A Journey Through

A DYNAMIC **AND** FAST LANGUAGE

THIBAUT CUVELIER

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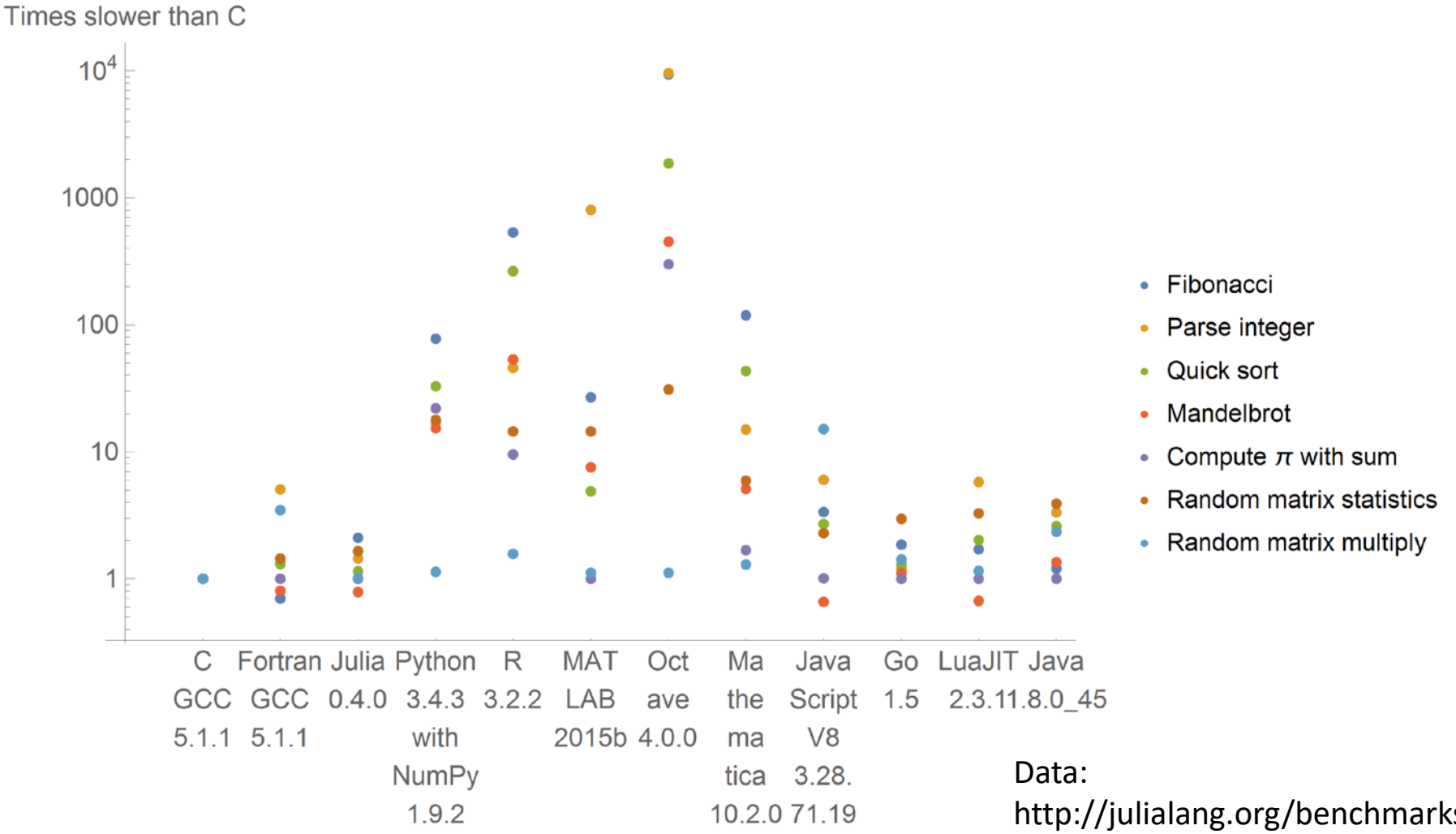
What is julia?

- A programming language
  - For scientific computing first: running times are important!
  - But still dynamic, “modern”… and extensible!

- Often compared to MATLAB, with a similar syntax…
  - … but much faster!
    - … without the need for compilation!
  - … with a large community!
  - … and free (MIT-licensed)!

How fast is julia?

Comparison of run time between several languages and C



Data: http://julialang.org/benchmarks/

How to install julia?

