

# **Your first steps with Julia**

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# Installing and running Julia

- Download Julia
  - Free and Open Source
  - **<https://julialang.org/downloads/>**
  - v1.8.3 – the latest stable version
- Programming environment – VS Code
  - <https://code.visualstudio.com/download/>
- Jupyter notebook
  - Available via IJulia package

# Julia Command Line (REPL)

```
>julia
```

```
(_)      (-)      (-)
```

```
- - - | - - - |
```

```
| | | | | / \ |
```

```
_/_\_|_--'|_-|_|_\--'|
```

```
|_--/
```

```
julia> |
```

```
Documentation: https://docs.julialang.org
```

```
Type "?" for help, "]"?" for Pkg help.
```

```
Version 1.8.3 (2022-11-14)
```

```
Official https://julialang.org/ release
```

pressing ] changes REPL to package installation mode

```
(v1.2) pkg> |
```

pressing ; changes REPL to package installation mode

```
shell> |
```

pressing **?** changes REPL to help mode

```
help?>
```

to go back to normal mode press **BACKSPACE**

```
julia> |
```

# Adding Julia packages

- Start Julia REPL
- Press **]** to start the Julia package manager  
(prompt **(v1.8) pkg>** will be seen)
- Sample package installation command

```
(v1.8) pkg> add PyPlot DataFrames Distributions
```

to go back to normal mode press **BACKSPACE**

# Managing packages

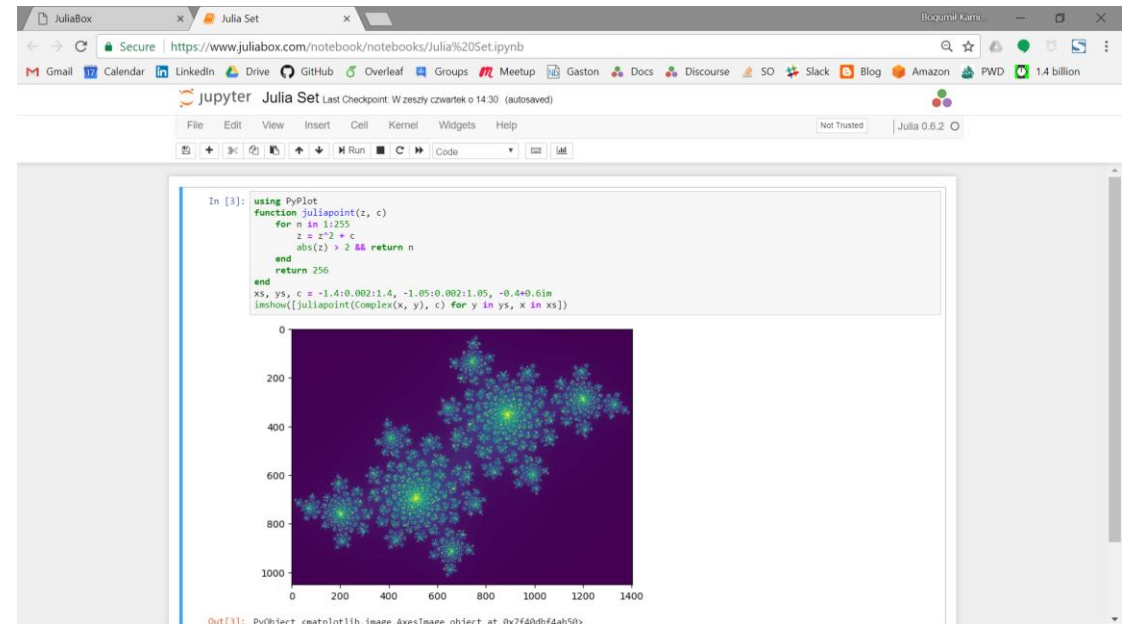
(press **J** for the package management REPL mode)

```
(@v1.6) pkg> status
Status `C:\JuliaPkg\Julia-1.6.3\
[46ada45e] Agents v4.5.6
[6e4b80f9] BenchmarkTools v1.2.0
[336ed68f] CSV v0.8.5
[34f1f09b] ClusterManagers v0.4.2
[5ae59095] Colors v0.12.8
[8f4d0f93] Conda v1.5.2
[a93c6f00] DataFrames v1.2.2

(@v1.6) pkg> add RCall
Updating registry at `C:\JuliaPkg\Julia-1.6.3\registries\General`
Updating git-repo `https://github.com/JuliaRegistries/General.git`
Resolving package versions...
Installed ShiftedArrays v1.0.0
Installed WinReg v0.3.1
Installed StatsModels v0.6.26
Installed RCall v0.13.12
Installed CategoricalArrays v0.10.1
Updating `C:\JuliaPkg\Julia-1.6.3\environments\v1.6\Project.toml`
[6f49c342] + RCall v0.13.12
Updating `C:\JuliaPkg\Julia-1.6.3\environments\v1.6\Manifest.toml`
[324d7699] + CategoricalArrays v0.10.1
[6f49c342] + RCall v0.13.12
[1277b4bf] + ShiftedArrays v1.0.0
[3eaba693] + StatsModels v0.6.26
[1b915085] + WinReg v0.3.1
Building RCall → `C:\JuliaPkg\Julia-1.6.3\scratchspaces\44cfe95a-1eb2-52ea-b672-
Precompiling project...
4 dependencies successfully precompiled in 13 seconds (282 already precompiled)
```

