Introduction to Julia:
Why are we doing this to you?

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MIT classes 18.06, 18.303, 18.330, 18.08[56], 18.335, 18.337, …

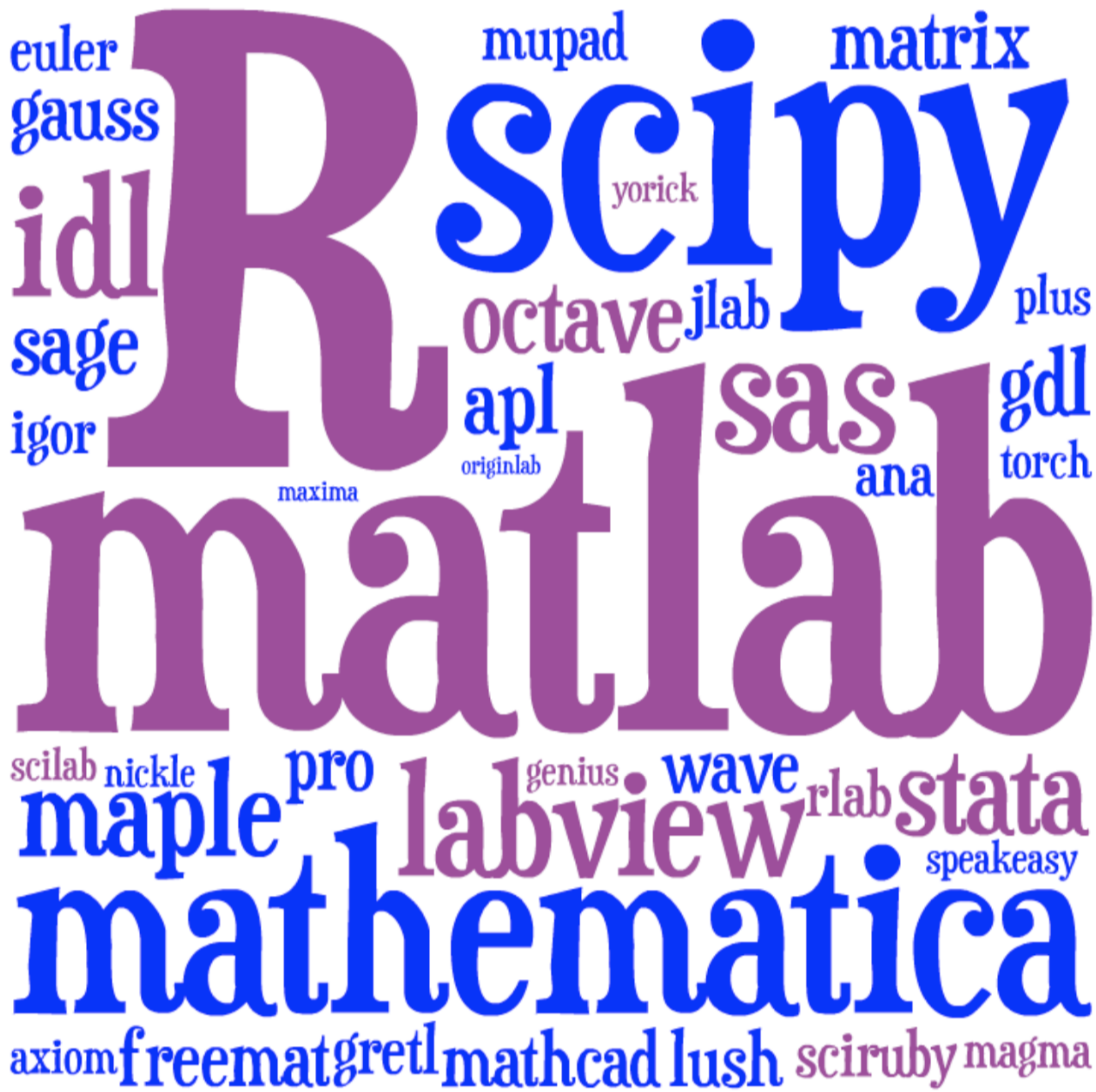
What language for teaching scientific computing?

For the most part, these are not hard-core programming courses,
and we only need little “throw-away” scripts and toy numerical experiments.

