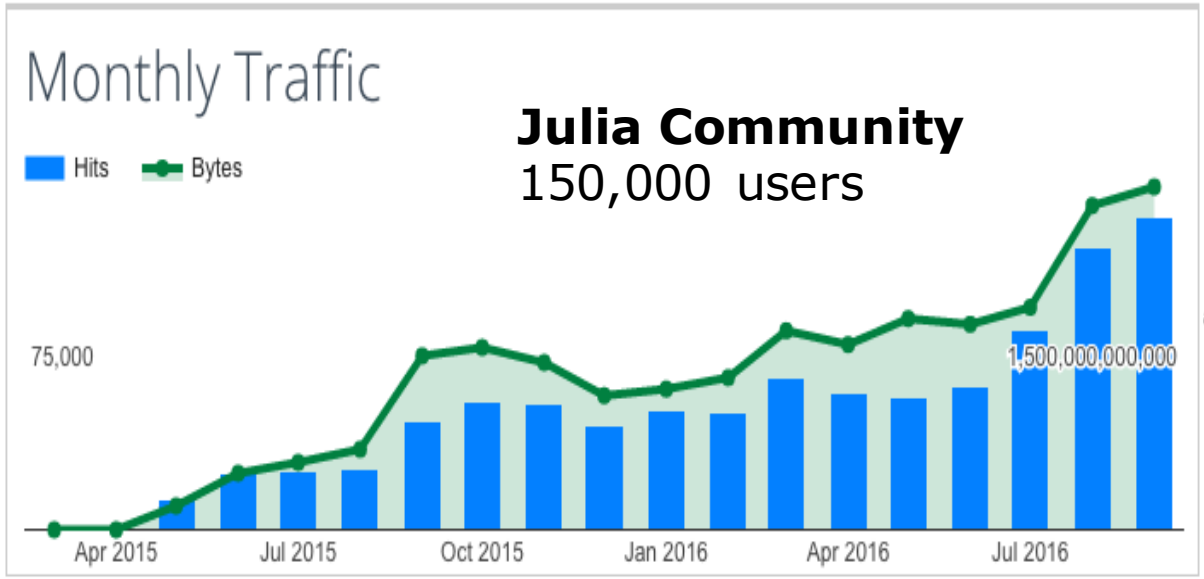
Compress the innovation cycle with Julia