- Website: http://julialang.org/

- IDEs?
  - Juno: Atom with Julia extensions
    - Install Atom: https://atom.io/
    - Install Juno: in Atom, **File > Settings > Install**, search for **uber-juno**
  - JuliaDT: Eclipse with Julia extensions

  - Also: JuliaPro, a Julia distribution "with batteries included"
    - https://juliacomputing.com/products/juliapro.html

- Notebook environment?
  - IJulia (think IPython)

Notebook environment

- The default console is not the sexiest interface
  - The community provides better ones!

- **Purely online**, free: JuliaBox
  - https://juliabox.com/

- Offline, based on Jupyter (still in the browser): IJulia
  - Install with:

```
julia> Pkg.add(”IJulia”)
```

  - Run with:

```
julia> using IJulia; notebook()
```

Contents of this presentation

- Basic syntax
- Core concepts
- Julia community
  - Plotting
  - Image processing
  - Mathematical optimisation
  - Data science
- Parallel computing
  - Message passing (MPI-like)
  - Multithreading (OpenMP-like)
  - GPUs
- Concluding words

Basic syntax

A small taste of Julia

```
# Solves 0 = a x² + b x + c for x
function quad(a::Float64, b::Float64, c::Float64)
    discriminant = b^2 - 4a * c
    r1 = (- b + sqrt(discriminant)) / 2a
    r2 = (- b - sqrt(discriminant)) / 2a
    r1, r2
end
```

Core concepts

What makes Julia dynamic?

- Dynamic type system with type inference
  - Multiple dispatch (see later)
  - But static typing is preferable for performance
- Macros to generate code on the fly
  - See later
- Garbage collection
  - Automatic memory management
  - No destructors, memory freeing
- Shell (REPL)

Function overloading

- A function may have multiple implementations, depending on its arguments
  - One version specialised for integers
  - One version specialised for floats
  - Etc.

- In Julia parlance:
  - A **function** is just a name (for example, +)
  - A **method** is a “behaviour” for the function that may depend on the types of its arguments
    - `+(::Int, ::Int)`
    - `+(::Float32, ::Float64)`
    - `+(::Number, ::Number)`
    - `+(x, y)`

Function overloading: multiple dispatch

- All parameters are used to determine the method to call
  - C++'s virtual methods, Java methods, etc.: **dynamic** dispatch on the first argument, **static** for the others
  - Julia: **dynamic** dispatch on **all** arguments
- Example:
  - Class Matrix, specialisation Diagonal, with a function `add()`
  - `m.add(m2)`: standard implementation
  - `m.add(d)`: only modify the diagonal of `m`
  - What if the type of the argument is dynamic? Which method is called?

Function overloading: multiple dispatch

- What does Julia do?

- The user defines methods:
  - `add(::Matrix, ::Matrix)`
  - `add(::Matrix, ::Diagonal)`
  - `add(::Diagonal, ::Matrix)`
- When the function is called:
  - All types are **dynamically** used to choose the right method
  - Even if the type of the matrix is not known at compile time

Fast Julia code?

- First: Julia compiles the code before running it (JIT)

- To fully exploit multiple dispatch, write **type-stable** code
  - Multiple dispatch is slow when performed at run time
  - A variable should keep its type throughout a function

- If the type of a variable is 100% known, then the method to call is too
  - All code goes through JIT before execution

Object-oriented code?

- Usual syntax makes little sense for mathematical operations
  - `+(::Int, ::Float64)`: belongs to Int or Float64?
- Hence: syntax very similar to that of C
  - `f(o, args)` instead of `o.f(args)`
- However, Julia has:
  - A type hierarchy, including **abstract** types
  - Constructors

Real macros

- C-like macros are limited
  - Only text replacement
- Julia macros: can rewrite code!
  - Function that takes code in argument and outputs code

- Basic example:

```
julia> @show sqrt(complex(-1.))
sqrt(complex(-1.0)) = 0.0 + 1.0im
0.0 + 1.0im
```

Real macros

- Building block for DSLs, e.g. for differential equations:

```
g = @ode_def LorenzExample begin
    dx = σ*(y-x)
    dy = x*(ρ-z) - y
    dz = x*y - β*z
end σ=>10.0 ρ=>28.0 β=(8/3)
u0 = [1.0;0.0;0.0]
tspan = (0.0,1.0)
prob = ODEProblem(g,u0,tspan)
sol = solve(prob)
```

Community and packages

A vibrant community

- Julia has a large community
  with many extension packages available:
  - For plotting: Plots.jl, Gadfly, Winston, etc.
  - For graphs: Graphs.jl, LightGraph.jl, Graft.jl, etc.
  - For statistics: DataFrames.jl, Distributions.jl, TimeSeries.jl, etc.
  - For machine learning: JuliaML, ScikitLearn.jl, etc.
  - For Web development: Mux.jl, Escher.jl, WebSockets.jl, etc.
  - For mathematical optimisation: JuMP.jl, Convex.jl, Optim.jl, etc.