# Jupyter notebook

- Jupyter notebook
  - `using Pkg; Pkg.add("IJulia")`
  - `using IJulia`
  - `notebook(dir=".")`
- Press Ctrl+C to exit



# Julia 10,000 feet overview

- Exponential growth, in several areas becomes a standard for scientific and high performance computing
- “walks like Python runs like C”
- Syntax in-between Python/numpy and Matlab
- Compiles to assembly
- Compiles to GPU
- Distributed computing built into the language (known to scale up to millions of CPU cores)
- Best option for number crunching



# Why another language for data science?

Two language problem of data science – programming languages

- are either fast (C++, Fortran)
- or are convenient (Python, R, Matlab)

Main features of Julia

1. Efficiency
2. Expressiveness
3. Integrability
4. Metaprogramming – DSLs for various data science subproblems
5. Integration and toolboxes





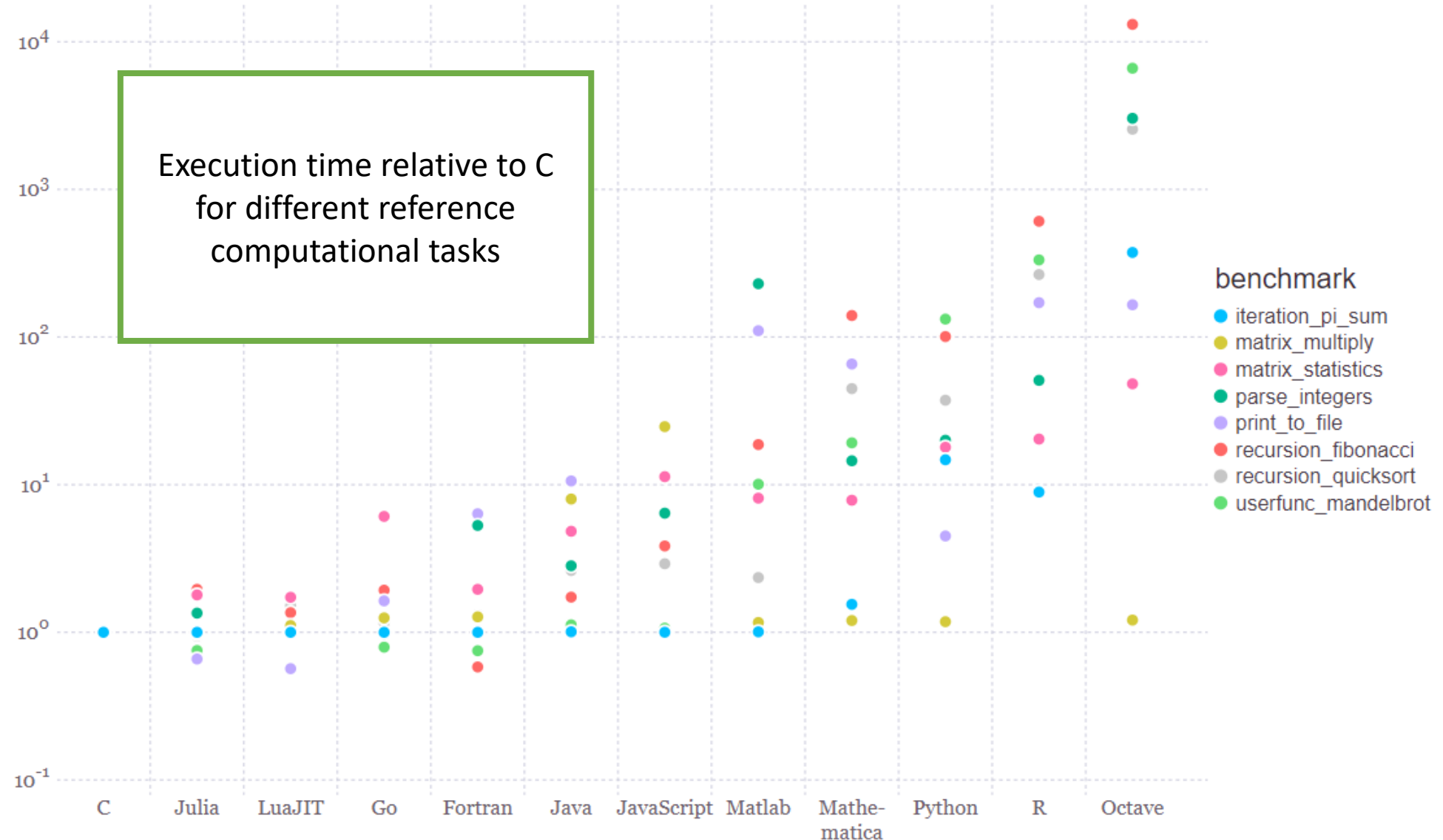
# Methods of achieving high performance in different data science environments

Ecosystem	Glue	Hot code	GPU
R-based	R	RCpp	C
Python-based	Python	Numba/Cython/C	C
Julia-based	Julia	Julia	Julia
Matlab-based	Matlab	C	GPU coder