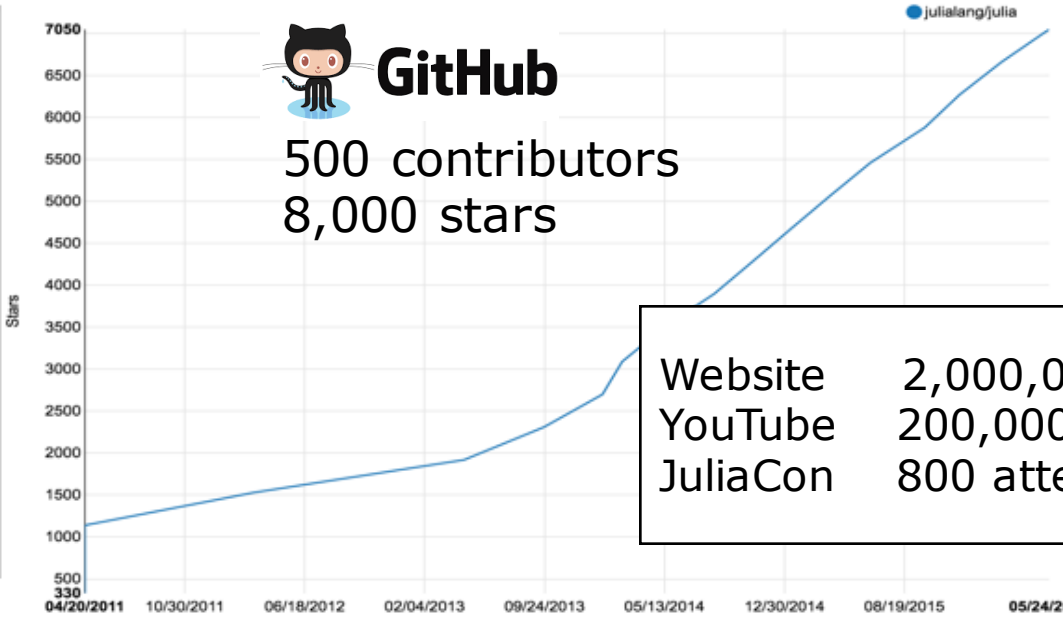
julia


JuliaCon 2016: 50 talks and 250 attendees

The user base is doubling every 9 months

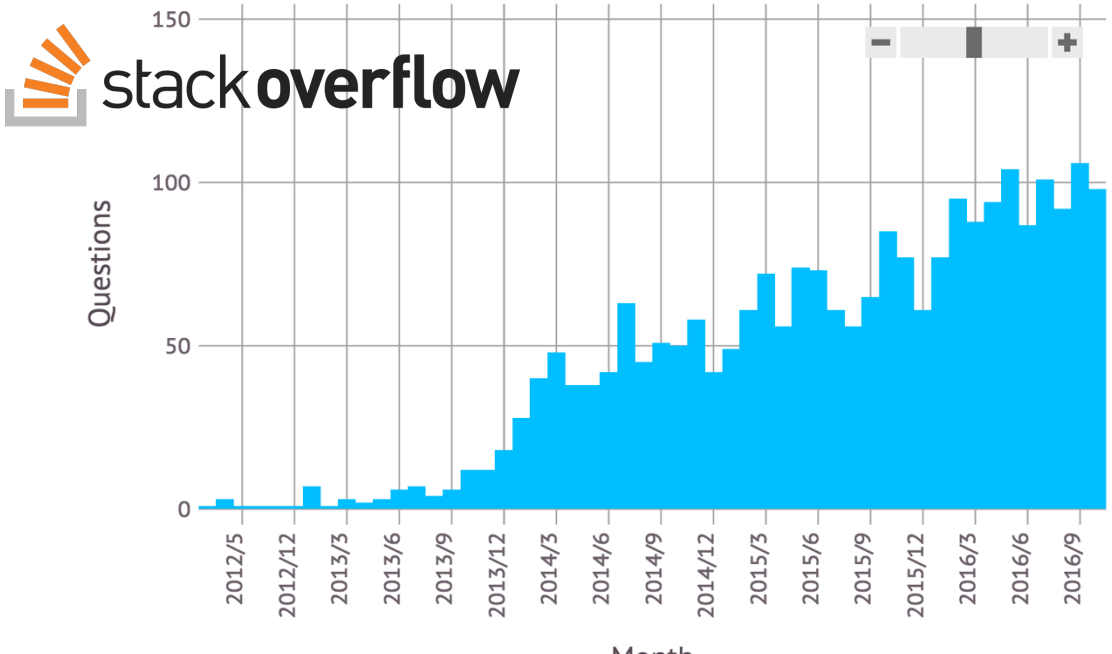


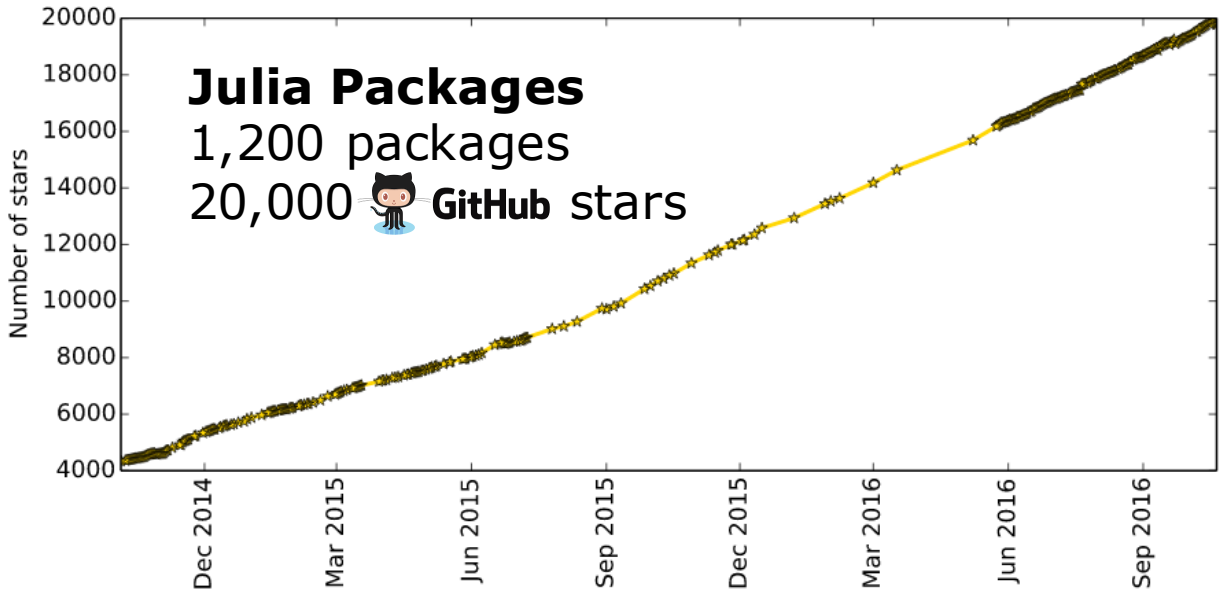
Julia Community
150,000 users



GitHub
500 contributors
8,000 stars

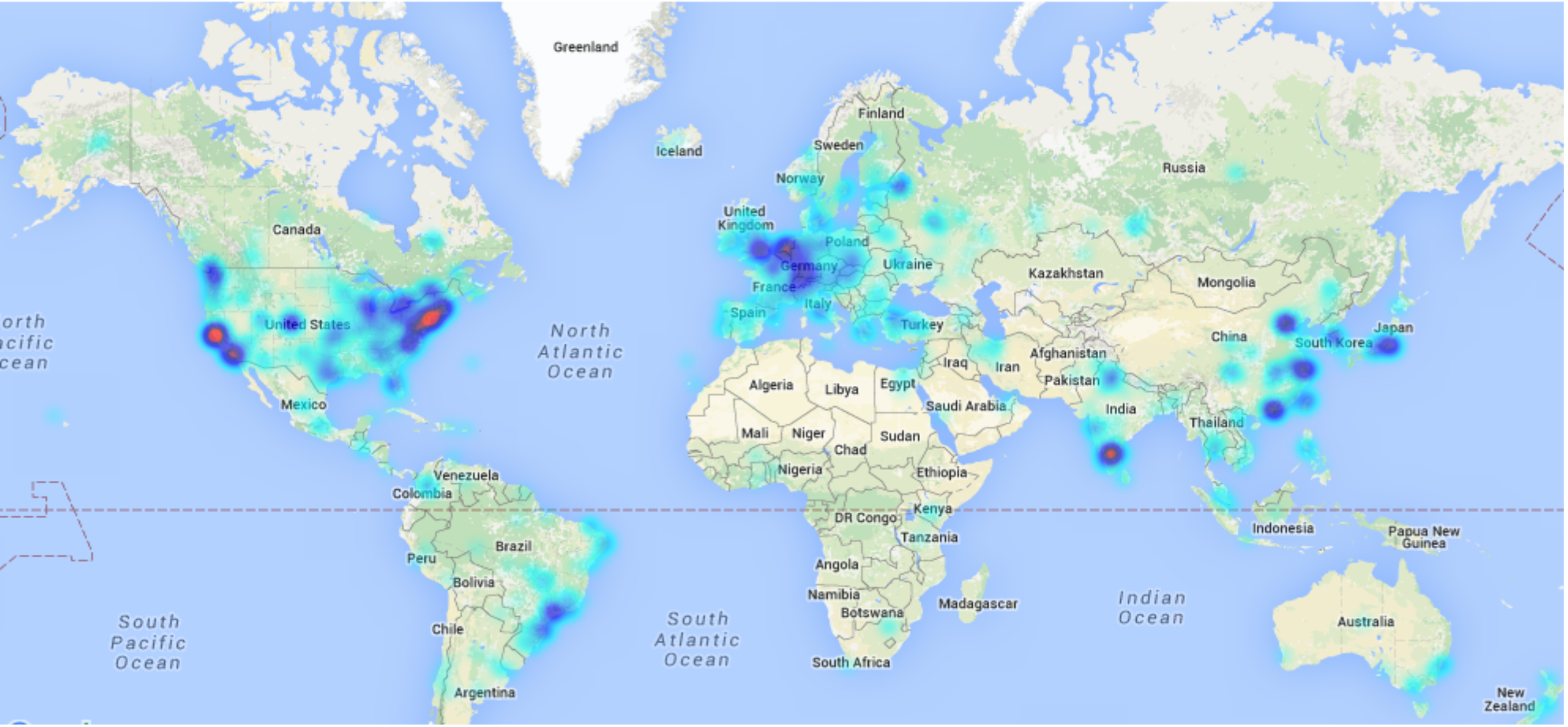
Website	2,000,000 visitors
YouTube	200,000 views
JuliaCon	800 attendees



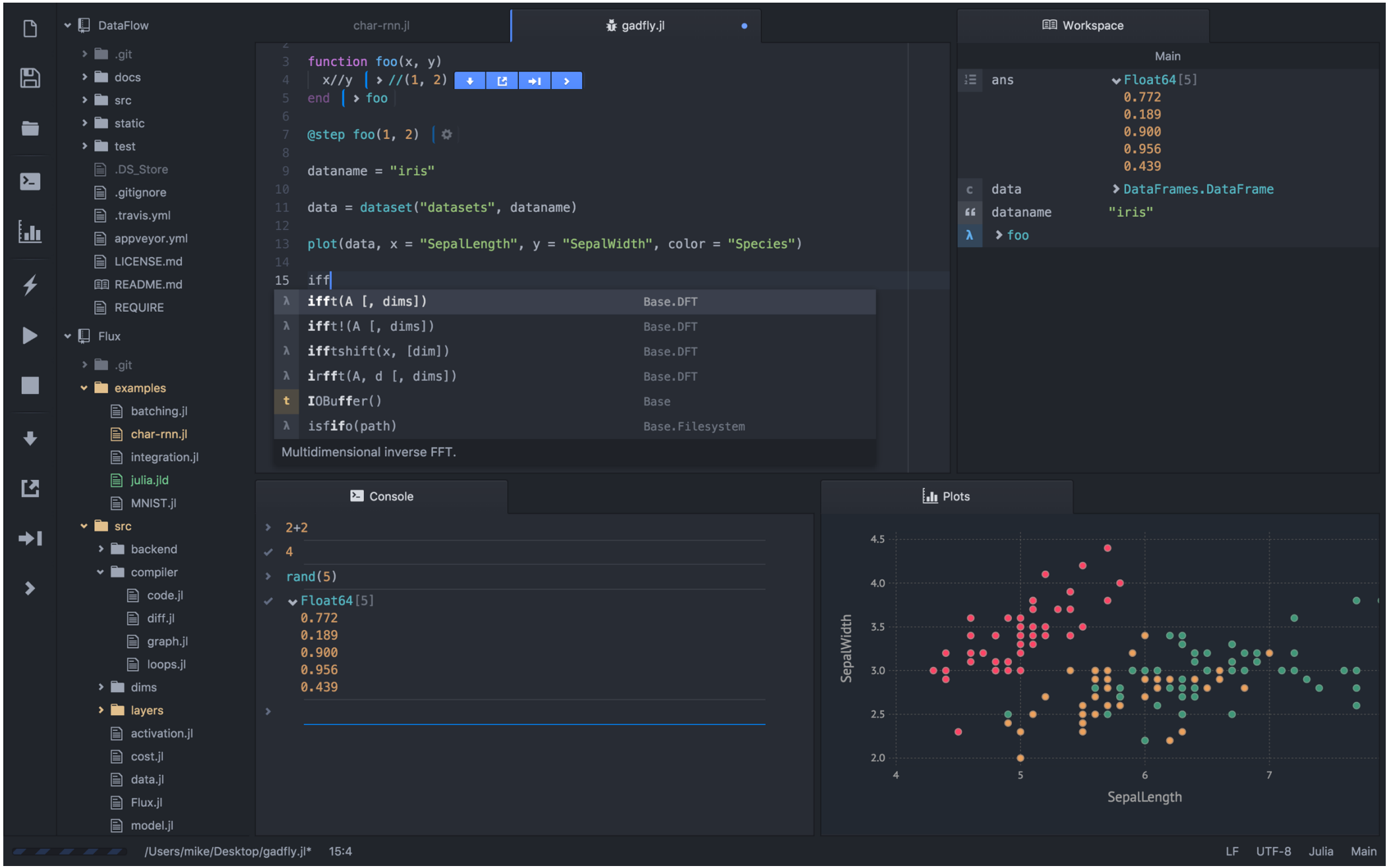


Julia Packages
1,200 packages
20,000 GitHub stars

The Julia community: 150,000 users



The Julia IDE



JuliaBox beta

Run Julia from the Browser. No setup.

