Julia: superglue for scientific computing

Joosep Pata
<pata@phys.ethz.ch>

ETH Zürich, Institute of Particle Physics

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Motivation

While we take data and discover Higgses/susies, the world does not stand still.

If we want to get the best people to HEP, need openness to ideas.

If we want to stay on the cutting edge, we should be ready to study the competition: we can't invent everything ourselves.

This talk is about how julia can benefit our computing needs.

Why another language?

The two-language problem

- static languages: great for experts, large, low-level applications, real-time
- data analysis and exploration: iteration, experimentation, unstructured

Data analysis now massively popular, a typical physicist has limited (quality) experience with C++: **just wants the result**(TM)

Enter Python, R: surging popularity in data analysis, science.

But **no** knowledge of types $\Rightarrow$ **no** fast machine code.

```
p = Particle()
foo(p) #must do explicit type checks every time
```

What has been tried?

Vectorize and offload "heavy" stuff to a dedicated kernel?

- Leads to "expert" and "non-expert" code
- Artificial boundaries: user functions not callable
- Not every problem (easily) vectorizable: user-defined types
- Cost(human time) > Cost(machine time): but don't want to iterate weeks to try ideas!

Let the compiler do the hard work, write code as is most natural.

vectorized

```
rows = [row1, ...]
analyzeAll(rows)
```

serial

```
for (i=0;i<100;i++) {
  row = getRow(i);
  analyze(row);
}
```

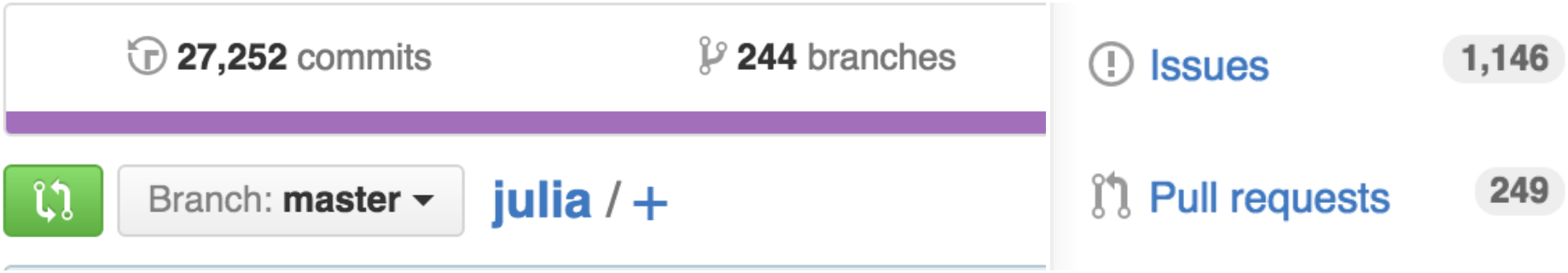
The solution

High-level, fast, dynamically compiled numerics.

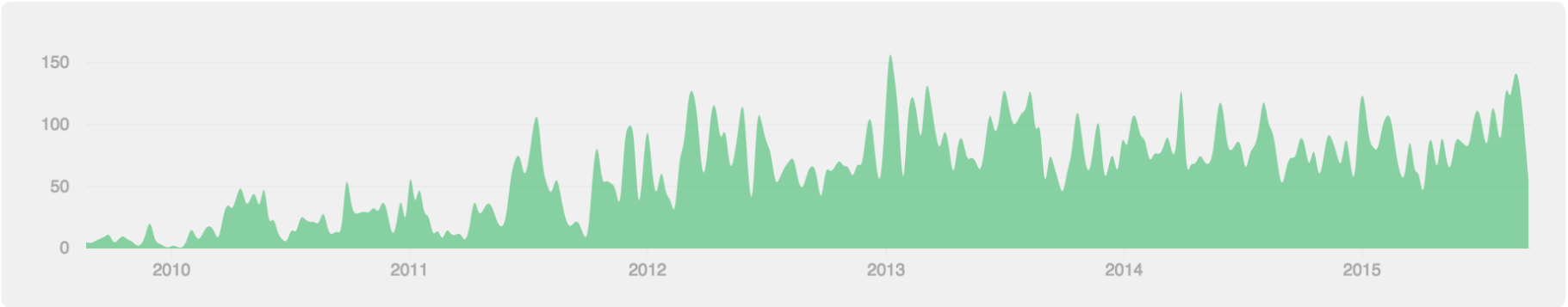
- Started at MIT CSAIL in 2011, now open-source, worldwide activity.
- Easy to use (like MATLAB, R), for generic numerical computing
- Used for physics, bio-informatics, statistics, image processing, finance
- Modular design: well-tested core + packages
- Code and issues tracked on github, (too) easy to contribute.
- Based on LLVM, OpenBLAS/Intel MKL