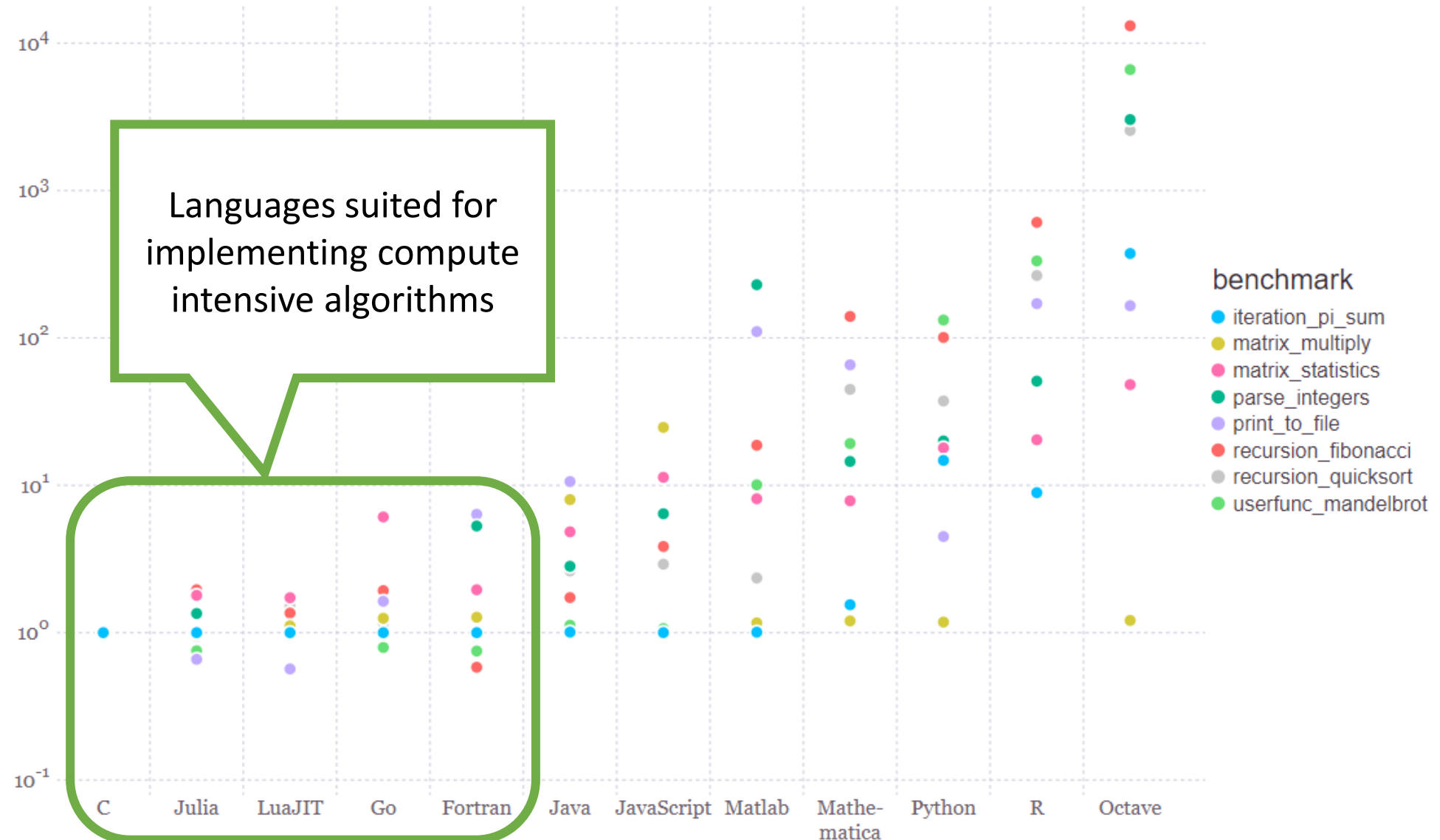
# Matlab?

*“We had to renew our licenses and got a bill for 30’000’000 USD”* – overheard during a talk with a director of big supercomputer research center

