Performance and profiling in Julia

Fredrik Bagge Carlson[1]

[1]Julia Computing

Outline

1. Write code with performance in mind (think like a compiler)
2. Profile your code
3. Optimize your code

Step one, put your code in functions

A global variable might have its value and its type change at any point. This makes it difficult for the compiler to optimize code using global variables.

$\Downarrow$

Any code that is performance critical or being benchmarked should be inside a function.

```
a = 1
@btime for i = 1:100_000
    global a
    a += 1
end
    1.543 ms
    (100000 allocations: 1.53 MiB)
```

```
function foo()
    a = 1
    for i = 1:100_000
        a += 1
    end
    a
end
@btime foo()
    1.270 ns
    (0 allocations: 0 bytes)
```

Avoid global variables (unless declared `const` or type annotated)

```julia
PRINT = false
function foo()
  for i = 1:1_000_000_000
    if PRINT
      print(i)
    end
  end
end
@time foo()
  0.795711 seconds
```

```julia
const PRINT = false
function foo()
  for i = 1:1_000_000_000
    if PRINT
      print(i)
    end
  end
end
@time foo()
  0.000002 seconds
```

`PRINT` is `false` in both cases, but the compiler can rely on it in the second case

Type declarations, type stability

Useful as assertion for debugging, but does not make the code faster (unless mitigating type instability).
Exception: Declare specific types for fields of composite types so that the compiler knows the memory layout

```julia
struct Foo
    field
end
```

```julia
struct Foo
    field::Type
end
```

It is in general bad for performance when the type of a variable can be changed at runtime, type annotation will prevent this.

Type stability

An example of type instability

```julia
stable(i) = rand() > .5 ? 1 : -1

function foo()
    a = 1
    for i = 1:100_000
        a += stable(i)
    end
    a
end

@btime foo()
  162.940 μs
```

```julia
unstable(i) = rand() > .5 ? 1. : -1

function bar()
    a = 1
    for i = 1:100_000
        a += unstable(i)
    end
    a
end

@btime bar()
  684.704 μs
```

In `bar` the compiler does not know ahead of time which `+` method to call (`Int` or `Float64`) and dispatch happens at runtime.

Type stability

```
quasistable(i) = rand() > 1.5 ? 1. : -1

function baz()
    a = 1
    for i = 1:100_000
        a += quasistable(i)::Int
    end
    a
end
```

```
@btime foo()
162.940 μs
@btime bar()
684.704 μs
@btime baz()
170.997 μs

julia> @code_warntype quasistable(1)
 Body::Union{Float64, Int64}
```

Now the compiler knows that the type is `Int` after the type assertion, and dispatch can be determined at compile time, even though the return type of `quasistable` is set valued.

Julia uses column major convention

```julia
function foo()
    x = Matrix{Float64}(undef, 4096, 4096)
    for i = 1:size(x,1)
        for j = 1:size(x,2)
            x[i,j] = i*j
        end
    end
end
@btime foo()
102.165 ms (2 allocations: 128.00 MiB)
```

```julia
function bar()
    x = Matrix{Float64}(undef, 4096, 4096)
    for j = 1:size(x,2)
        for i = 1:size(x,1)
            x[i,j] = i*j
        end
    end
end
@btime bar()
19.745 ms (2 allocations: 128.00 MiB)
```

Think about this when you are choosing how to store your data!

Avoid unnecessary memory allocation

Julia passes arrays as references.[1] Use this to re-use already allocated memory.

```julia
function food()
    A = Matrix{Int64}(undef,100,100)
    for i = eachindex(A)
        A[i] = i
    end
    return A
end

function eat()
    for i = 1:10_000
        chicken = food()
        sum(chicken)
    end
end
@btime eat()
144.466 ms (20000 allocations: 763.70 MiB)
```

New plate every time, lots of time to clean! (garbage collect)

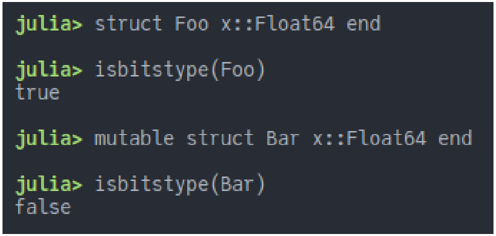
```julia
function beer!(A)
    for i = eachindex(A)
        A[i] = i
    end
end

function drink()
    glass = Matrix{Int64}(undef,100,100)
    for i = 1:10_000
        beer!(glass)
        sum(glass)
    end
end
@btime drink()
54.119 ms (2 allocations: 78.20 KiB)
```

Use the same glass every time, drink beer faster!

