Julia for Technical Computing

Josh Day

https://github.com/joshday

emailjoshday@gmail.com

To run the examples

```julia
pkgs = [
    "Distributions",
    "Plots",
    "PyPlot",
    "GR",
    "RCall",
    "BenchmarkTools",
    "Query",
    "DataTables"
]

for pkg in pkgs
    Pkg.add(pkg)
end
```

Overview

- What is Julia?
- Design, Type System, and Multiple Dispatch
- Julia Packages
- Macros (if time)

What is Julia?

What is Julia?

> Julia is a high-level, high-performance dynamic programming language for technical computing, with syntax that is familiar to users of other technical computing environments.

- http://julialang.org

What is Julia?

- Solves the "Two-Language Problem"
- High-level code which produces fast, low-level machine code that has traditionally only been generated by static languages.

Benchmarks

10^4
10^3
10^2
10^1
10^0
10^{-1}
Fortran
Go
Java
JavaScript
Julia
Lua
Mathematica
Matlab
Octave
Python
R
benchmark
mandel
parse_int
pi_sum
printfd
quicksort
rand_mat_mul
rand_mat_stat

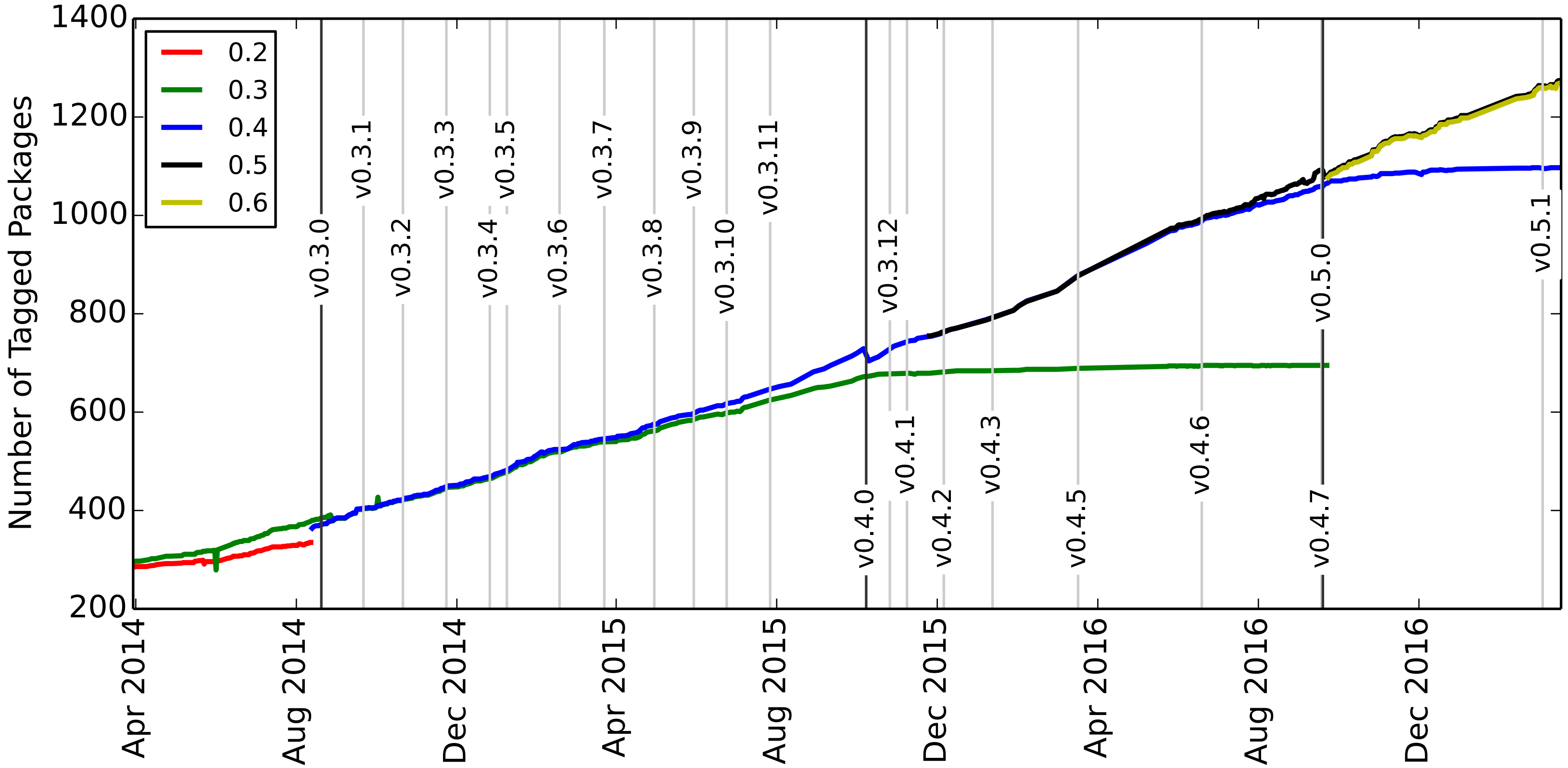
More than "Fast R" or "Fast Python"