- A list of all **registered** packages: http://pkg.julialang.org/

Package manager

- How to install a package?

```
julia> Pkg.add(”PackageName”)
```

  - No .jl in the name!

- Import a package (from within the shell or a script):

```
julia> import PackageName
```

- How to remove a package?

```
julia> Pkg.rm(”PackageName”)
```

- All packages are hosted on GitHub
  - Usually grouped by interest: JuliaStats, JuliaML, JuliaWeb, JuliaOpt, JuliaPlots, JuliaQuant, JuliaParallel, JuliaMaths…
  - See a list at http://julialang.org/community/

Plots

Creating plots: **Plots.jl**

- Plots.jl: an interface to multiple plotting engines (e.g. GR or matplotlib)

- Install the interface and one plotting engine (GR is fast):

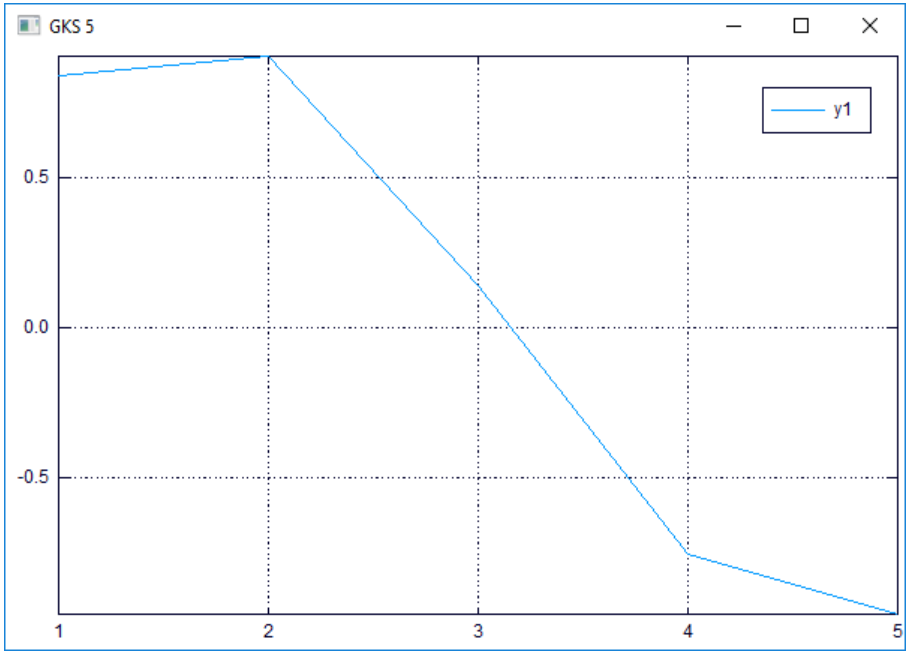
```
julia> Pkg.add(”Plots”)
julia> Pkg.add(”GR”)
julia> using Plots
```