[1] Technically, by *sharing*

Try to keep structs immutable

- Mutable structs (typically) end up on the heap.
- `isbits` structs (typically) end up on the stack.
- Mutability is bug prone.



```
julia> struct Foo x::Float64 end

julia> isbitstype(Foo)
true

julia> mutable struct Bar x::Float64 end

julia> isbitstype(Bar)
false
```

Profile your code

Profiling

Profiling

Your goto-tool is always `@btime` from `BenchmarkTools.jl`, watch memory allocation and GC-time

- Type instability
- Allocations
- Do not benchmark in global scope
- Do not benchmark compilation time (unless it gets insanely long)
- Interpolate global variables `@btime testfun($a)`
- `@btime` runs the expression several times and reports the minimum

Profiling

Julia has built in profiling capabilities

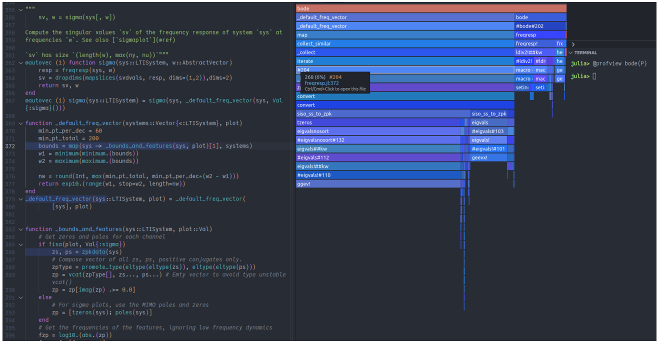
```
julia> @profile foo()
```

```
julia> Profile.print()
      23 client.jl; _start; line: 373
        23 client.jl; run_repl; line: 166
           23 client.jl; eval_user_input; line: 91
              23 profile.jl; anonymous; line: 14
                 8  none; myfunc; line: 2
                  8 dSFMT.jl; dsfmt_gv_fill_array_close_open!; line: 128
                 15 none; myfunc; line: 3
                  2  reduce.jl; max; line: 35
                  2  reduce.jl; max; line: 36
                  11 reduce.jl; max; line: 37
```

Vscode profile view

The profile viewer in Vscode is nicer

```julia
@profview bode(P)
```



```julia
"""
    sv, w = sigma(sys[, w])

Compute the singular values `sv` of the frequency response of system `sys` at
frequencies `w`. See also [`sigmaplot`](@ref)

`sv` has size `(length(w), max(ny, nu))`"""
@autovec (1) function sigma(sys::LTISystem, w::AbstractVector)
    resp = freqresp(sys, w)
    sv = dropdims(mapslices(svdvals, resp, dims=(1,2)),dims=2)
    return sv, w
end
@autovec (1) sigma(sys::LTISystem) = sigma(sys, _default_freq_vector(sys, Val
{:sigma}()))

function _default_freq_vector(systems::Vector{<:LTISystem}, plot)
    min_pt_per_dec = 60
    min_pt_total = 200
    bounds = map(sys -> _bounds_and_features(sys, plot)[1], systems)
    w1 = minimum(minimum.(bounds))
    w2 = maximum(maximum.(bounds))

    nw = round(Int, max(min_pt_total, min_pt_per_dec*(w2 - w1)))
    return exp10.(range(w1, stop=w2, length=nw))
end
_default_freq_vector(sys::LTISystem, plot) = _default_freq_vector(
        [sys], plot)


function _bounds_and_features(sys::LTISystem, plot::Val)
    # Get zeros and poles for each channel
    if !isa(plot, Val{:sigma})
        zs, ps = zpkdata(sys)
        # Compose vector of all zs, ps, positive conjugates only.
        zpType = promote_type(eltype(eltype(zs)), eltype(eltype(ps)))
        zp = vcat(zpType[], zs..., ps...) # Emty vector to avoid type unstable
        vcat()
        zp = zp[imag(zp) .>= 0.0]
    else
        # For sigma plots, use the MIMO poles and zeros
        zp = [tzeros(sys); poles(sys)]
    end
    # Get the frequencies of the features, ignoring low frequency dynamics
    fzp = log10.(abs.(zp))
```

```
julia> @profview bode(P)
julia>
```