The Julia community is doing amazing things.

We want you in on it!

Sign in via LinkedIn

Sign in via GitHub

Sign in via Google

Jupyter

Create Jupyter Notebooks and share them.

Console

Use in-browser terminal emulator to fully control your Docker instance.

Google Drive

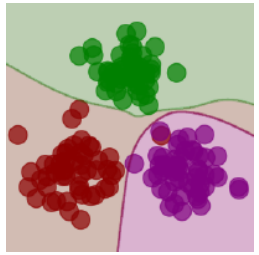
Collaborate with others. Sync notebooks and data via Google Drive.

Sync & Share

Setup folders to sync with remote git repositories.

Machine Learning: Write once Run everywhere

Many machine learning frameworks



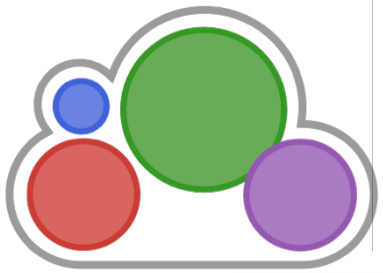
dmlc
mxnet

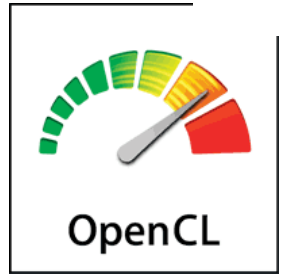
Mocha.jl

Merlin.jl

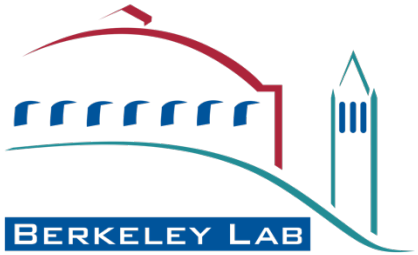
Knet.jl

Run on hardware of your choice





A few of the organizations using Julia



Traction across industries

Finance: Economic Models at the NY Fed

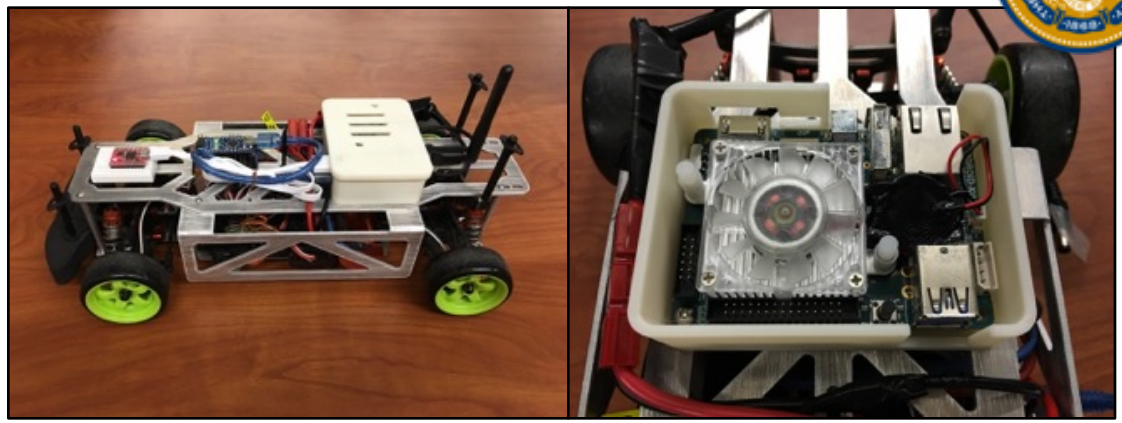
Engineering: Air Collision Avoidance for FAA

FEDERAL AVIATION ADMINISTRATION

APL
JOHNS HOPKINS
APPLIED PHYSICS LABORATORY

Retail: Modeling Healthcare Demand

Robotics: Self-driving Cars at UC Berkeley



Julia in the Press

Parallelize without rewriting code

```
# Sequential method for calculating pi

julia> function findpi(n)
  inside = 0
  for i = 1:n
    x = rand(); y = rand()
    inside += (x^2 + y^2) <= 1
  end
  4 * inside / n
end

julia> nprocs()
1

julia> @time findpi(10000);
elapsed time: 0.0001 seconds

julia> @time findpi(100_000_000);
elapsed time: 1.02 seconds

julia> @time findpi(1_000_000_000);
elapsed time: 10.2 seconds
```

```
# Parallel method for calculating pi

julia> addprocs(40);

julia> @everywhere function findpi(n)
  inside = 0
  for i = 1:n
    x = rand(); y = rand()
    inside += (x^2 + y^2) <= 1
  end
  4 * inside / n
end

pfindpi(N)= mean( pmap(n->findpi(n),
        [N/nworkers() for i=1:nworkers()] ));

julia> @time pfindpi(1_000_000_000);
elapsed time: 0.33 seconds

julia> @time pfindpi(10_000_000_000);
elapsed time: 3.21 seconds
```

Not restricted to Monte Carlo only

A hierarchy of parallel constructs:

- Multiprocessing to go across a cluster
- Multithreading on the same node
- Concurrency within a process for I/O bound code
- Instruction level parallelization with SIMD codegen

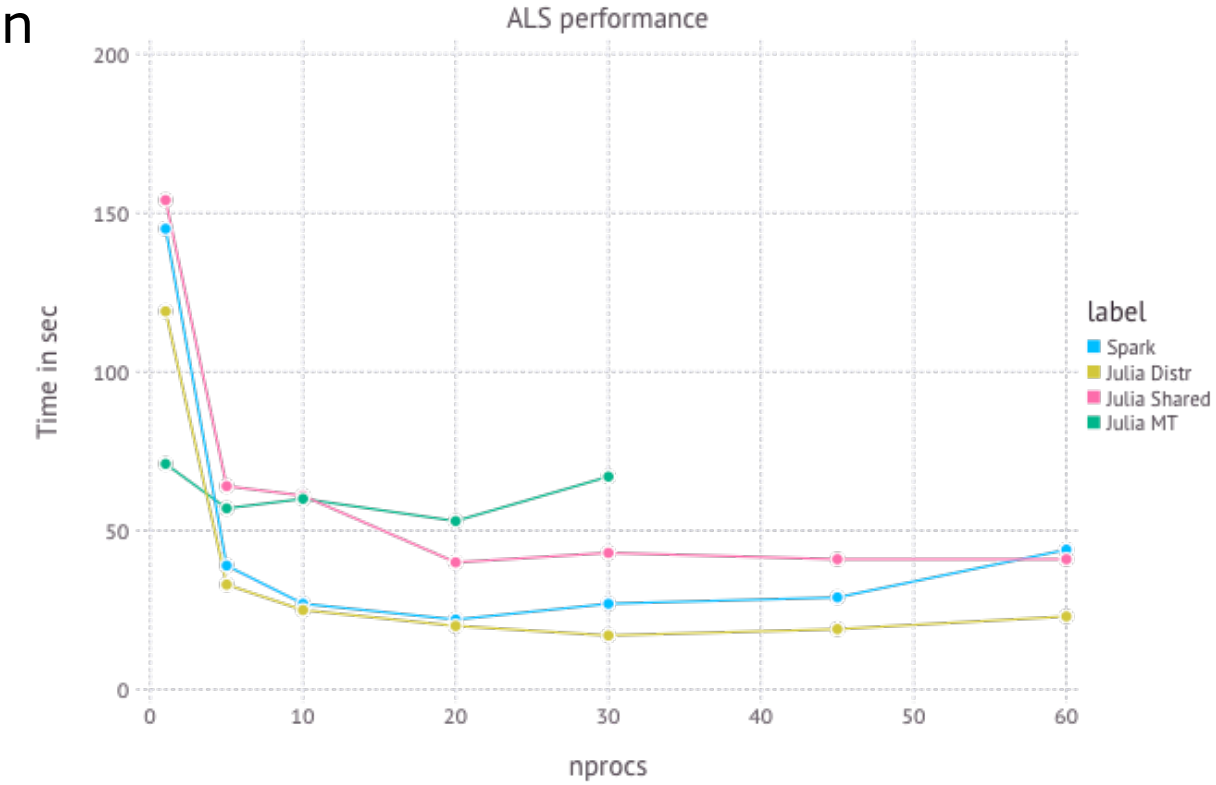
Composable parallel programming model comprising of:

- Single thread of control
- SPMD with messaging (designed for multiple transports)

Case Study 1

Parallel Recommendation Engines

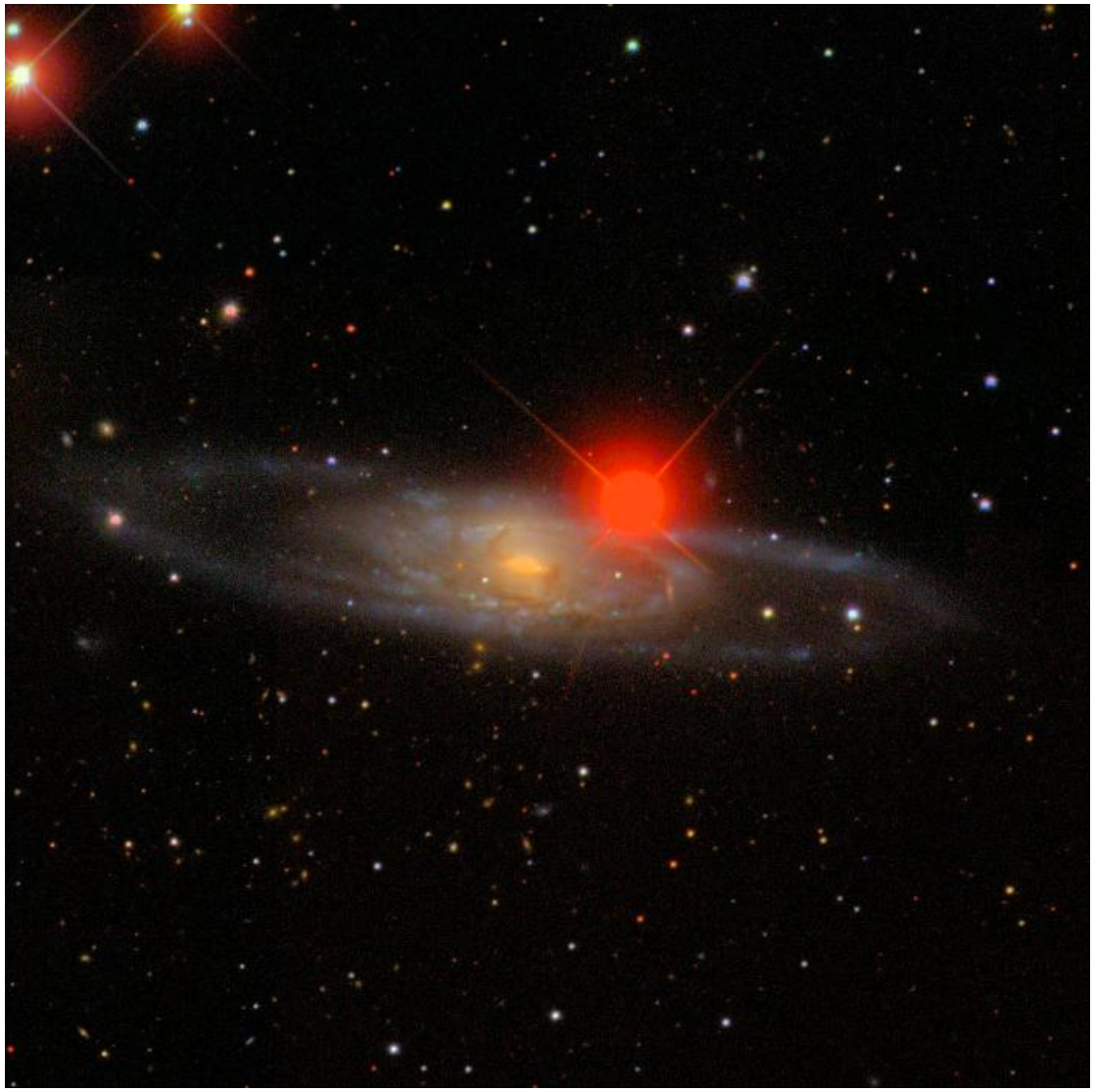
- RecSys.jl - Large movie data set (500 million parameters)
- Distributed Alternating Least Squares SVD-based model executed in Julia and in Spark
- Faster:
  - Original code in Scala
  - Distributed Julia nearly 2x faster than Spark
- Better:
  - Julia code is significantly more readable
  - Easy to maintain and update



http://juliacomputing.com/blog/2016/04/22/a-parallel-recommendation-engine-in-julia.html

Case Study 2

Enhancing Sky Surveys with Celeste.jl



Learning an Astronomical Catalog of the Visible Universe through Scalable Bayesian Inference

Jeffrey Regier*, Kiran Pamnany†, Ryan Giordano‡, Rollin Thomas¶, David Schlegel§, Jon McAuliffe‡ and Prabhat¶

*Department of Electrical Engineering and Computer Science, University of California, Berkeley

†Parallel Computing Lab, Intel Corporation

‡Department of Statistics, University of California, Berkeley

§Physics Division, Lawrence Berkeley National Laboratory

¶NERSC, Lawrence Berkeley National Laboratory

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Julia computing

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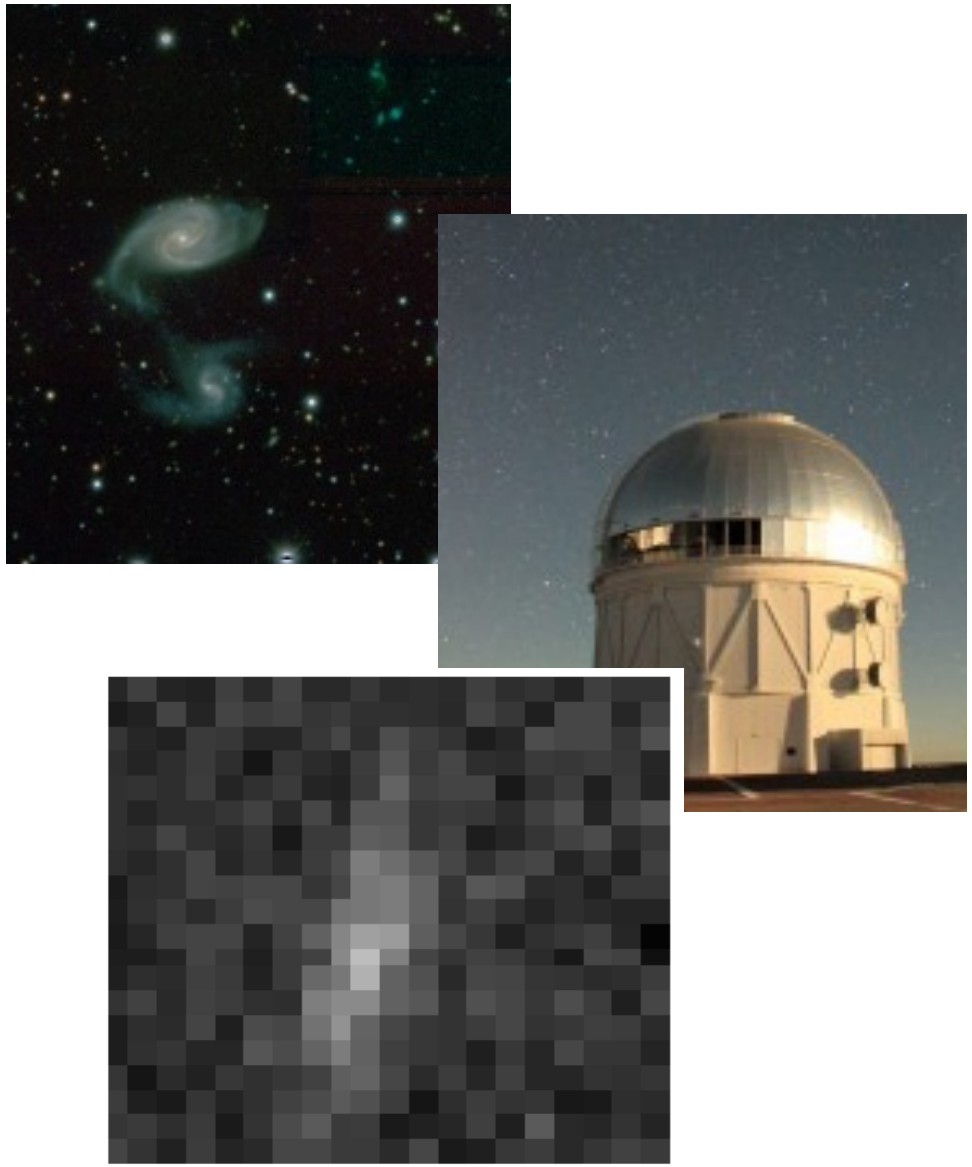
Celeste: A Generative Model of the Universe