Almost any high-level, interactive (dynamic) language with easy facilities for linear algebra ($Ax=b$, $Ax=\lambda x$), plotting, mathematical functions, and working with large arrays of data would be fine.

And there are lots of choices…

Lots of choices for interactive math…



[image: Viral Shah]

Just pick the most popular?
Matlab or *Python* or *R*?

We feel guilty pushing a language on you that we are starting to abandon ourselves.

Traditional HL computing languages
hit a performance wall in "real" work
… eventually force you to C, Cython, …

A new programming language?

Viral Shah

Jeff Bezanson

Alan Edelman

[MIT]

Stefan Karpinski

julia

julialang.org

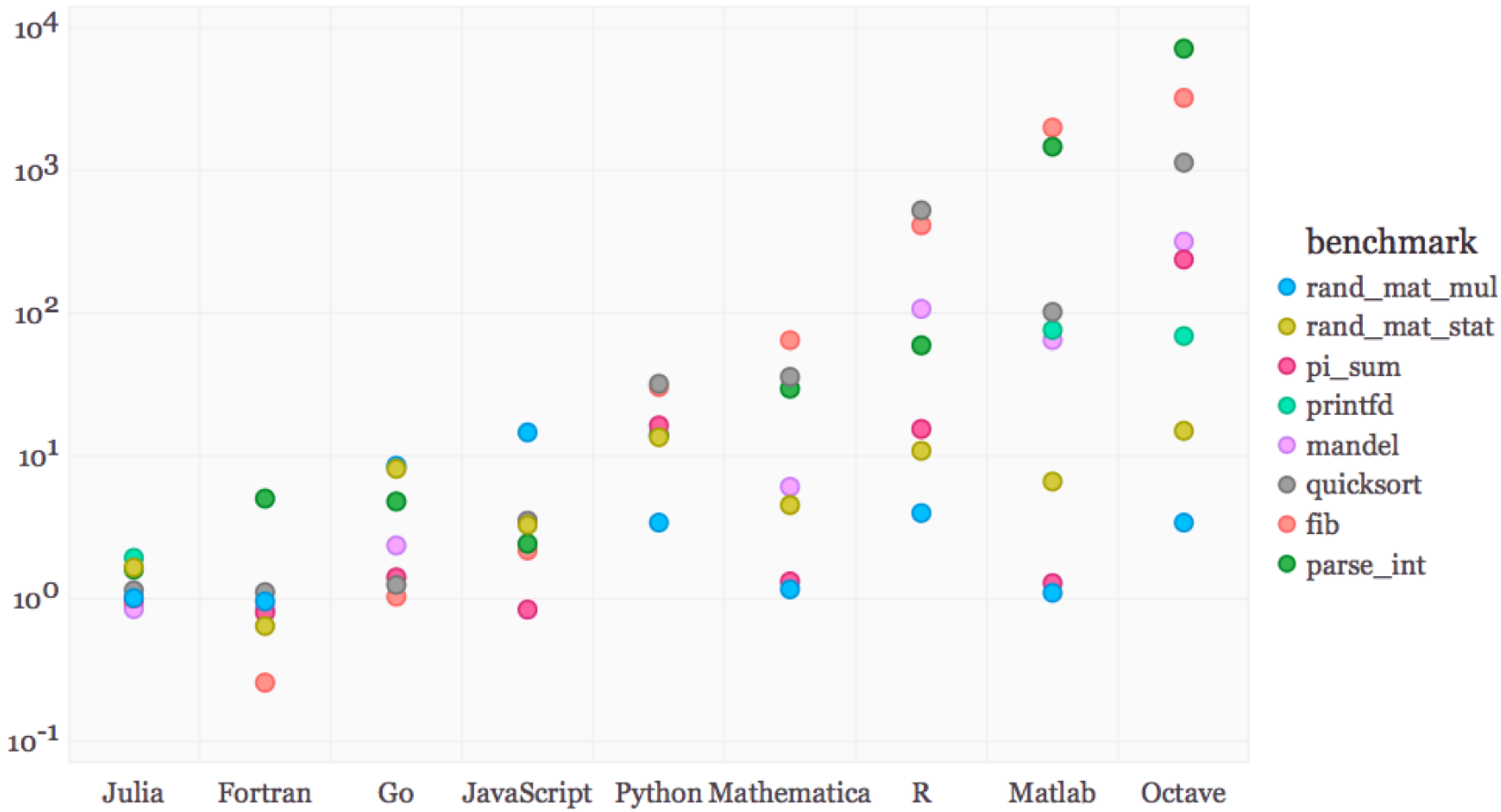
[30+ developers with 100+ commits,
1000+ external packages, 3rd JuliaCon in 2016]

[begun 2009, "0.1" in 2013, ~35k commits,
"0.5" release in Fall 2016]

As high-level and interactive as Matlab or Python+IPython,
as general-purpose as Python,
as productive for technical work as Matlab or Python+SciPy,
but as **fast as C**.