- Julia is fast because of features which work well together
- You can't just take the magic dust that makes Julia fast and apply it to your favorite language

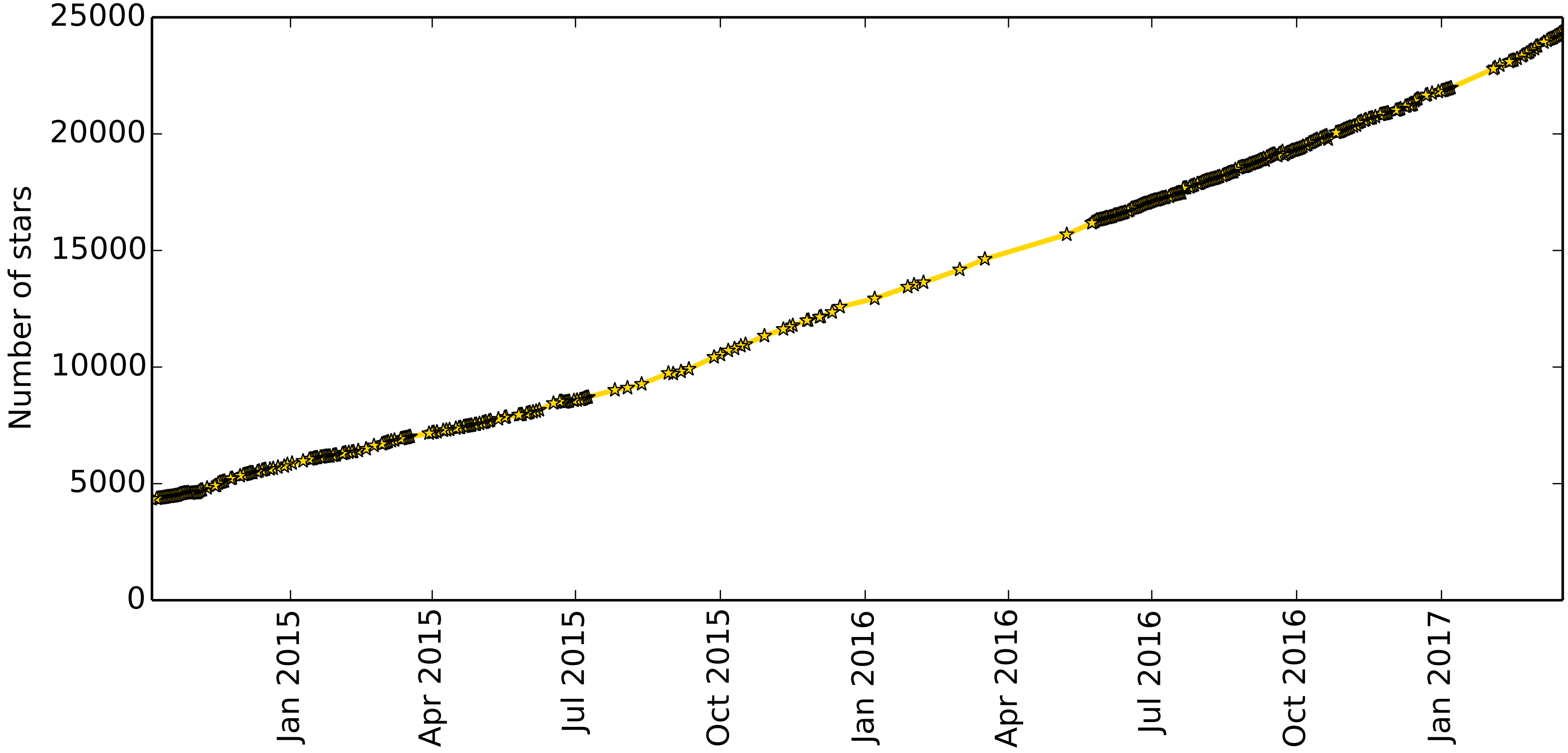
Julia Language Design

- Type system
- Multiple dispatch
- Type inference
- Metaprogramming (macros)
- Just-in-time (JIT) compilation using LLVM
- Clean, familiar syntax

Julia's Growth (Number of Packages)



Julia's Growth (Stars on GitHub)



Design, Type System, and Multiple Dispatch

Julia Basics

Everything has a type

```julia
1     # typeof(1) == Int64

1.0   # Float64

# Arrays have 1-based indexing
[1.0, 2.0]  # Vector{Float64}
```

Julia Basics

Supports Unicode Characters

- Julia's main focus is numerical computing, so creators want code to look similar to mathematical formulas:

$$\hat{\beta} = (X^T X)^{-1} X^T y$$

```
β̂ = inv(x'x)x'y  # Implicit multiplication

β̂ = inv(x' * x) * x' * y
```

- Compare this to R:

```
betahat = solve(t(x) %*% x) %*% t(x) %*% y
```

Julia Basics

Functions

```julia
f(x) = x ^ 2

# Code blocks require an `end`
function f(x)
    x ^ 2
end
```