Development status

Core workflow and discussions on: github.com/JuliaLang/julia



Daily commit activity:



How it looks like...

Download binaries for OSX/Linux/Win, run REPL:

```
julia> 1+2
3
julia> Pkg.update()
julia> Pkg.add("Distributions")
julia> using Distributions, ROOT
julia> h = TH1D("h", "Hist", Int32(10), -10, 10)
```

- Run code in batch mode (e.g. on cluster): `julia code.jl`.
- Run interactive environment: `jupyter notebook`

Types are optional

Types may be specified or inferred automatically. User-side code auto-typed (time saver), library-side explicit-typed

```
julia> x = 1
1
julia> s = "asd"
"asd"
julia> bla = Uint32(2)
0x00000002
```

Operations with `x, s, bla` will be **machine-level**!

Functions may be typed, compiler figures out what to do at runtime:

```
julia> f(x::Int64) = x^2
julia> g(y, z) = sqrt(y^2 + z^2)
```

Underlying code

What code is actually generated for a function?

```
#define a new simple function
julia> f(x) = x > 0 ? -1 : 1
f (generic function with 2 methods)
#check produced code if x is Int64
julia> code_llvm(f, (Int64, ))
#that's the low-level LLVM code
define i64 @julia_f_21502(i64) {
top:
  %1 = icmp slt i64 %0, 1
  %. = select i1 %1, i64 1, i64 -1
  ret i64 %.
```

As fast as clang/C++!

Speed

fast basic functionality: loops, floating-point operations, external C/Fortran calls

Python:

```
In [11]: %time
for i in range(100000000):
  x+=random.random()
Out [11] Wall time: 20.2 s
```

julia:

```
julia> @time (
for i=1:100000000
  x += rand()
end)
> 3.501108 seconds
```

Type system

Types are simple, low-overhead and fast! Can make types based on input data at runtime.