See also ProfileView.jl and StatProfilerHTML.jl

Profiling tools

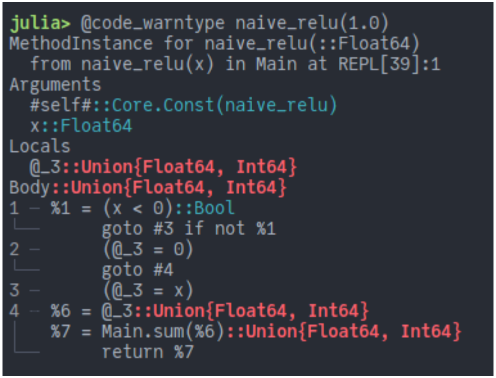
`@profview_allocs`

An allocation profiler, similar to the time profiler.

`@code_warntype`

Ask the compiler what it thinks about your types

```
julia> naive_relu(x) = sum(x < 0 ? 0 : x)
```



```
julia> @code_warntype naive_relu(1.0)
MethodInstance for naive_relu(::Float64)
  from naive_relu(x) in Main at REPL[39]:1
Arguments
  #self#::Core.Const(naive_relu)
  x::Float64
Locals
  @_3::Union{Float64, Int64}
Body::Union{Float64, Int64}
1 ─ %1 = (x < 0)::Bool
└──      goto #3 if not %1
2 ─      (@_3 = 0)
└──      goto #4
3 ─      (@_3 = x)
4 ┄ %6 = @_3::Union{Float64, Int64}
│   %7 = Main.sum(%6)::Union{Float64, Int64}
└──      return %7
```

Benchmarking

- Put your code in functions
- Let the function compile before timing (or use `@btime`)
- Watch out for unexpected memory allocation
- Read the performance tips!

Optimize your code

Optimization

Optimize your code

- Write a test before you start optimizing to make sure you are still calculating the same thing
- Use the result of `@profview`, `@profview_allocs`, `@btime`
- If your code spends 50% doing garbage collection, you can sometimes reduce your running time with *more than* 50% by better memory management.

Optimize your code

```
function slowfunc(x)
    a = foo(x)
    for i = 1:1000
        b = bar(a, randn(2))
        for j = 1:1000
            c = randn(5)
            b += baz(c)
        end
        a += b
    end
    a
end
```

Where do you start looking?

SIMD

Single Instruction Multiple Data

```julia
a64 = randn(1000000)
a32 = randn(Float32, 1000000)
function regular_sum(x)
    s = zero(eltype(x))
    for i = eachindex(x)
        s += x[i]
    end
    s
end
```

```julia
function simd_sum(x)
    s = zero(eltype(x))
    @inbounds @simd for i = eachindex(x)
        s += x[i]
    end
    s
end
```

```
@btime regular_sum($a64)
646.580 μs (0 allocations: 0 bytes)
@btime regular_sum($a32)
610.543 μs (0 allocations: 0 bytes)
```

```
@btime simd_sum($a64)
62.899 μs (0 allocations: 0 bytes)
@btime simd_sum($a32)
31.910 μs (0 allocations: 0 bytes)
```

SIMD

LoopVectorization.jl

```
using LoopVectorization
function turbo_sum(x)
    s = zero(eltype(x))
    @tturbo for i = eachindex(x)
        s += x[i]
    end
    s
end

@btime turbo_sum($(a64))
12.624 μs (0 allocations: 0 bytes)
@btime turbo_sum($(a32))
11.332 μs (0 allocations: 0 bytes)
```

StaticArrays

One of the biggest speed-ups (after choosing the right algorithm) if often to use StaticArrays where available

- Size known at compile time
- Optimized operations
- Stack allocated (as opposed to heap allocated)