Julia Basics

JIT

- live example with `@code_llvm` macro

```
f(x) = x ^ 2
```

Julia Basics

For loops

Input:

```julia
for i in 1:3
    println(i)
end
```

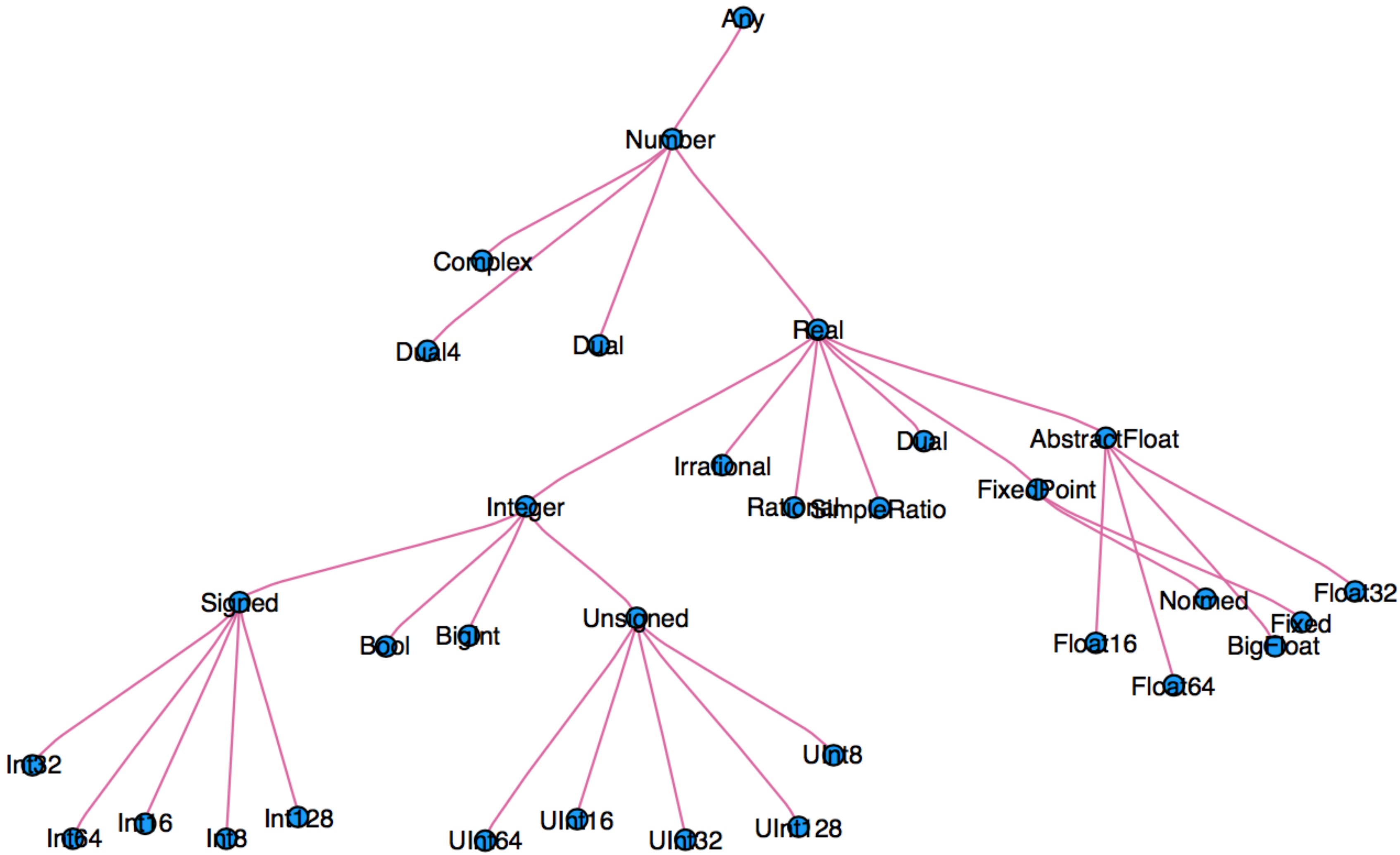
Output:

```
1
2
3
```

Type System

- When thinking about types, think about sets
- An abstract type defines a set of other types
- One abstract type in Julia is `Number`

Number


Any
Number
Complex
Dual4
Dual
Real
Integer
Irrational
Rational
SimpleRatio
Dual
FixedPoint
AbstractFloat
Signed
Bool
BigInt
Unsigned
Normed
Fixed
Float16
Float32
BigFloat
Float64
Int32
Int64
Int16
Int8
Int128
UInt64
UInt16
UInt32
UInt128
UInt8

`Number`

- What should a `Number` be able to do?
  `+`, `-`, `*`, etc.

```
methods(*)
```

```
# 178 methods for generic function "*":
*(x::Bool, z::Complex{Bool}) in Base at complex.jl:225
*(x::Bool, y::Bool) in Base at bool.jl:91
*(x::Bool, y::T) where T<:Unsigned in Base at bool.jl:104
*(x::Bool, z::Complex) in Base at complex.jl:232
*(x::Bool, y::Irrational) in Base at irrationals.jl:105
*(x::Bool, y::T) where T<:Number in Base at bool.jl:101
*(a::Float16, b::Float16) in Base at float.jl:368
*(x::Float32, y::Float32) in Base at float.jl:374
*(x::Float64, y::Float64) in Base at float.jl:375
...
```

Multiple Dispatch

- The idea of calling different code depending on the types of the arguments is called multiple dispatch.
- Consider the Distributions package, where every distribution has its own type.

```
using Distributions

mean(Normal(0,1)) == 0.0

mean(Gamma(10,6)) == 60.0
```

Abstraction

- Consider these three function definitions:

```julia
# Too broad:  Not everything can be added
f(x) = x + x


# Too specific:  Numbers besides Float64 can be added
g(x::Float64) = x + x


# Just right:  Every number has a `+` method, so this
# works on the entire type tree in the previous slide
h(x::Number) = x + x
```

Quantile Example

- Suppose I want to find quantiles using Newton's method:

$$\theta_{t+1} = \theta_t - \frac{F(\theta_t) - q}{F'(\theta_t)}$$

where F is the CDF of a distribution

- In R, I would need a different function for every distribution!
- In Julia, we can do this in one function