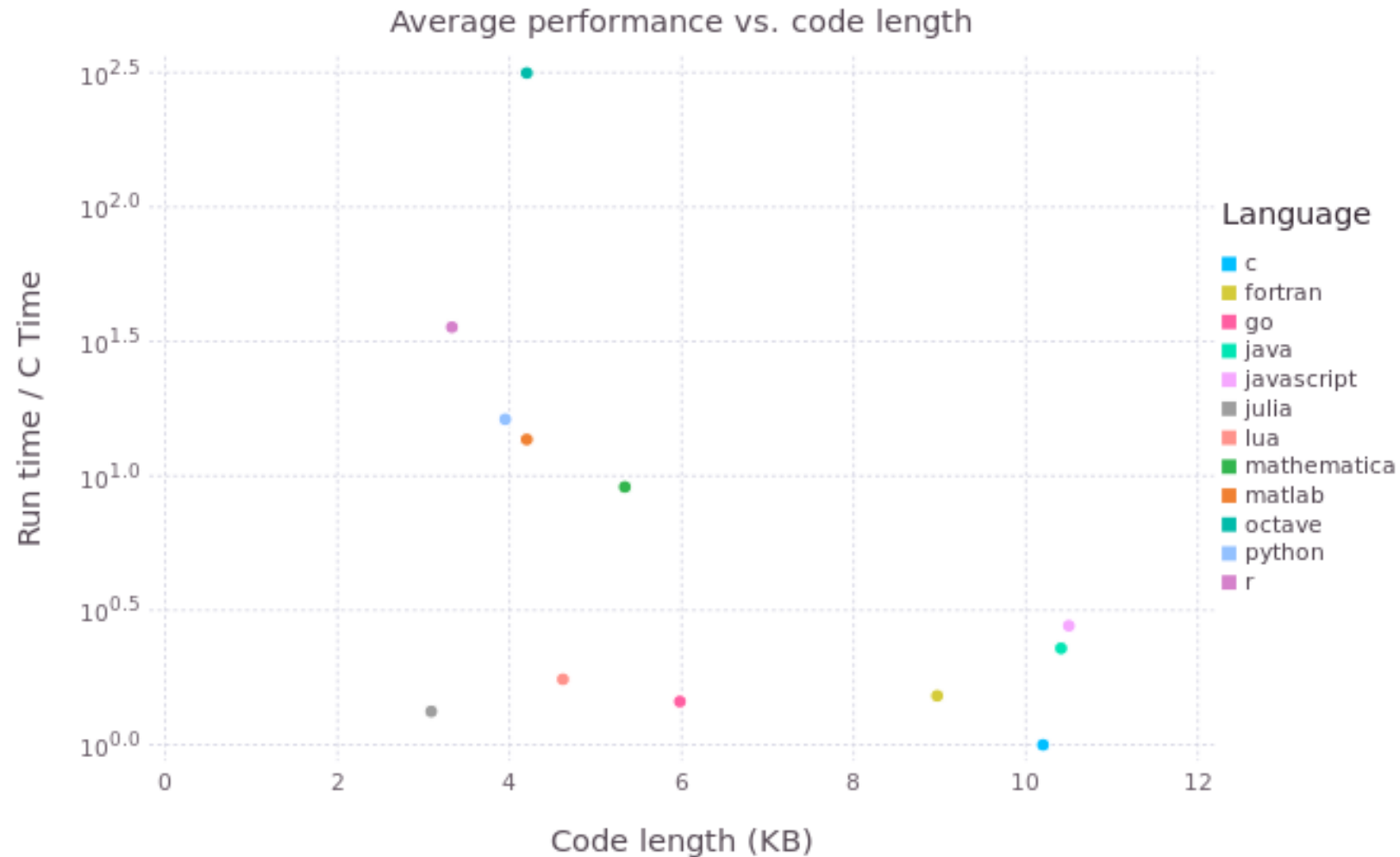
# Reference benchmarks from Julia website



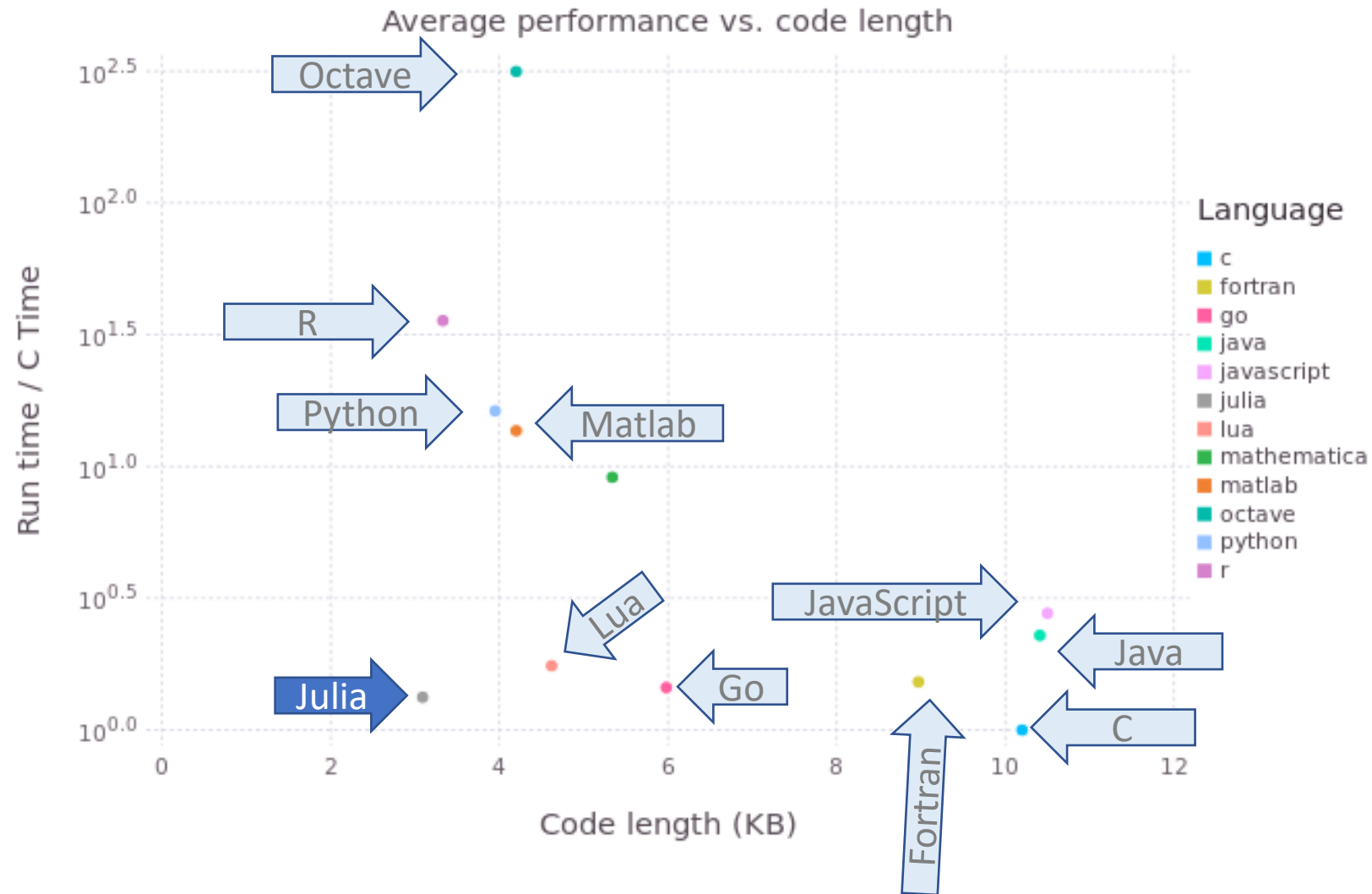
# Reference benchmarks from Julia website



