Introduction to the Julia language



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motivations

- motivations
- Julia as a numerical language

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- types and methods

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- about performance

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- → Why do not try a new language for numerical computation?

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- → let us have a look to some examples

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- functions are not supposed to modify their arguments, otherwise they follow the! convention like sort!

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- support for distributed arrays in the standard library

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```
ccall(:function, "lib"), return_type, (type_1,...,type_n), arg
```

```
None <: Int64 <: Number <: Real <: Any
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• There is a graph type in Julia reflecting the hierarchy of types

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 - type aliases

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- let us define f

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f(x::Float64,y::Float64) = 2x + y
f(x::Int,y::Int) = 2x + y
f(2.,3.) # returns 7.0
f(2,3) # returns 7.0
f(2,3.) # throw an ERROR: no method f(Int64,Float64)
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- supports parametric methods

```
myappend{T}(v::Vector{T}, x::T) = [v..., x]
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appli	fib	mandel	quicksort	pisum	randstat	randmul
Matlab	191	22	28	57	97	69
Octave	924	310	1138	21159	484	109
Python	4	7	14	1107	253	101
Руру	8	3(faux)	13	44	XXX	XXX
Julia	0.09	0.28	0.57	45	34	49
Fortran	0.08	$\leqslant 10^{-6}$	0.62	44	16	275(16)

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- more info at http://julialang.org/