The Power of Julia: Abstraction

- Define functions for the "highest" type you can
- A `UnivariateDistribution` has methods `mean`, `cdf`, `pdf`

```
using Distributions

function myquantile(d::UnivariateDistribution, q::Number)
    θ = mean(d)
    tol = Inf
    while tol > 1e-5
        θold = θ
        θ = θ - (cdf(d, θ) - q) / pdf(d, θ)
        tol = abs(θold - θ)
    end
    θ
end
```

Input:

```julia
for d in [Normal(), Gamma(5,1), TDist(4)]
    println("For $d")
    println("  > myquantile: $(myquantile(d, .4))")
    println("  > quantile:   $(quantile(d, .4))\n")
end
```

Output:

```
For Distributions.Normal{Float64}(μ=0.0, σ=1.0)
  > myquantile: -0.2533471031356957
  > quantile:   -0.2533471031357997

For Distributions.Gamma{Float64}(α=5.0, θ=1.0)
  > myquantile: 4.1477358804705435
  > quantile:   4.1477358804705435

For Distributions.TDist{Float64}(ν=4.0)
  > myquantile: -0.27072229470638115
  > quantile:   -0.27072229470759746
```

Defining types

- Your own types are just as performant as Julia's built-ins.
- Most of Julia is written in Julia

```julia
# Can change `a` after creating a new instance
type MyType
    a::Int64
end

# Can NOT change `a` after creation
immutable MyOtherType{T <: Number}
   a::T
end
```