# Language Code Complexity vs Execution Speed



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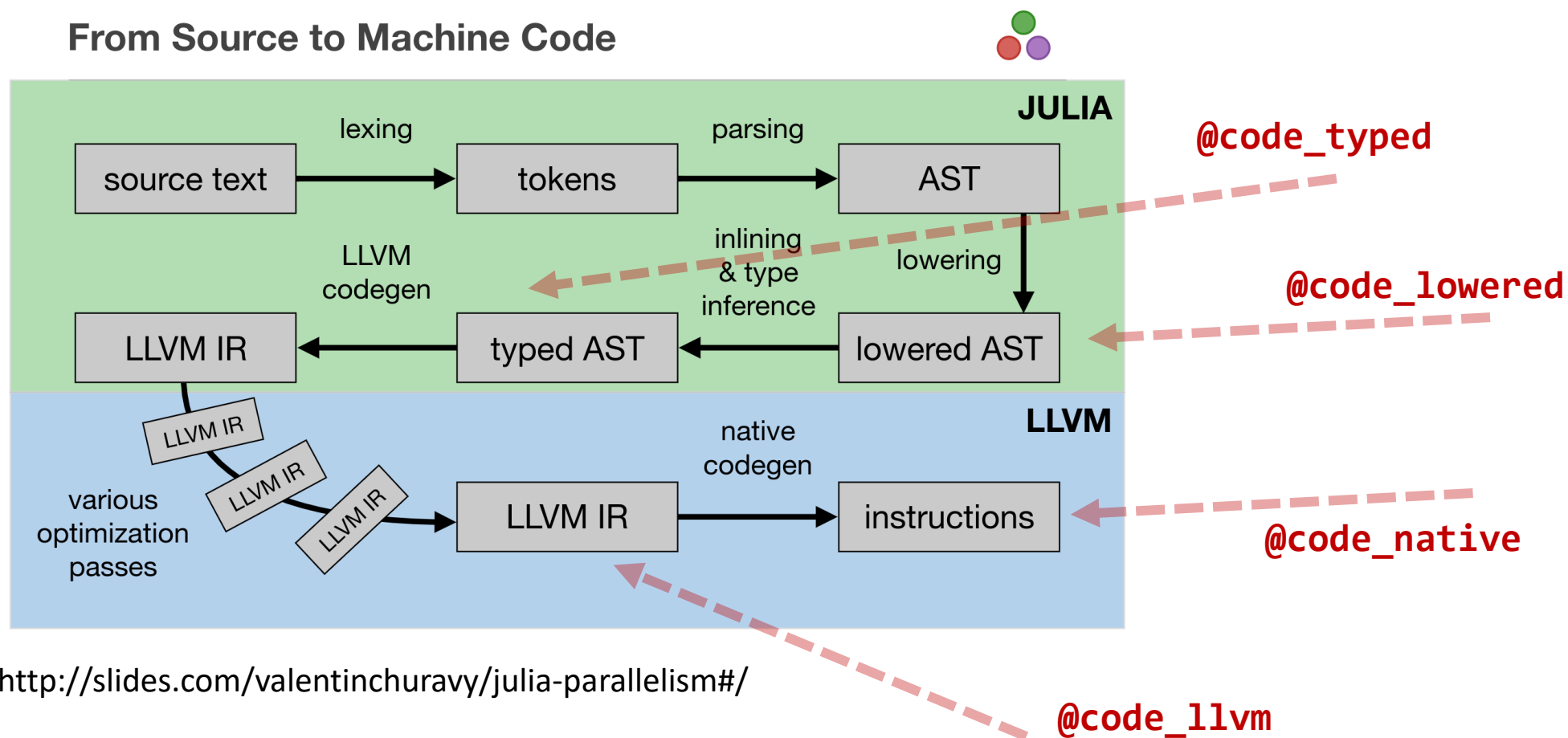