Aim: produce a comprehensive catalog of everything in the sky, using all available data.



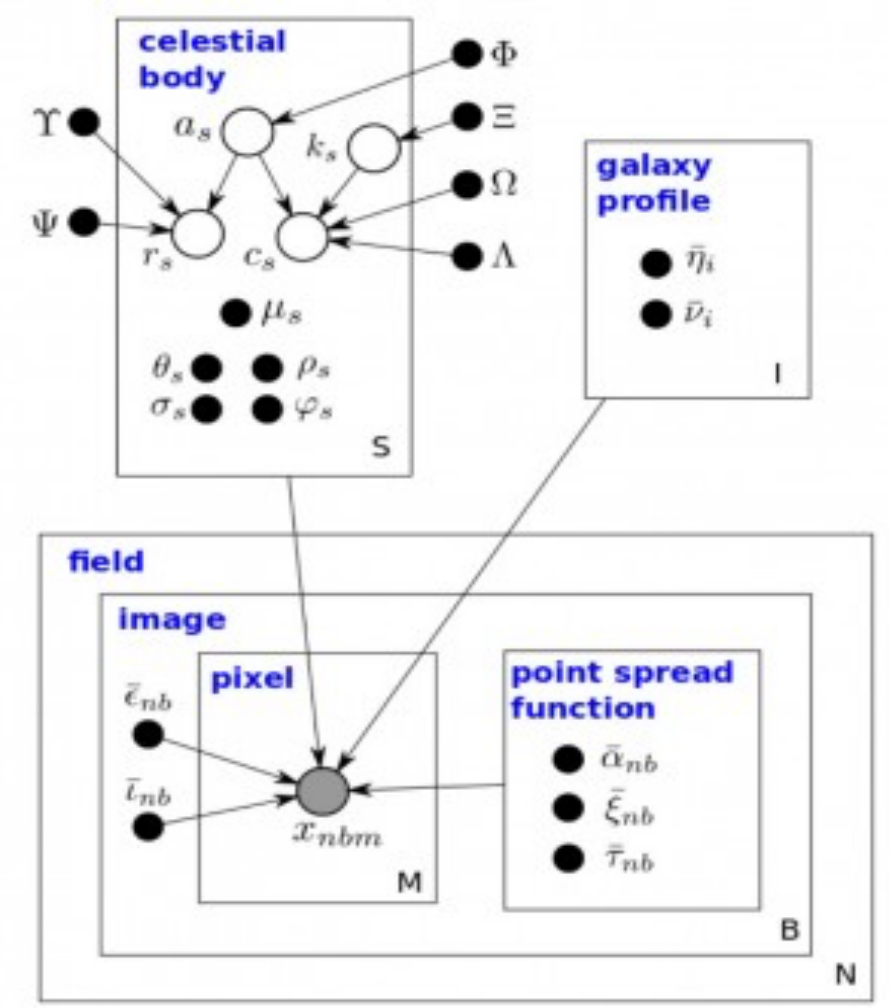
- Infer properties of stars, galaxies, quasars from the combination of all available telescope data
- Big Data problem: ~500TB, requires petascale systems and data-efficient algorithms.
- Largest Graphical Model in Science: $O(10^9)$ pixels of telescope image data; $O(10^6)$ vertices; $O(10^8)$ edges.

A Generative Model for Astronomical Images

- Each pixel intensity x_{nbm} is modeled as an observed Poisson random variable, whose rate is a deterministic function of latent random variables describing the celestial bodies nearby.

- Inference methods: variational Bayes (UC Berkeley), MCMC (Harvard)

- Celestial bodies' locations determined 10% more accurately; Celestial bodies' colors determined 50% more accurately (Regier, J., et al, ICML, 2015)



Celeste Scaling Results

A. Single node, multi-threaded performance

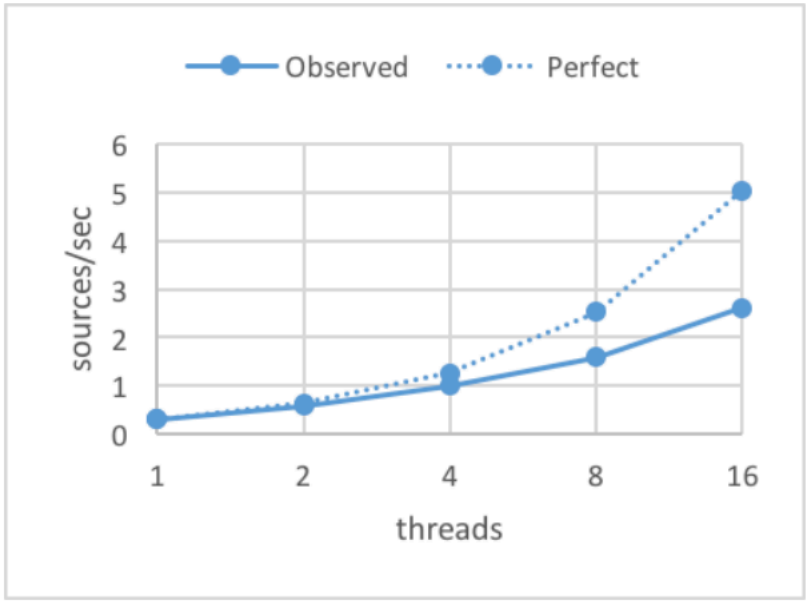


Figure 3: Multi-threaded performance. Strong-scaling Celeste on 154 light sources over up to 16 threads on a Cori Phase I node. Observe that scalability drops off beyond 4 threads; this is due to serial garbage collection.