Benchmarks for 3×3 Float64 matrices

```
Matrix multiplication                 -> 8.2x speedup
Matrix multiplication (mutating)      -> 3.1x speedup
Matrix addition                       -> 45x speedup
Matrix addition (mutating)            -> 5.1x speedup
Matrix determinant                    -> 170x speedup
Matrix inverse                        -> 125x speedup
Matrix symmetric eigendecomposition -> 82x speedup
Matrix Cholesky decomposition         -> 23.6x speedup
```

StaticArrays

Details

- Size and type hard coded, known at compile time
- `VectorSVector` has same memory layout as `Matrix`

```
using StaticArrays
a  = [randn(3) for _ = 1:1000]
am = randn(3,1000)
as = [@SVector randn(3) for _ = 1:1000]
@btime sum($a)
    27.917 μs (999 allocations: 109.27 KiB)
@btime sum($am, dims=2)
    2.798 μs (7 allocations: 304 bytes)
@btime sum($as)
    759.379 ns (0 allocations: 0 bytes)
```

Misc.

FillArrays.jl Represent special arrays efficiently

`repmat`,`repeat` If you use these to force your problem into a vectorized form, you need to de-matlabify yourself

`collect(1:10)` You often do not need to collect.

Avoid allocating slices
`A[:,i]` allocates and copies data, `@view(A[:,i])` doesn't. (`A[i,:]` might however be worth it.)

Parallel Threading and distributed computing

dot-fusion `R = sin.(exp.(A.^2))` compiles into a single loop

- No temporary arrys
- Single pass over data

```
R = similar(a)
for i in eachindex(a)
    R[i] = sin(exp(a[i]^2))
end
```

Other resources

- I would first and foremost recommend the performance tips section in the manual, it's quite comprehensive and readable: `https://docs.julialang.org/en/v1/manual/performance-tips/index.html`
- Chris Rackaukas has some tutorials on solving ODEs and PDEs in Julia. He highlights a lot of neat Julia functionality and goes through a lot of performance optimizations that extend also outside the realm of ODEs and PDEs `https://youtu.be/KPEqYtEd-zY` Watch around minute 49 for performance optimization `https://youtu.be/okGybBmihOE`
- An introduction to high performance custom arrays | Matt Bauman `https://www.youtube.com/watch?v=jS9eouMJf_Y&t=1831s&list=PLP8iPy9hna6Qsq5_-zrg0NTwqDSDYtfQB&index=82`

Homework

Monte-Carlo simulation of a bootstrap particle filter

- I provide the baseline code
- My code provides a decent particle filter implementation
- The code is bad from a julia-performance point of view
- Your job is to optimize it
- Optimized code has to be equivalent (do not implement different algorithm)

$$x^+ = 0.5x + \frac{25x}{1+x^2} + 8\cos(1.2(t-1)) + w$$
$$y = 0.05x^2 + v$$
$$w, v \sim \mathcal{N}(0, \sigma_w),\ \mathcal{N}(0, \sigma_v) \quad E(wv^\top) = 0$$

The particle filter

```
for t = 2:T # Main loop
    # Resample
    j = resample(w[t-1,:])
    # Time update
    xp[t,:] = f(xpT,t-1) + σw*randn(1,N)
    # Measurement update
    w[t,:] = wT + g(y[t]-0.05xp[t,:].^2)
    # Normalize weights
    w[t,:] -= log(sum(exp(w[t,:])))
end
```

⋮

The Monte-Carlo simulation

```julia
particle_count = [5 10 20 50 100 200 500 1000 10_000]
time_steps = [20, 200, 2000]
for (Ti,T) in enumerate(time_steps)
  for (Ni, N) in enumerate(particle_count)
    # Calculate how many Monte-Carlo runs to perform for the current
    # T,N configuration
    montecarlo_runs =
        maximum(particle_count)*maximum(time_steps) / T / N
    for mc_iter = 1:montecarlo_runs
      for t = 1:T-1 # Simulate one realization of the model
        x[t+1] = f(x[t],t) + σw*randn()
        y[t+1] = 0.05x[t+1]^2  + σv*randn()
      end # t
      xh = pf(y, N, g, f, σw0) # Run the particle filter
      RMS += rms(x-xh) # Store the error
    end # MC
```

⋮