Source: <http://www.oceanographerschoice.com/2016/03/the-julia-language-is-the-way-of-the-future/>

# Key features

- Performance
  - Dynamically compiled to optimized native machine code
- Scalability
  - SIMD, Threading, Distributed computing
- Modern design of the language
  - multiple dispatch, metaprogramming, type system
- MIT License
  - corporate-use friendly (also package ecosystem)

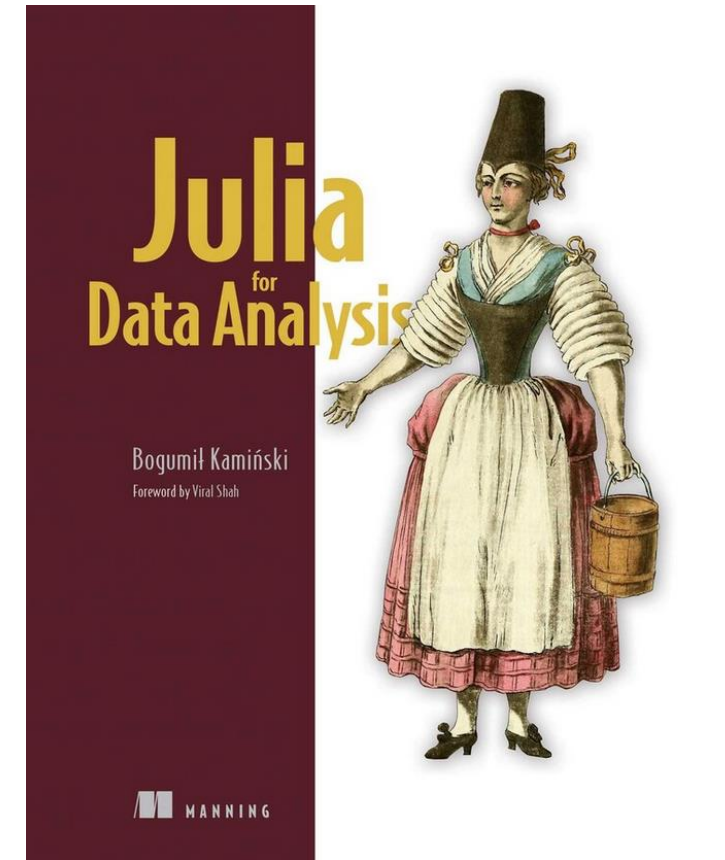
# Julia code compilation process





# Learning more about Julia

- Website: <https://julialang.org/>
- Learning materials: <https://julialang.org/learning/>
- Blogs about Julia: <https://www.juliabloggers.com/>
- <https://github.com/bkamins/The-Julia-Express>
- Julia forum: <https://discourse.julialang.org/>
- Q&A for Julia: <https://stackoverflow.com/questions/tagged/julia-lang>



# Some basic commands

(zobacz też <https://github.com/bkamins/The-Julia-Express>)

```
@less(max(1,2))  
    # show function source code
```

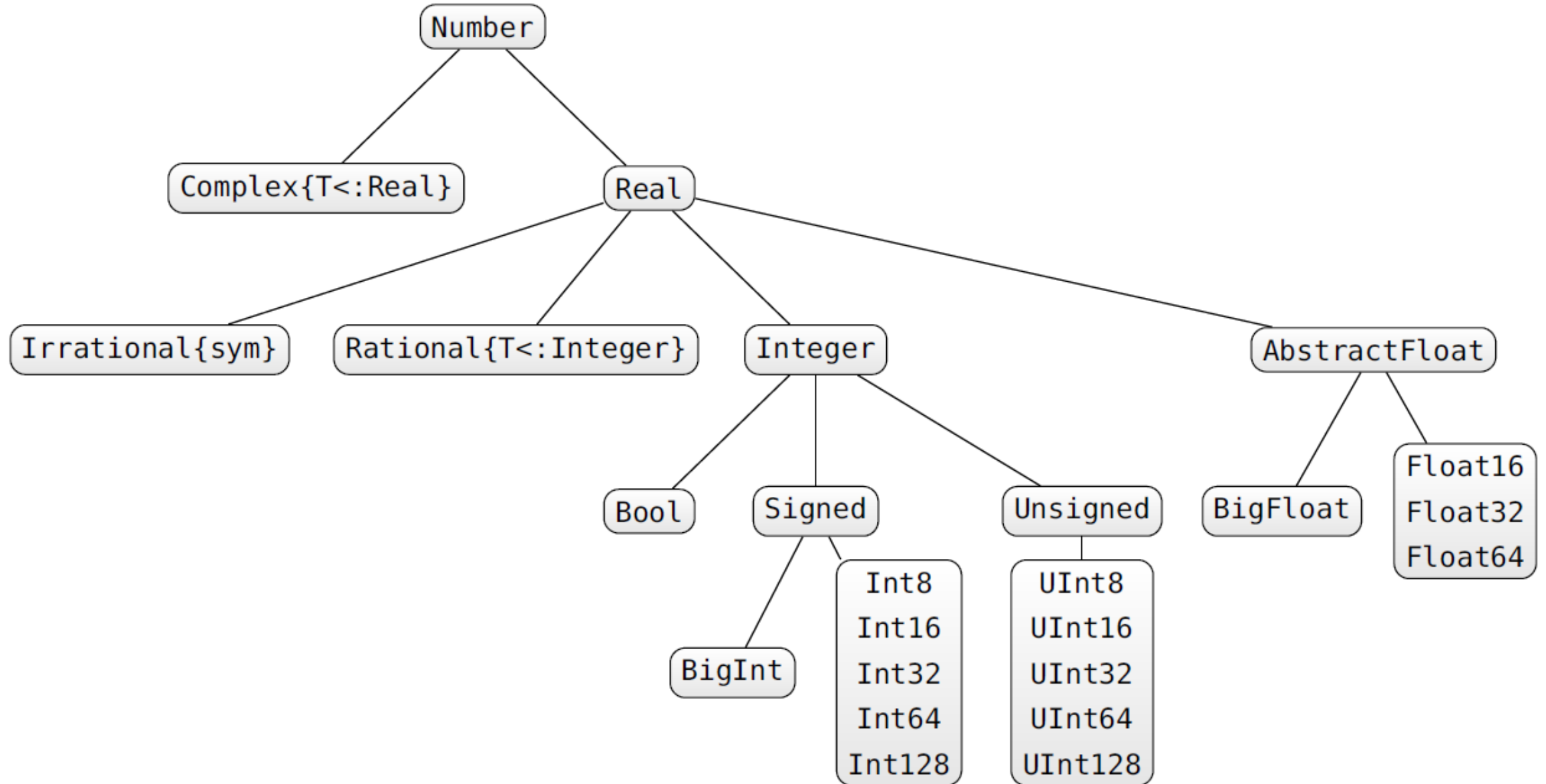
```
cd("D:/") # change working directory to D:/  
cd(raw"C:\temp")
```

```
pwd() # current directory
```

```
include("file.jl") # run file
```

```
exit() # end your Julia session
```