Defining methods

Input:

```
f(m::MyType) = o.a + o.a

o = MyType(4)
f(o)
```

Output:

```
8
```

Julia's Package Ecosystem

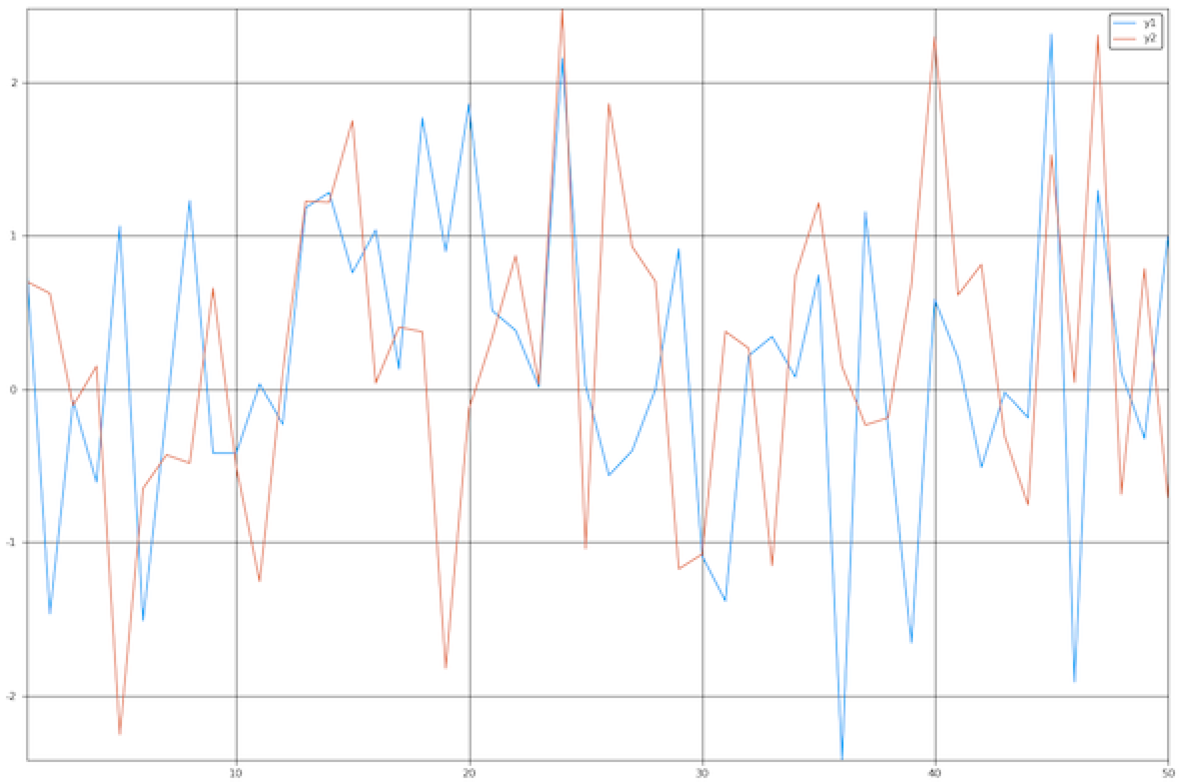
Plotting and Graphics

Julia does not have a built-in plotting package

- Plots