Performance on synthetic benchmarks

[loops, recursion, etc., implemented in most straightforward style]



(normalized so that C speed = 1)

Special Functions in Julia

Special functions s(x): classic case that cannot be vectorized well
… switch between various polynomials depending on x

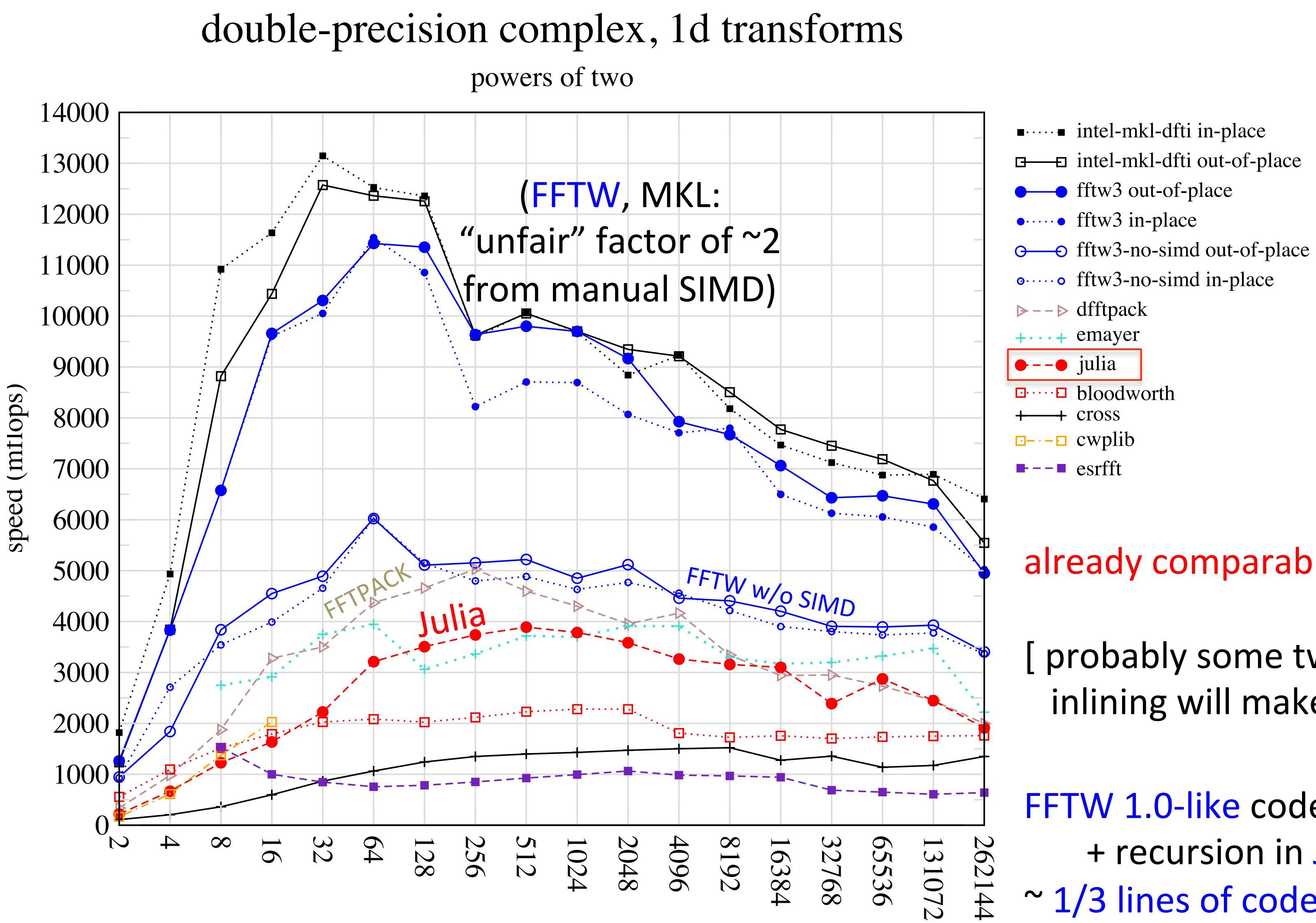
Many of Julia's special functions come from the usual C/Fortran libraries, but some are written in pure Julia code.