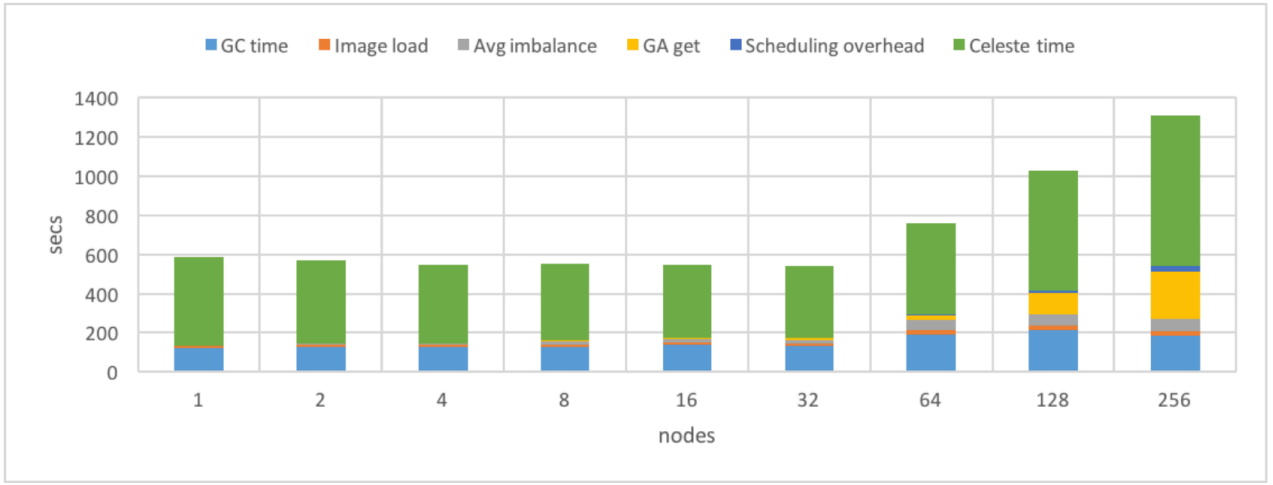


Figure 4: Weak-scaling Celeste. While the total runtime shown is precise, the components of runtime shown are averaged across nodes and thus should be treated as being representative rather than exact.

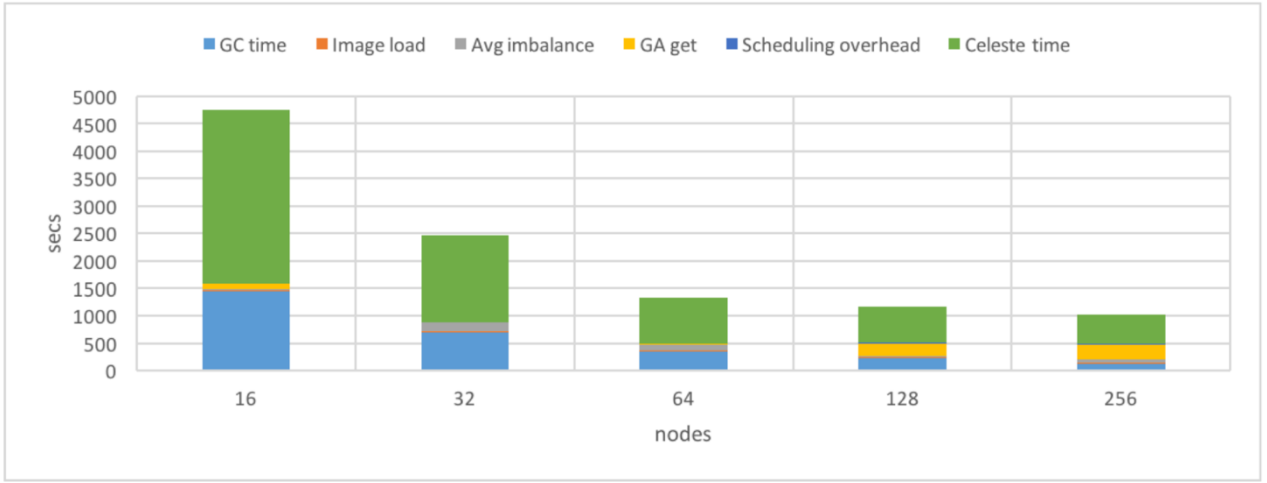


Figure 5: Strong-scaling Celeste. Note the reduction in GC time correlates with reduction in runtime, whereas the increase in global arrays fetch time correlates with the increase in nodes.

Case Study 3

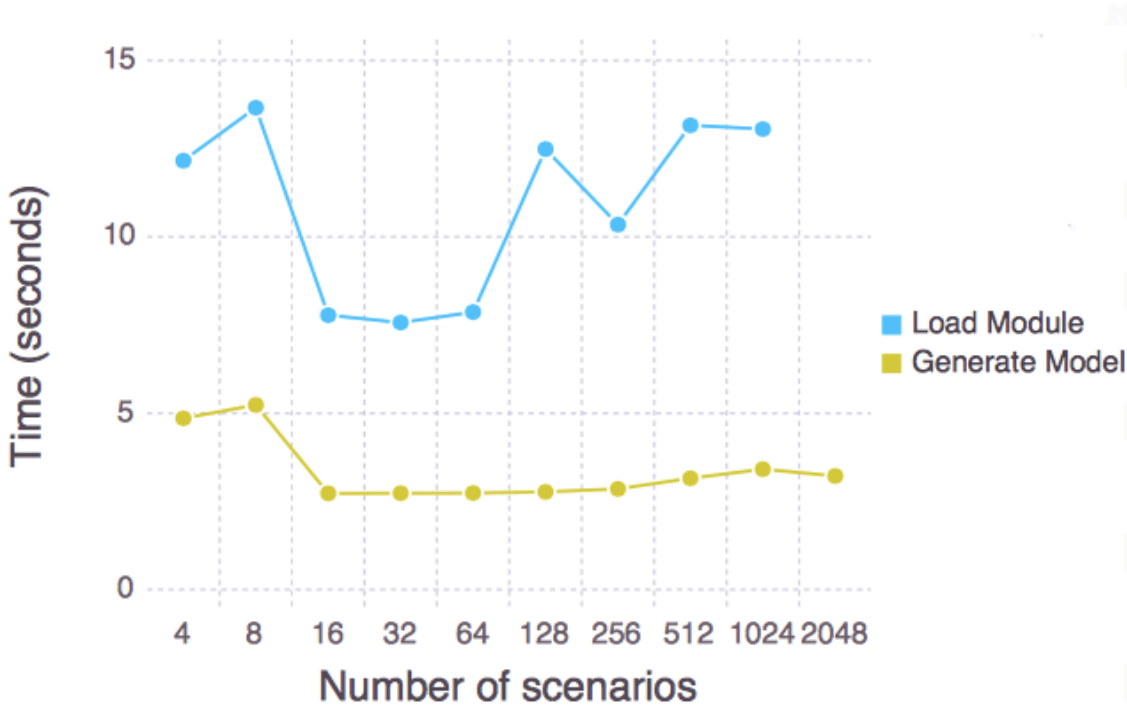
Stochastic Optimization of Energy Networks Economics

StructJuMP.jl - Cosmin G. Petra, Joey Huchette, Miles Lubin

- (150 LOC) Extension to JuMP.jl for modeling large-scale block-structured optimization problems across an HPC cluster
- Interface to PIPS-NLP optimization solver (300 LOC) for scale-out computation or Ipopt.jl for local computation
- Adds Benders Decomposition capabilities to JuMP

Results:

- StructJuMP.jl significantly decreases the time necessary for scalable model generation compared to competing modeling language approaches
- Successfully used for driving scale out optimization problem across a supercomputer at Argonne National Labs on over 350 processors