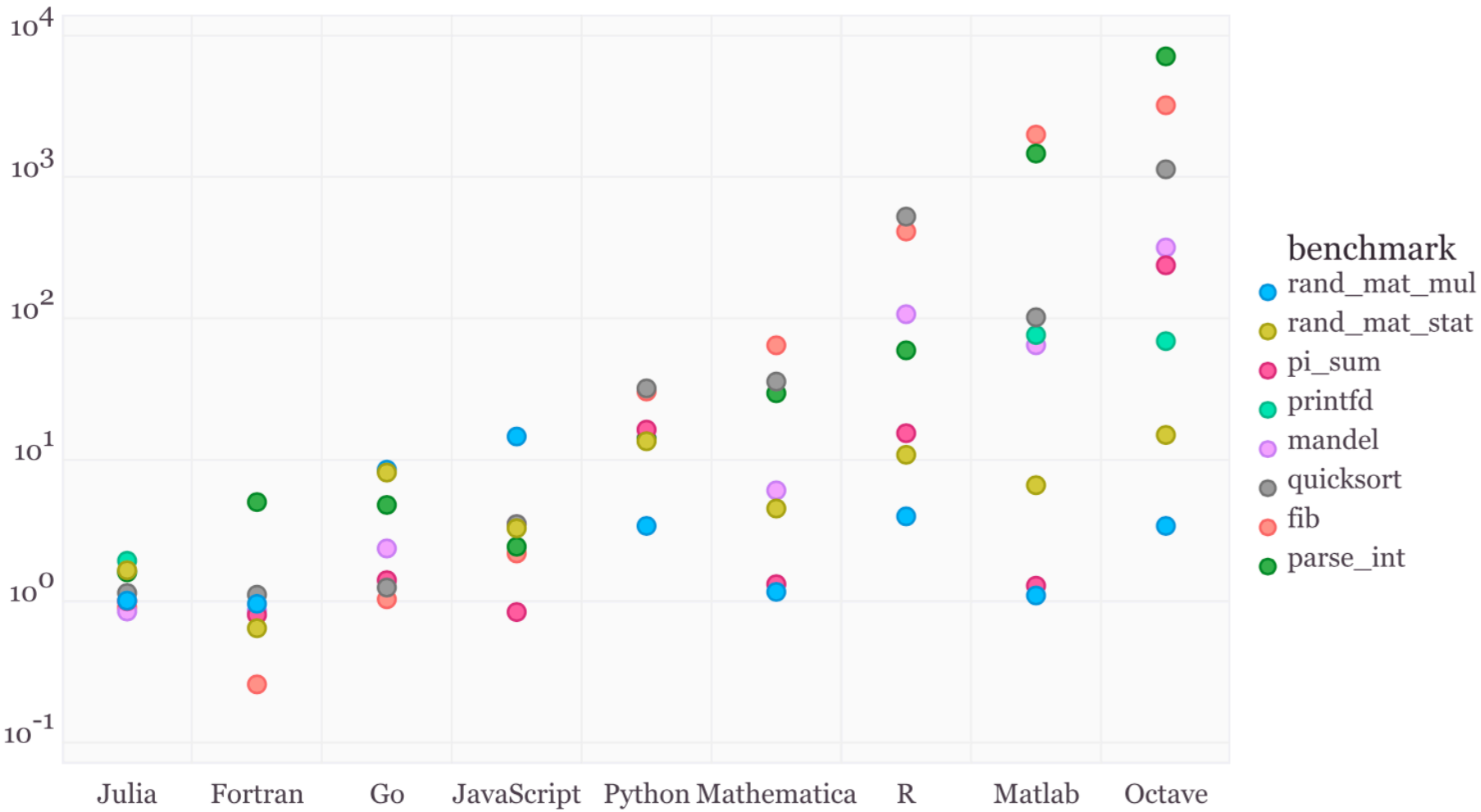
```
type Particle
  momentum::Float64 #explicitly specified
  name #no specified type, can be Anything
  friends::Vector{Particle} #complex type
end
my_p = Particle(0, "muon", [])
foo(p::Particle) = p.momentum^2
```

- Types are compiled: no overhead for e.g. `particle.momentum`
- code is specialized based on exact type specification information
- **no speed difference** with respect to built-in types
- types specify only data: multiple dispatch for member functions
- Easily add additional functions to types, e.g. `foo(t::TTree)`

Simple Mandlebrot example

```
function mandel(z)
    c = z
    maxiter = 80
    for n = 1:maxiter
        if abs(z) > 2
            return n-1 #asd
        end
        z = z^2 + c
    end
    return maxiter
end
```

Speed comparisons



Naive julia implementation often similar to or better than C / Fortran,

C/Fortran interop

Can call C or Fortran libraries natively, no overhead.

```
const LIBOL = "libopenloops.so"
#id - process id (numeric)
#pp - array of particle momenta (4*N 1D)
#m2_tree - array with amplitude
function ol_evaluate_tree(id, pp, m2_tree)
  ccall(
      (:ol_evaluate_tree, LIBOL),
      Void,
      (Cint, Ptr{Cdouble}, Ptr{Cdouble}),
      Cint(id), pp, m2_tree
      )
end
ol_setparameter_int("order_ew", 1)
ol_evaluate_tree(id, pp, m2_tree)
```