Pure Julia erfinv(x) [= $\mathrm{erf}^{-1}(x)$]
3–4× faster than Matlab's and 2–3× faster than SciPy's (Fortran Cephes).

Pure Julia polygamma(m, z) [= $(m+1)^{th}$ derivative of the ln Γ function]
~ 2× faster than SciPy's (C/Fortran) for real *z*
… and unlike SciPy's, *same code* supports complex argument *z*

Julia code can actually be faster than typical "optimized" C/Fortran code, by using techniques [metaprogramming/ code generation] that are hard in a low-level language.

Pure-Julia FFT performance



already comparable to FFTPACK

[probably some tweaks to inlining will make it better]

FFTW 1.0-like code generation + recursion in Julia

~ 1/3 lines of code compared to FFTPACK, more functionality

Generating Vandermonde matrices

given x = [α_1, α_2, …], generate:

$$V = \begin{bmatrix} 1 & \alpha_1 & \alpha_1^2 & \dots & \alpha_1^{n-1} \\ 1 & \alpha_2 & \alpha_2^2 & \dots & \alpha_2^{n-1} \\ 1 & \alpha_3 & \alpha_3^2 & \dots & \alpha_3^{n-1} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & \alpha_m & \alpha_m^2 & \dots & \alpha_m^{n-1} \end{bmatrix}$$

NumPy (`numpy.vander`): *[follow links]*

Python code …wraps C code
… wraps generated C code

type-generic at high-level, but
low level limited to small set of types.

Writing fast code "in" Python or Matlab = mining the standard library for pre-written functions (implemented in C or Fortran).

If the problem doesn't "vectorize" into built-in functions,
if you have to write your own inner loops … sucks for you.

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NumPy (`numpy.vander`): *[follow links]*