  - Defines a plotting API that can use several "backends"
- Gadfly
  - Grammar of graphics for Julia
- Others: PyPlot, UnicodePlots, GR, GLPlot, Winston, ...

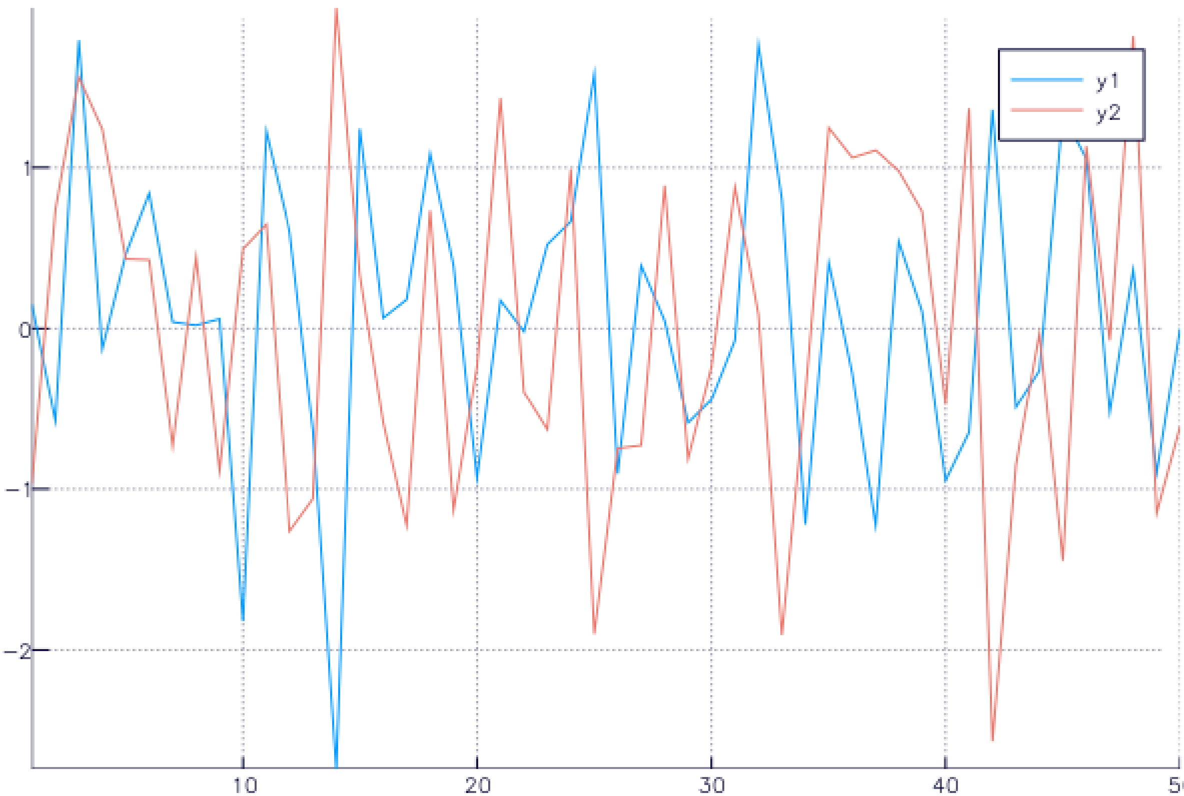
Plots with PyPlot

```
using Plots
pyplot()  # use PyPlot backend
plot(randn(50, 2))
```