http://dl.acm.org/citation.cfm?id=2688224

Argonne NATIONAL LABORATORY

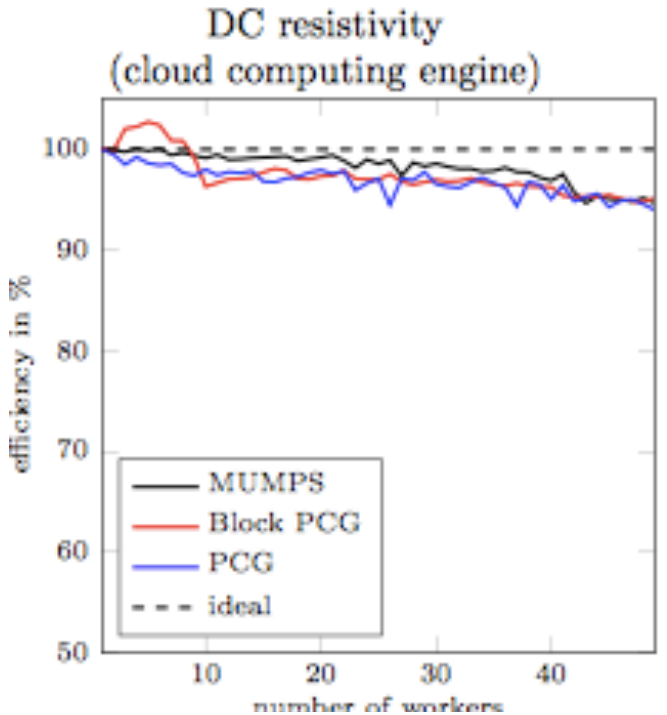
MIT MANAGEMENT SLOAN SCHOOL

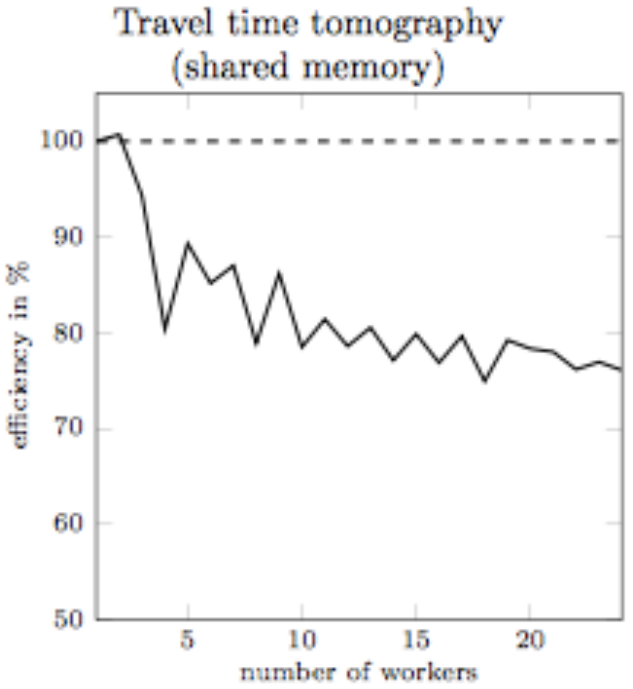
Case Study 4

JINV - PDE Parameter Estimation

Lars Ruthotto, Eran Treister, Eldad Haber

- jInv.jl – A Flexible Framework for Parallel PDE Parameter Estimation
  - Provides functionality for solving inverse and ill-posed multiphysics problems found in geophysical simulation, medical imaging and nondestructive testing.
  - Incorporates both shared and distributed memory parallelism for forward linear PDE solvers and optimization routines
- Results:
  - Weak scaling tests on AWS EC2 (c4.large) instances achieves almost perfect scaling (minimum 93%)
  - Strong scaling tests on DC resistivity problem scales from 1 to 16 workers providing 5.5x overall problem speedup





https://arxiv.org/pdf/1606.07399v1.pdf

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UBC

The future is automatic parallelism

ParallelAccelerator.jl by Intel's Parallel Computing Lab

A compiler framework on top of the Julia compiler for high-performance technical computing

- Identifies parallel patterns – array operations, stencils
- Applies parallelization, vectorization, fusion
- Generates OpenMP or LLVM IR
- Delivers 20-400x speedup over standard Julia
- #13 most popular Julia package out of >1000

Available at:
https://github.com/IntelLabs/ParallelAccelerator.jl

Example: Black-Scholes

Accelerate this function

```
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)
```

Implicit parallelism exploited

Example (2): Gaussian blur

runStencil construct

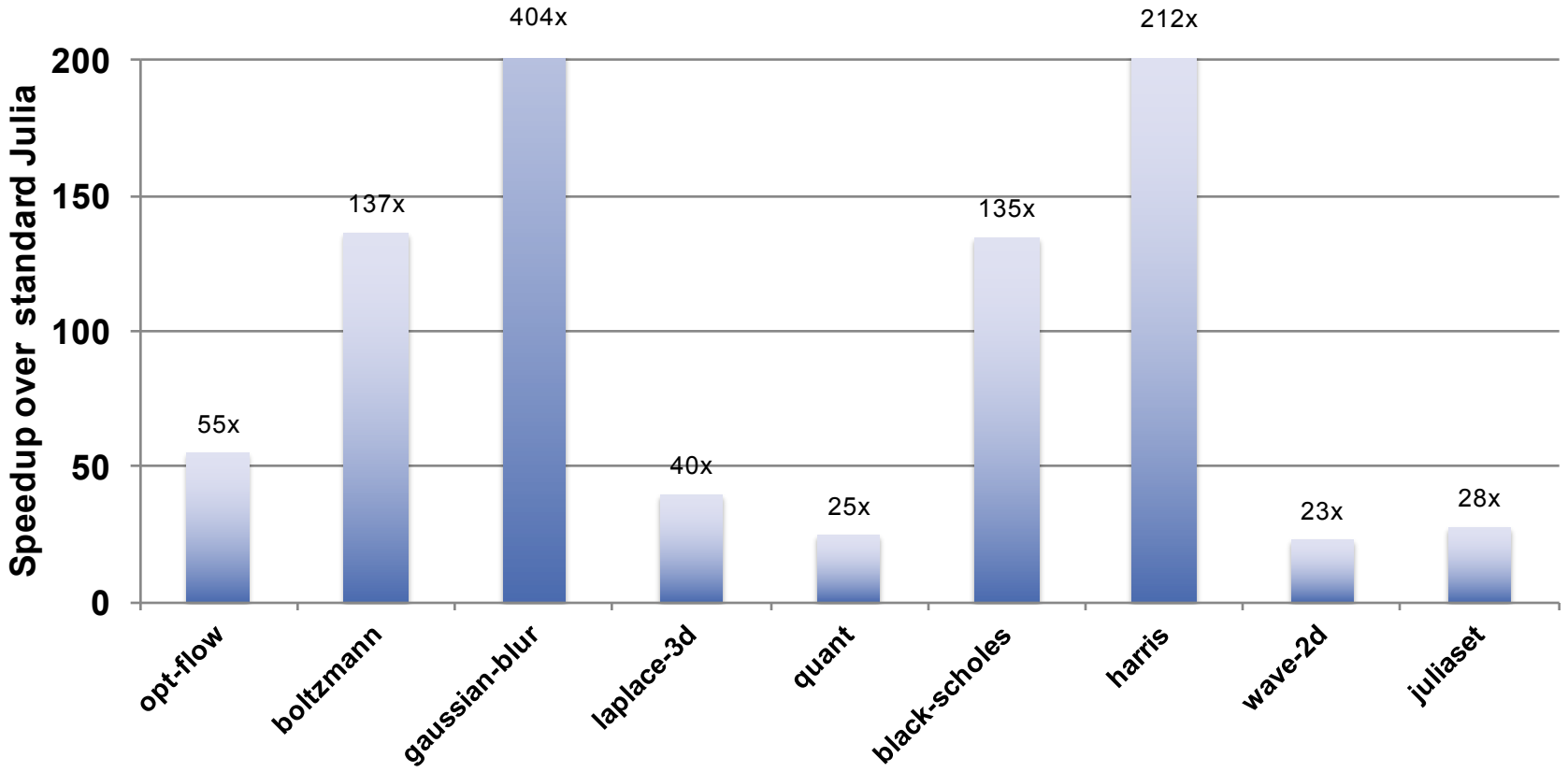
```
using ParallelAccelerator

@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)
```

ParallelAccelerator.jl Performance

Evaluation Platform:
Intel(R) Xeon(R) E5-2699 v3
36 cores



ParallelAccelerator enables ~20-400× speedup over standard Julia

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The future is automatic parallelism

HPAT.jl by Intel Parallel Computing Lab

High performance data analytics with scripting ease of use

- Translates data analytics Julia to optimized MPI
- Supports operations on arrays and data frames
- Automatically distributes data and generates communication
- Outperforms Python/MPI by >70x