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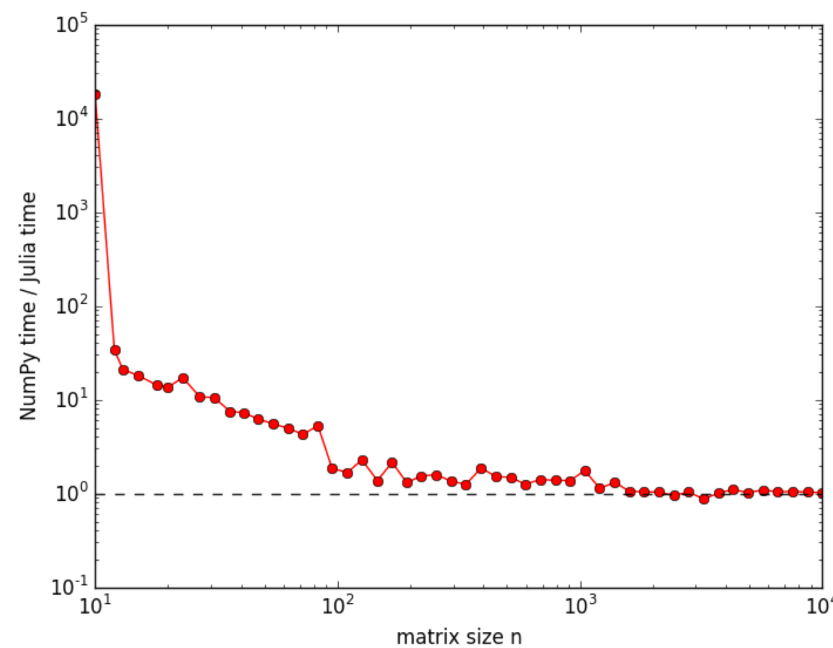
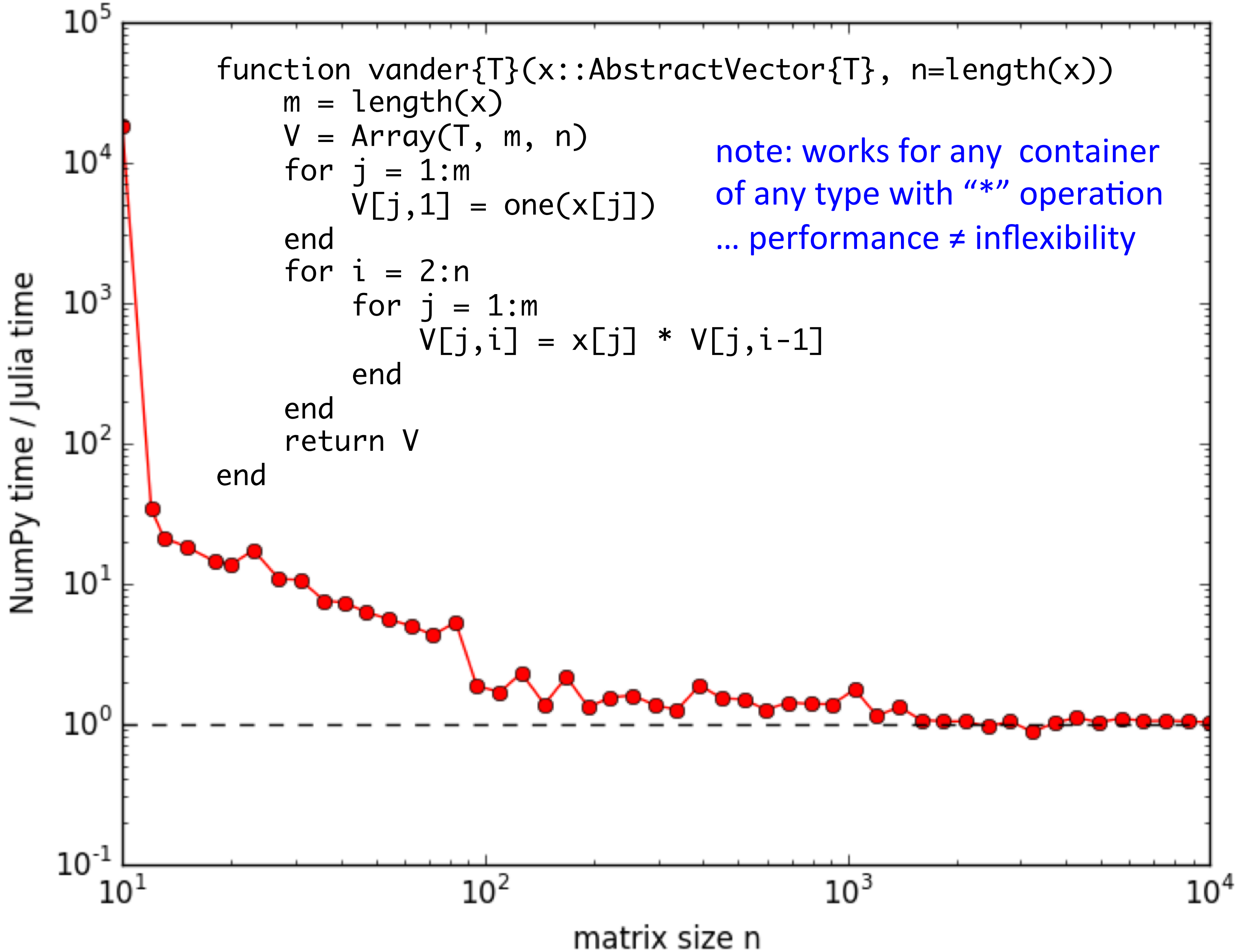
Julia (type-generic code):

```
function vander{T}(x::AbstractVector{T}, n=length(x))
    m = length(x)
    V = Array(T, m, n)
    for j = 1:m
        V[j,1] = one(x[j])
    end
    for i = 2:n
        for j = 1:m
            V[j,i] = x[j] * V[j,i-1]
        end
    end
    return V
end
```



Generating Vandermonde matrices



But I don't "need" performance!

For lots of problems, especially "toy" problems in courses, Matlab/Python performance is good enough.

But if use those languages for all of your "easy" problems, then you won't be prepared to switch when you hit a hard problem. When you **need** performance, it is too late.