- Documentation: https://juliaplots.github.io/

Basic plots

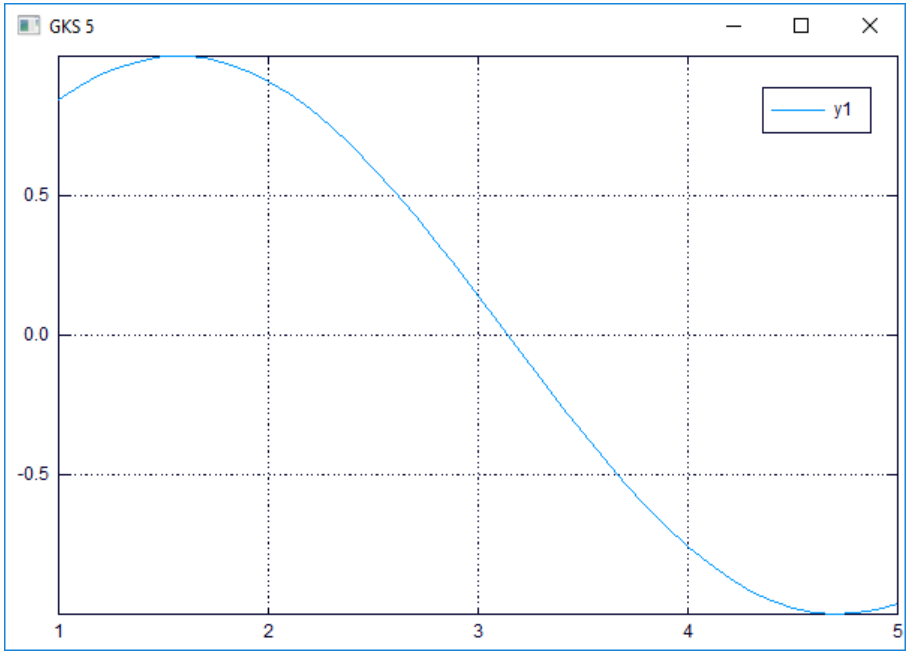
- Basic plot:

```
julia> plot(1:5, sin(1:5))
```



- Plotting a mathematical function:

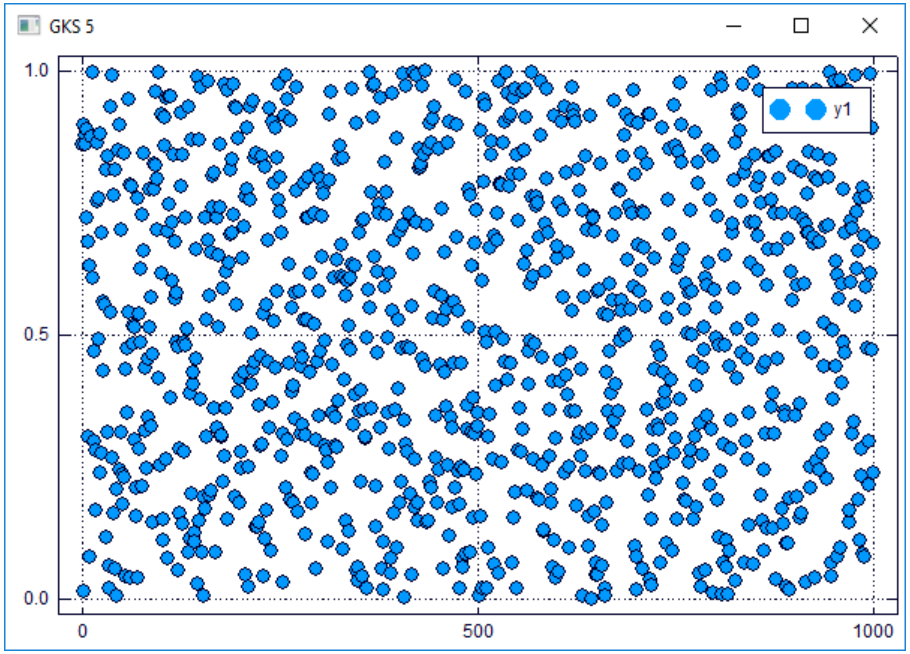
```
julia> plot(sin, 1:.1:5)
```



More plots

- Scatter plot:

```
julia> scatter(rand(1000))
```



- Histogram:

```
julia> histogram(rand(1000),
                 nbins=20)
```

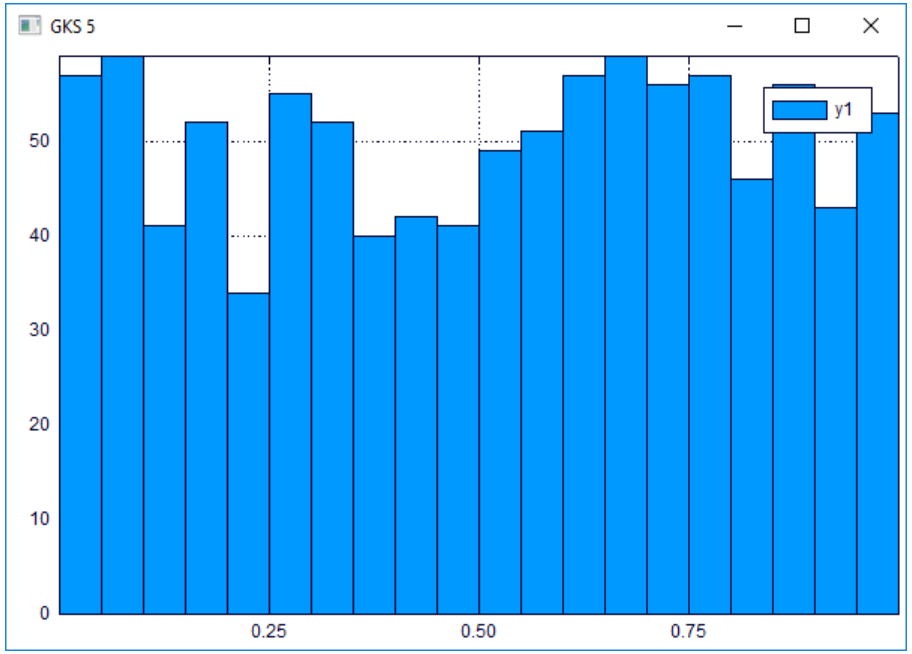


Image processing

Basic processing: **Images.jl** and family

- Part of the JuliaImages organisation
- MATLAB-like interface, with many features:
  - Filtering: ImageFiltering
  - Feature extraction: ImageFeatures
  - Not full yet
- A repository of test images: TestImages
- Standalone visualisation (outside IJulia): ImageView

Show and process an image

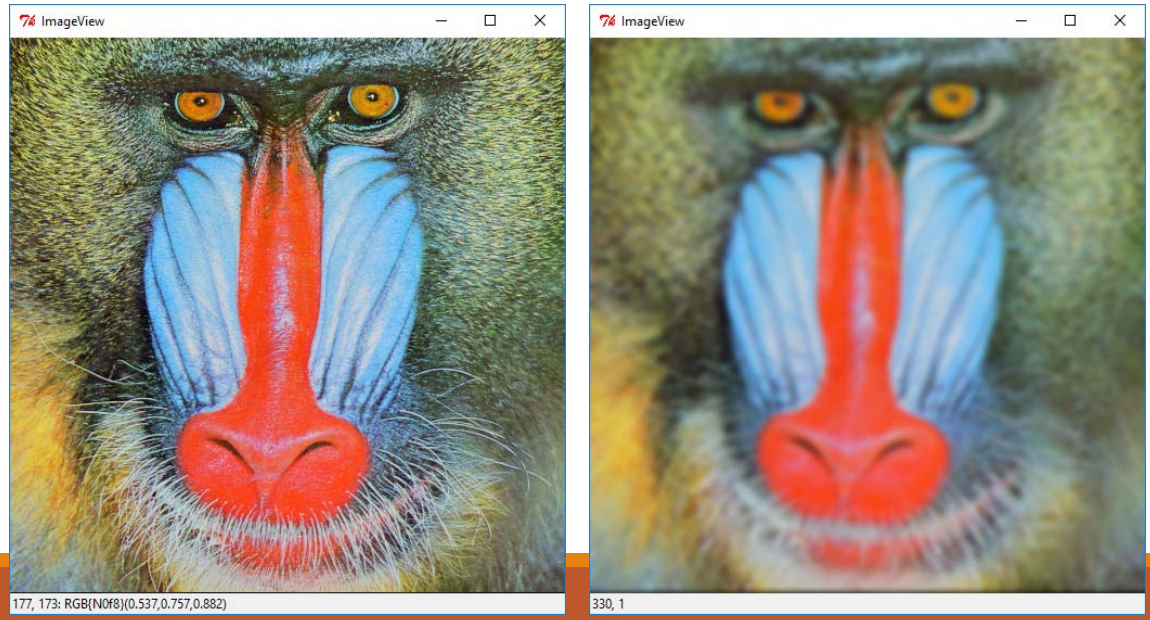
```
using Images, TestImages, ImageView,
ImageFiltering

img = testimage("mandrill")

imshow(img)

imgg = imfilter(img, Kernel.gaussian(3))

imshow(imgg)
```



Mathematical optimisation

AND MACROS!