C++ interoperability

```
# include headers
using Cxx
cxx""" #include<iostream> """

# Declare the function
cxx"""
  void mycppfunction() {
    int z = 0;
    int y = 5;
    int x = 10;
    z = x*y + 2;
}
"""
# Convert C++ to Julia function
julia> julia_function() = @cxx mycppfunction()
```

Interfacing with ROOT

- Need to run on terabyte data with parallelization.
- Project histograms, make subtables (i.e. events -> particles)
- save to files, share with colleagues
- Enter `ROOT`, wrapped in julia: ROOT.jl, ROOTDataFrames.jl, ROOTHistograms.jl
- **Decouple statistical procedures and visualization!**

julia's C interface $\rightarrow$ call ROOT libraries, interface around most useful objects: `TFile, TTree, TH*`

Histograms

Directly create ROOT histograms on the julia side with C speed.

```
h1 = TH1D(
  "myhist", "My Histogram",
  Int32(100), -30.0, 30.0
)

#fill with random gaussian
for i=1:1000000
  Fill(h1, randn())
end
```

Hist has julia repr. (N-dim!), compat with existing stats libraries:

```
hj = from_root(h1) #also to_root
sw = sqrt(sum(errors(hj).^2))
```

No concept of julia histogram name and overwriting! It's a variable with predictable scope.

Trees

Simple C-like manual access:

```
tf = TFile("test.root", "RECREATE")
x = Float64[0]
px = convert(Ptr{Void}, pointer(x))
br = Branch(ttree, "x", px, "x/D")
ttree = TTree("my_tree", "My Tree")
for i=1:10000
  x[1] = i^2
  Fill(ttree)
end
Write(tf);Close(tf)
```

Trees as DataFrames

Don't want to write all branch names, types manually every time...
JIT code generation: parse branches, create static data struct on the fly.

```
#TChain underneath
tdf = TreeDataFrame("test.root")
enable_branches(tdf, ["njets", "jets_*"])
for i=1:nrow(tdf)
  load_row(tdf, i) #GetEntry
  #do something with jets
  njets = df.row.njets()
end
mu = mean(df[:njets])
```

Data exploration

Also support for Draw-like formula parsing:

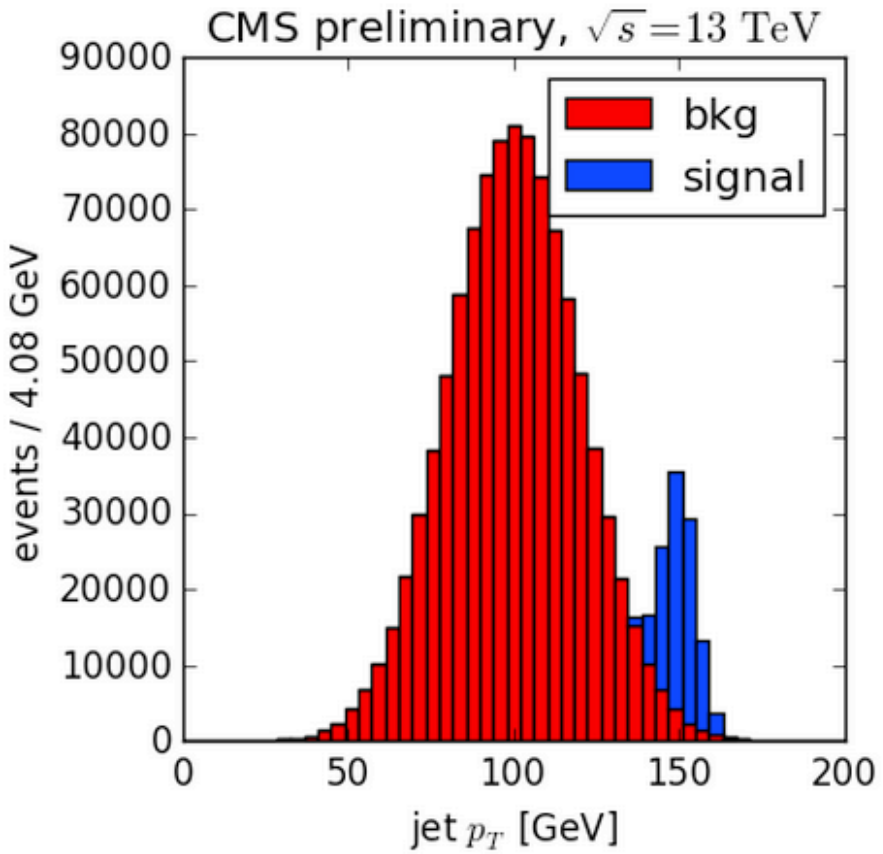
```
# tdf->Draw("jets_pt[1]+jets_pt[2]", "njets>3")
#equivalent
r = with(
  tdf, #input tree
  row -> sum(row.jets_pt()[1:2]), #to evaluate
  row -> row.njets()>3, #to select
)
julia> r[1:3]
3-element Array{Float64,1}:
 564.202
 552.618
```