Plots with GR

```
gr()  # use GR backend
plot(randn(50, 2))
```



Easy Animations

```
anim = @animate for i in 1:20
    plot(sin, 0, i, xlim = (0,20), ylim = (-1, 1))
end
gif(anim, "/Users/joshday/Desktop/my_animation.gif")
```

```
INFO: Saved animation to /Users/joshday/Desktop/my_animat
```

Calling R from Julia

- Side note: REPL modes
  - `;` (shell mode)
  - `?` (help mode)
- RCall adds
  - `$` (R mode)

```
using RCall
R"rnorm(5)"
```

Calling Python from Julia

Input:

```
using PyCall
@pyimport math

math.pi
```

Output:

```
3.141592653589793
```

Statistics, Working with Data, Machine Learning, etc.

- StatsBase, GLM, DataFrames, Query, MixedModels, Distributions, KernelDensity, OnlineStats, LossFunctions,

StatsBase

Much of the functionality built into R

```
using StatsBase

sample(1:5, 5, replace = false)
```

DataFrames and DataTables

- Both for working with tabular data
- DataTables is a fork of DataFrames
    - Behind the scenes containers are different
        - `DataArray` vs. `NullableArray`

DataTables

Input:

```
iris = readtable(joinpath(Pkg.dir("DataTables"), "test/da
head(iris)
```

Ouput:

```
6×5 DataTables.DataTable
│ Row │ SepalLength │ SepalWidth │ PetalLength │ PetalWid
├─────┼─────────────┼────────────┼─────────────┼─────────
│ 1   │ 5.1         │ 3.5        │ 1.4         │ 0.2
│ 2   │ 4.9         │ 3.0        │ 1.4         │ 0.2
│ 3   │ 4.7         │ 3.2        │ 1.3         │ 0.2
│ 4   │ 4.6         │ 3.1        │ 1.5         │ 0.2
│ 5   │ 5.0         │ 3.6        │ 1.4         │ 0.2
│ 6   │ 5.4         │ 3.9        │ 1.7         │ 0.4
```

Query (query almost any data source)

```
using Query

x = @from i in iris begin
    @where i.Species == "setosa" && i.PetalLength > 1.7
    @select i
    @collect DataTable
end
```

```
2×5 DataTables.DataTable
│ Row │ SepalLength │ SepalWidth │ PetalLength │ PetalWid
├─────┼─────────────┼────────────┼─────────────┼─────────
│ 1   │ 4.8         │ 3.4        │ 1.9         │ 0.2
│ 2   │ 5.1         │ 3.8        │ 1.9         │ 0.4
```

Macros

Macros

- Macros are functions of expressions
- They change an expression before it is run, and can therefore do many things!

```
x = randn(1000);

@time sum(x)  # JIT at work
#   0.031018 seconds (12.86 k allocations: 602.013 KB)
# -34.195601715147035

@time sum(x)
#   0.000003 seconds (5 allocations: 176 bytes)
# -34.195601715147035
```

Macros (turn off bounds checking)

```
x = rand(1000)

for i in eachindex(x)
    @inbounds x[i] *= 5.0
end
```

Macros (benchmarking)

```
using BenchmarkTools
@benchmark sum(x)
```

```
BenchmarkTools.Trial:
  memory estimate:  16 bytes
  allocs estimate:  1
  --------------
  minimum time:     223.916 ns (0.00% GC)
  median time:      231.385 ns (0.00% GC)
  mean time:        237.263 ns (0.86% GC)
  maximum time:     7.247 μs (95.52% GC)
  --------------
  samples:          10000
  evals/sample:     455
  time tolerance:   5.00%
  memory tolerance: 1.00%
```

Macros (Other)

```
@which sum(x)  # find the method being called
@edit sum(x)   # open file where the method is
```

Summary

- Julia is ideal for developing projects from scratch/with few dependencies
- The package ecosystem grows fast but is still lacking much of the functionality you can find in R.
- There are also many interesting things in Julia that R doesn't have:
    - Plots, Convex, JuMP, OnlineStats, Distributions, LossFunctions, ...

Thank You