Mathematical optimisation: **JuMP**

- JuMP provides an easy way to translate optimisation programs into code
- First: install it along with a solver

```
julia> Pkg.add(”JuMP”)
julia> Pkg.add(”Cbc”)
julia> using JuMP
```

$$\begin{aligned} &\max x + y \\ &\text{s.t. } 2x + y \leq 8 \\ &\quad 0 \leq x \leq +\infty \\ &\quad 1 \leq y \leq 20 \end{aligned}$$

```
m = Model()
@variable(m, x >= 0)
@variable(m, 1 <= y <= 20)
@objective(m, Max, x + y)
@constraint(m, 2 * x + y <= 8)
solve(m)
```

Data science

Data frames: **DataFrames.jl**

- R has the data frame type: an array with named columns

```
df = DataFrame(N=1:3, colour=[“b”, “w”, “b”])
```

- Easy to retrieve information in each dimension:

```
df[:colour]
df[1, :]
```

- The package has good support in the ecosystem
  - Easy plot with Plots.jl: just install StatPlots.jl, it just works
  - Understood by machine learning packages, etc.

Data selection: **Query.jl**

- SQL is a nice language to query information from a data base: select, filter, join, etc.
- C# has a similar tool integrated into the language (LINQ)
- Julia too, with a syntax inspired by LINQ: Query.jl
- On data frames:

```
@from i in df begin
      @where i.N >= 2
      @select {i.colour}
      @collect DataFrame
end
```

Machine learning

- Many tools to perform machine learning

- A few to cite:
  - JuliaML: generic machine learning project, highly configurable
  - GLM: generalised linear models
  - Mocha: deep learning (similar to Caffe in C++)
  - ScikitLearn: uniform interface for machine learning

Parallel programming

MULTITHREADING

MESSAGE PASSING

ACCELERATORS

Message passing

- Multiple machines (or processes) communicate over the network
  - For scientific computing: like MPI
  - For big data: like Hadoop (close to message passing)

- The Julia way?
  - Similar to MPI… but useable
  - Only one side manages the communication

Message passing

- Two primitives:
  - `r = @spawn`: start to compute something
  - `fetch(r)`: retrieve the results of the computation

  - Start Julia with `julia -p 2` for two processes on the current machine

- Example: generate a random matrix on another machine (#2), retrieve it on the main node

```
r = @spawn 2 rand(2, 2)
fetch(r)
```

Multithreading

- New (and experimental) with Julia 0.5: multithreading
- Current API (not set in stone):
  - `@Threads.threads` before a loop
  - As simple as MATLAB's `parfor` or OpenMP!
- Add the environment variable `JULIA_NUM_THREADS` before starting Julia

Multithreading

```
array = zeros(20)
@Threads.threads for i in 1:20
      array[i] = Threads.threadid()
end
```

GPU computing: **ArrayFire.jl**

- GPGPU is a hot topic currently, especially for deep learning
  - Use GPUs to perform computations
  - Many cores available (1,000s for high-end ones)
  - Very different architecture
- ArrayFire provides an interface for GPUs and other accelerators:
  - Easy way to move data
  - Premade kernels for common operations
  - Intelligent JIT rewrites operations to use as few kernels as possible
    - For example, linear algebra: **A b + c** in one kernel
- Note: CUDA offloading will probably be included in Julia
  https://github.com/JuliaLang/julia/issues/19302
  Similar to OpenMP offloading

GPU computing

- Installation:
  - First install the ArrayFire library:
    http://arrayfire.com/download/
  - Then install the Julia wrapper:

```
Pkg.add("ArrayFire")
```

  - Load it:

```
using ArrayFire
```

GPU computing

- Ensure the OpenCL backend is used (or CUDA, or CPU):

```
setBackend(AF_BACKEND_OPENCL)
```

- Send an array on the GPU:

```
a_cpu = rand(Float32, 10, 10);
a_gpu = AFArray(a_cpu);
b_gpu = AFArray(rand(Float32, 10, 10));
```

- Then work on it as any Julia array:

```
c_gpu = a_gpu + b_gpu;
```

- Finally, retrieve the results:

```
c_cpu = Array(c_gpu);
```

Concluding remarks

And so… shall I use Julia?

- First drawback of Julia: no completely stable version yet
  - Syntax can still change (but not a lot)
  - Also for packages: nothing is really 100% stable
- Quite young: appeared in 2012
  - 0.5 in September 2016 (original plans: June 2016)
  - 0.6 in January 2017 (original plans: September 2016), 1.0 just after
- … but likely to survive!
  - Enterprise backing the project: JuliaComputing
  - 7 books about Julia (5 in 2016)
- Not ready for production… yet