# Numeric type hierarchy



# Type conversion functions

- `Int64('a')` *# character to integer*
- `Int64(2.0)` *# float to integer*
- `Int64(1.3)` *# inexact error*
- `Int64("a")` *# error no conversion possible*
- `Float64(1)` *# integer to float*
- `Bool(1)` *# converts to boolean true*
- `Bool(0)` *# converts to boolean false*
- `Char(89)` *# integer to char*
- `zero(10.0)` *# zero of type of 10.0*
- `one(Int64)` *# one of type Int64*
- `convert(Int64, 1.0)` *# convert float to integer*
- `parse(Int64, "1")` *# parse "1" string as Int64*

# Special types

- `Any` # *all objects are of this type*
- `Union{}` # *subtype of all types, no object can have this type*
- `Nothing` # *type indicating nothing, subtype of Any*
- `nothing` # *only instance of Nothing*

# Tuples – just like in Python

- `()` *# empty tuple*
- `(1,)` *# one element tuple*
- `("a", 1)` *# two element tuple*
- `('a', false)::Tuple{Char, Bool}` *# tuple type assertion*
- `x = (1, 2, 3)`
- `x[1]` *# first element*
- `x[1:2]` *# (1, 2) (tuple)*
- `x[4]` *# bounds error*
- `x[1] = 1` *# error - tuple is not mutable*
- `a, b = x` *# tuple unpacking a==1, b==2*

**Tuples are immutable, and the Julia compiler makes a good use of that!**

# Arrays

```
Array{Char}(undef, 2, 3, 4)      # 2x3x4 array of Chars
Array{Any}(undef, 2, 3)         # 2x3 array of Any
zeros(5)                       # vector of Float64 zeros
ones{Int64, 2, 1}              # 2x1 array of Int64 ones
trues(3), falses(3)           # tuple of vector of trues and of falses

x = range(1, stop=2, length=5)
    # iterator having 5 equally spaced elements (1.0:0.25:2.0)
collect(x)                     # converts iterator to vector
1:10                           # iterable from 1 to 10
1:2:10                         # iterable from 1 to 9 with 2 skip
reshape(1:12, 3, 4)            # 3x4 array filled with 1:12 values
```

# Data structures

```
mutable struct Point
```

```
    x::Int64
```

```
    y::Float64
```

```
    meta
```

```
end
```

```
p = Point(0, 0.0, "Origin")
```

```
println(p.x)                                # access field
```

```
p.meta = 2                                # change field value
```

```
fieldnames(typeof(p))                      # get names of instance fields
```

```
fieldnames(Point)                          # get names of type fields
```

**Julia is not object oriented language – multiple dispatch is used instead**



# Default values require a macro

```
Base.@kwdef struct A
    a::Int = 6
    b::Float64 = -1.1
    c::UInt8 = 1
end
A()
A(a=2, c=4)
```

# Dictionaries

```
x = Dict{Int, Float64}()
    # empty dictionary (types for keys and values are defined)
y = Dict{1=>5.5, 2=>4.5}    # dictionary
y[2]                        # return element
y[3] = 30.0                 # add element

keys(y), values(y)          # iterators
haskey(y)
```