You don't want to learn a new language at the same time that you are solving your first truly difficult computational problem.

Just vectorize your code?

= rely on mature external libraries,
operating on large blocks of data,
for performance-critical code

Good advice! But…

- Someone has to write those libraries.

- Eventually that person will be you.
  — some problems are impossible or
  just very awkward to vectorize.

But everyone else is using Matlab/Python/R/…

Julia is still a young, niche language. That imposes real costs — lack of familiarity, rough edges, continual language changes. These are real obstacles.

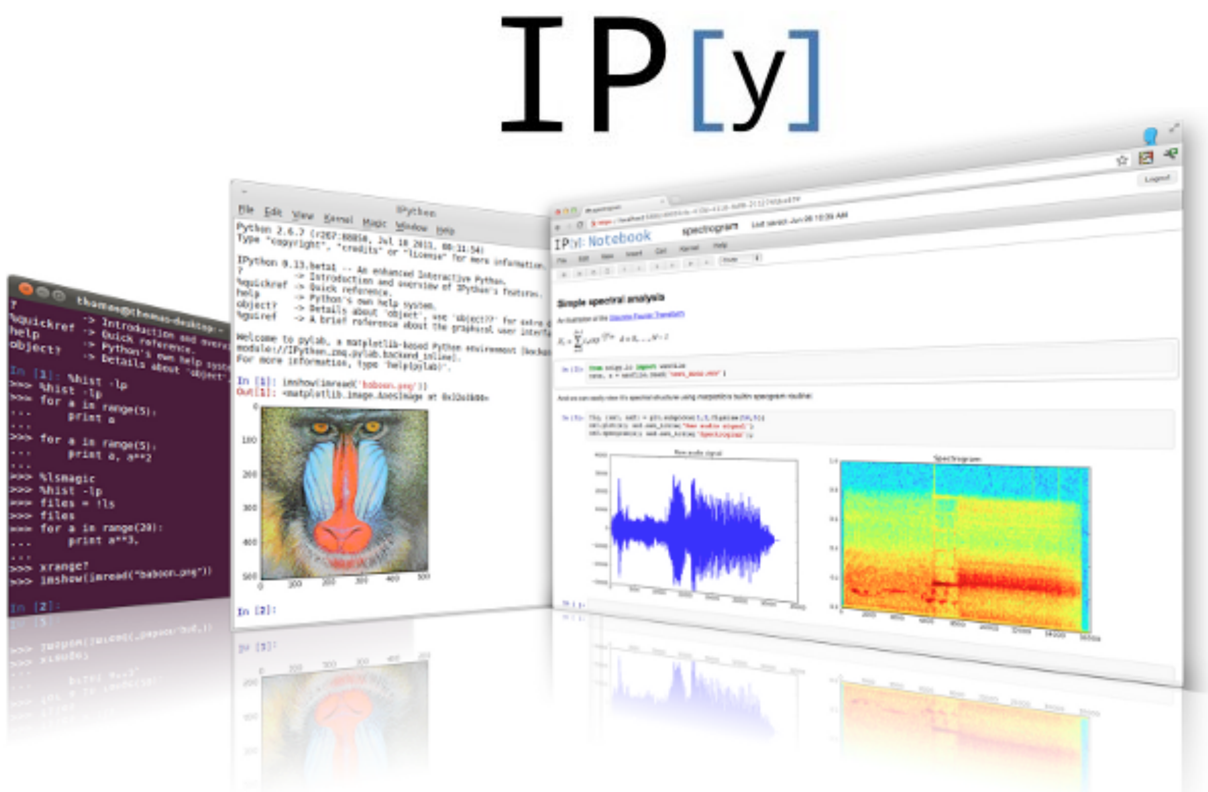
But it also gives you advantages that Matlab/Python users don't have.

But I lose access to all the libraries available for other languages?

Very easy to call C/Fortran libraries from Julia, and also to call Python…

Julia leverages Python…

Directly call Python libraries (PyCall package),
e.g. to plot with Matplotlib (PyPlot package)



[ipython.org]

via IPython/Jupyter:

Modern multimedia interactive notebooks mixing code, results, graphics, rich text, equations, interaction

"IJulia"

`goto` live IJulia notebook demo…

Go to juliabox.org for install-free IJulia on the Amazon cloud

See also julialang.org for more tutorial materials…