Speeds similar to C++-version of `TTree::Draw`, can parallelize. Evaluate any function, cache results. No need for string parsing, special syntax, segfaults from arrays.

Plotting

Many competing packages, matplotlib.pyplot very stable:

```
PyPlot.figure(figsize=(4, 4))
plot(h1, color="red", label="bkg");
plot(h2, color="blue", bottom=contents(h1), label="signal");
PyPlot.xlabel("jet \$p_T\$ [GeV]")
PyPlot.ylabel("events / $(round(diff(h1.edges[1])[1], 2)) GeV")
PyPlot.legend(loc="best")
PyPlot.title("CMS preliminary, \$\\sqrt{s} = 13\\ \\mathrm{TeV}\$")
```



One more thing...

- Support for automatic SIMD vectorization: `@simd for i=1:10000 x[i]*y[i] end` → linear speed-up
- Built-in parallelization, coroutines: one machine to a cluster, no `GIL` like in Python, memory-shared arrays
- Code = Data: can manipulate program code on the fly (think LISP)
- Interactivity through **Jupyter** kernel, one of the main foci
- Language interop: C, Fortran natively, all of Python; soon C++ through add-ons: can wrap a complex library in a weekend.
- Many mature packages: statistics, storage, optimization, plotting, MVAs
- Soon: compile directly to GPU code

Traction

Number of active GitHub repositories

Language	Q2 2012	Q3 2014	% Growth
Julia	77	1,258	1,534%
C	24,080	64,597	168%
Java	50,334	175,968	250%
R	1,153	36,343	3,052%
Matlab	1,070	7,385	590%
Python	50,607	142,272	181%
GitHub Average	17,061	51,452	202%

Data source: GitHut

Summary

High-level code can still be fast.

Julia gaining traction in teaching, research and industry.

Julia used in and useful for high-energy physics

ROOT and julia are complementary.

Teaching

Julia is used in teaching @ MIT since 2013. Optimization, linear algebra, mathematical programming, numerical computation, PDEs.

- University of Edinburgh, Spring 2016
  - MATH11146, Modern optimization methods for big data problems (Prof. Peter Richtarik)
- MIT, Fall 2015
  - 6.251/15.081, Introduction to Mathematical Programming (Prof. Dimitris J. Bertsimas)
  - 18.06, Linear Algebra (Dr. Alex Townsend)
  - 18.303, Linear Partial Differential Equations: Analysis and Numerics (Prof. Steven G. Johnson)
  - 18.337/6.338, Numerical Computing with Julia (Prof. Alan Edelman). (IJulia notebooks)
  - 18.085/0851, Computational Science And Engineering I (Prof. Pedro J. Sáenz)
- "Sapienza" Univeristy of Rome, Italy, Spring 2015
  - Operations Research (Giampaolo Liuzzi)

Industry

Several companies are working with julia and contributing to it (open-source).

- Intel working on adding multi-threading to julia.
- Facebook working on database interfaces.
- Google investigating, some work on static analysis tools.
- Finance companies: BlackRock


Thank you! Questions?