Prototype available at:

https://github.com/IntelLabs/HPAT.jl

Matrix Multiply in HPAT

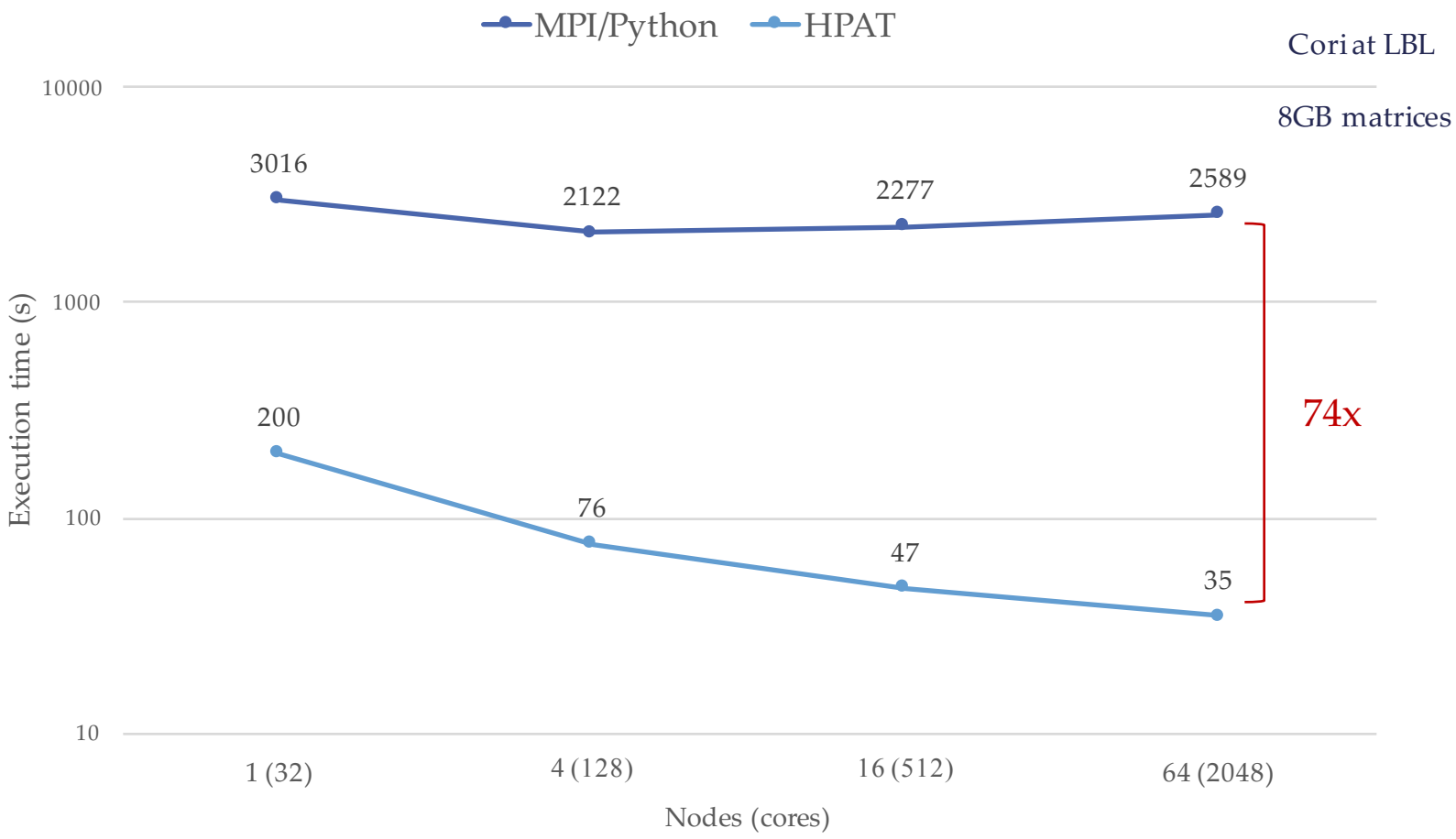
```
using HPAT
@acc hpat function p_mult(M_file, x_file, y_file)
  @partitioned(M,HPAT_2D)
  M = DataSource(Matrix{Float64},HDF5,"/M", M_file)
  x = DataSource(Matrix{Float64},HDF5,"/x", x_file)
  y = M*x
  y += 0.1*randn(size(y))
  DataSink(y,HDF5,"/y", y_file)
end
```

Generated code is 525 lines in MPI/C++

Set 96 indices for Parallel I/O

- Start, stride, count, block 2D indices for 4 hyperslabs, 3 matrices

Evaluation of Matrix Multiply

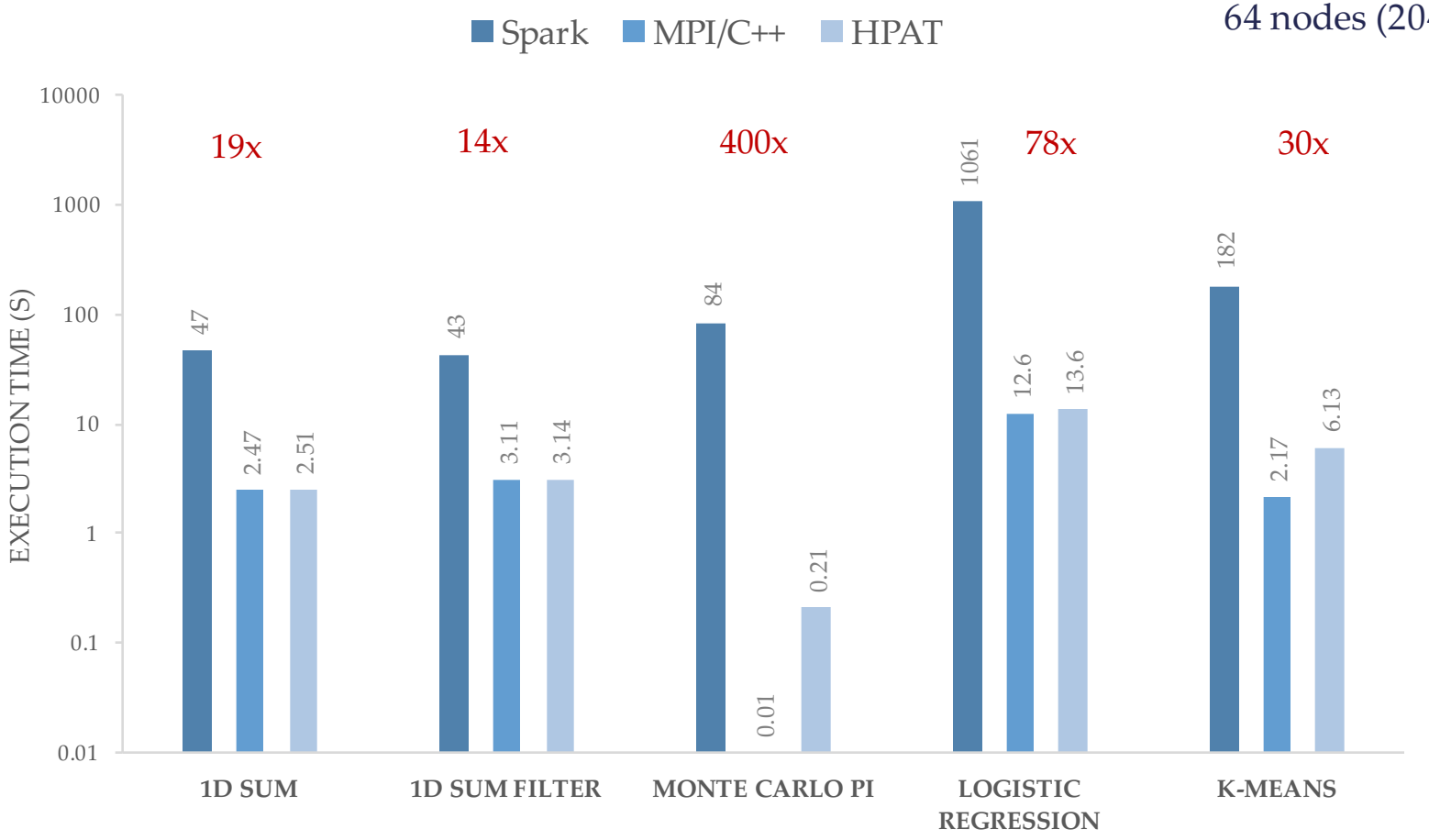


Also: 7x productivity improvement over MPI/Python

HPAT vs. Spark vs. MPI/C++

Speedup of HPAT over Spark in red

Cori at NERSC/LBL
64 nodes (2048 cores)



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Thank You

"If you have a choice of several languages, it is, all other things being equal, a mistake to program in anything but the most powerful one".

- Paul Graham in *Beating the Averages*
Co-Founder, Y-Combinator