**Jeżeli chcesz elastyczną strukturę danych - użyj słownika**

# Texts and interpolations

`"Hi " * "there!"` *# concatenation*

`string("a= ", 123.3)` *# concatenation*

`x = 123`

`"$x + 3 = $(x+3)"` *# \$ is used for interpolation*

`"\$199"` *# and needs to be escaped with a `\"`*

`occursin("CD", "ABCD")` *# occurrence*

`occursin(r"A|B", "ABCD")` *# occurrence with RegExp*

# Functions

```
f(x, y = 10) = x + y  
# default value for y is 10
```

```
function g(x::Int, y::Int)      # ograniczenie typu  
    return y, x # yields a tuple  
end
```

```
g(x::Int, y::Bool) = x * y    # multiple dispatch  
g(2, true)                  # 2nd definition will be called  
methods(g)                   # list of methods for g
```

# Operators

`true || false`    *# binary or operator (singeltons only)*

`1 < 2 < 3`    *# condition chaining*

`[1 2] .< [2 1]`    *# vectorization with a dot "."*

`a = 5`

`2a + 2(a+1)`    *# multiplication "\*" can be ommited*

`x = [1 2 3]`    *#matrix 1x3 Array{Int64,2}*

`y = [1, 2, 3]`    *#vector of 3-elements Array{Int64,1}*

*# Vectors are vertical and algebra rules apply*

`x + y`    *# error*

`x .+ y`    *# 3x3 matrix, dimension broadcasting*

`x + y'`    *# 1x3 matrix*

`x * y`    *# array multiplication, 1-element vector (not scalar)*

# Numerical example – pi approximation

$$\pi = 2 \sum_{n=0}^{+\infty} \frac{n!}{(2n+1)!!}$$

```
function our_pi(n, T)
    s = one(T)
    f = one(T)
    for i::T in 1:n
        f *= i/(2i+1)
        s += f
    end
    2s
end
```

# Testing...

```
for T in [Float16, Float64, BigFloat]
    display([our_pi(2^n, T) for n in 1:10] .- big( $\pi$ ))
end
```

# BigFloat

```
julia> our_pi(1000, BigFloat)-π  
1.03634022661133335504636222353604794853392004373235376620284  
4416420231e-76
```

```
julia> setprecision(1000) do  
    our_pi(1000, BigFloat)-π  
end  
3.73305447401287551596035817889526867846836578548683209848685  
7359183867643903102537817761308391524409438379959721296970496  
8619500854161295793660832688157230249376426645533006010959803  
0394360732604440196318506045247296205005918373516322071308450  
166041524279351541770592447787925691464383688807065164177119e  
-301
```



# Rational numbers

```
julia> [our_pi(n, Rational) for n in 1:10]
10-element Array{Rational{Int64},1}:
 8//3
44//15 64//21
976//315
10816//3465
141088//45045
47104//15015
2404096//765765
45693952//14549535
45701632//14549535
```

# Julia IO – writing files

- In Julia the open command can be used to read and write to a particular file stream.

```
julia> f = open("some_name.txt", "w")  
IOStream(<file some_name.txt>)
```

- The write command takes a stream handle as the first parameter accepts a wide range of additional parameters.

```
write(f, "first line\nsecond line\n")
```

- Close the stream

```
close(f)
```

# Julia IO – reading files

```
f = open("some_name.txt")
```

In order to read a single line from a file use the readline function.

```
julia> readline(f)
```

```
"first line"
```

```
julia> readline(f)
```

```
"second line"
```

```
julia> eof(f)
```

```
true
```

```
julia> close(f)
```

# Metaprogramming and symbolic computing

## JuliaDiff

Differentiation tools in [Julia](#). [JuliaDiff on GitHub](#).

---

## Stop approximating derivatives!

Derivatives are required at the core of many numerical algorithms. Unfortunately, they are usually computed *inefficiently* and *approximately* by some variant of the finite difference approach

$$f'(x) \approx \frac{f(x+h) - f(x)}{h}, h \text{ small}.$$

This method is *inefficient* because it requires  $\Omega(n)$  evaluations of  $f: \mathbb{R}^n \rightarrow \mathbb{R}$  to compute the gradient  $\nabla f(x) = \left( \frac{\partial f}{\partial x_1}(x), \dots, \frac{\partial f}{\partial x_n}(x) \right)$ , for example. It is *approximate* because we have to choose some finite, small value of the step length  $h$ , balancing floating-point precision with mathematical approximation error.

## What can we do instead?

One option is to explicitly write down a function which computes the exact derivatives by using the rules that we know from Calculus. However, this quickly becomes an error-prone and tedious exercise. **There is another way!** The field of [automatic differentiation](#) provides methods for automatically computing *exact* derivatives (up to floating-point error) given only the function  $f$  itself. Some methods use many fewer evaluations of  $f$  than would be required when using finite differences. In the best case, **the exact gradient of  $f$  can be evaluated for the cost of  $O(1)$  evaluations of  $f$  itself.** The caveat is that  $f$  cannot be considered a black box; instead, we require either access to the source code of  $f$  or a way to plug in a special type of number using operator overloading.

# Calculus.jl – symbolic differentiation at compile time

```
julia> using Calculus
```

```
julia> differentiate(:sin(x))  
:(1 * cos(x))
```

```
julia> expr = differentiate(:sin(x) + x*x+5x)  
:(1 * cos(x) + (1x + x * 1) + (0x + 5 * 1))
```

```
julia> x = 0; eval(expr)
```