SciencesPo Computational Economics
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1 The Julia-is-Fast Benchmark Fun: `sum`

(This material began life as a wonderful lecture by Steven Johnson at MIT: https://github.com/stevengj/18S096/blob/master/lectures/lecture1/Boxes-and-registers.ipynb.)

In this notebook we are going to compare performance of a very simple function across several different languages: The `sum`. This function computes

$$\mathrm{sum}(a) = \sum_{i=1}^{n} a_i$$

where n is the length of `a`. Let's get a vector of numbers:

```
In [1]: a = rand(10^7) # 1D vector of random numbers, uniform on [0,1)
```

```
Out[1]: 10000000-element Array{Float64,1}:
 0.1663319579196314
 0.30895312060879365
 0.6179474041044644
 0.061276443748349 73
 0.2573021832089899
 0.16796863745240764
 0.27852662730874767
 0.5086510453252497
 0.1560114763009781
 0.7288501465239252
 0.11324653454998068
 0.12629501636416296
 0.9000757666639296
 ⋮
 0.7236680378178086
 0.8672746082443499
 0.6332323213343003
 0.4469263836490769
 0.6862137821151018
 0.9506520059092591
```

```
0.17982818693745917
0.06950168957092684
0.7418679573560714
0.6435725623459287
0.9592755512624958
0.9511577329348149
```

We would expect to see 0.5*10^7, since each element has an expected value of 0.5.
Benchmarks in different languages
We will use BenchmarkTools.jl for this exercise. This is because the standard `@time` macro suffers from sample bias:

```
In [2]: @time sum(a)

        @time sum(a)

        @time sum(a)
```

```
  0.045626 seconds (94.66 k allocations: 4.730 MiB)
  0.004711 seconds (5 allocations: 176 bytes)
  0.004619 seconds (5 allocations: 176 bytes)
```

```
Out[2]: 5.000250466313629e6
```

```
In [3]: using BenchmarkTools
```

1.1 C is what you have to beat

C is often considered the gold standard: difficult on the human, nice for the machine. Getting within a factor of 2 of C is often satisfying. Nonetheless, even within C, there are many kinds of optimizations possible that a naive C writer may or may not get the advantage of.

One can compile C code in Julia. Note that the `"""` wrap a multi-line string.

```
In [4]: C_code = """
        #include <stddef.h>
        double c_sum(size_t n, double *X) {
            double s = 0.0;
            for (size_t i = 0; i < n; ++i) {
                s += X[i];
            }
            return s;
        }
        """

        const Clib = tempname()   # make a temporary file


        # compile to a shared library by piping C_code to gcc
```

```
# (works only if you have gcc installed):
using Libdl

open(`gcc  -fPIC -O3 -ffast-math -msse3 -xc -shared -o $(Clib * "." * Libdl.dlext) -`,
    print(f, C_code)
end

# define a Julia function that calls the C function:
c_sum(X::Array{Float64}) = ccall(("c_sum", Clib), Float64, (Csize_t, Ptr{Float64}), len

c_sum(a)

c_sum(a)  sum(a) # type \approx and then <TAB> to get the  symbolb

c_bench = @benchmark c_sum($a)

println("C: Fastest time was $(minimum(c_bench.times) / 1e6) msec")

d = Dict()  # a "dictionary", i.e. an associative array
d["C"] = minimum(c_bench.times) / 1e6  # in milliseconds
d
```

```
C: Fastest time was 4.414939 msec
```

Out[4]:
```
Dict{Any,Any} with 1 entry:
  "C" => 4.41494
```

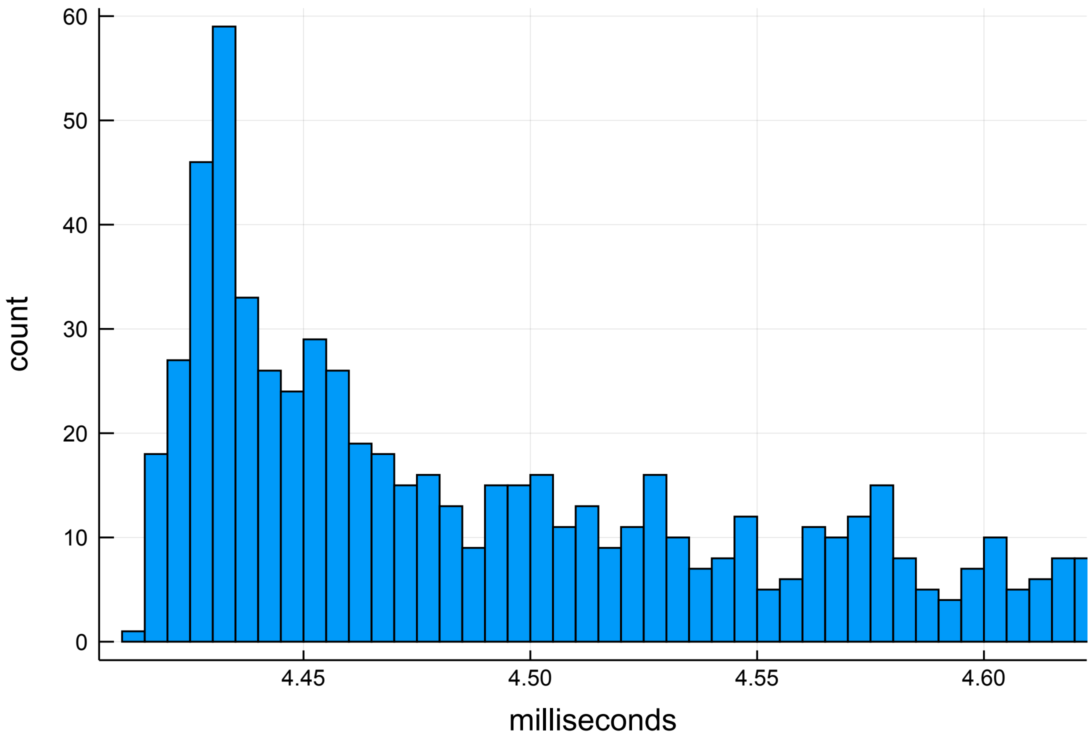
We can see above that the BenchmarkTools library takes many sample runs to account for machine noise in the benchmark. We can look at the distribution of times:

In [5]:
```
using Plots

t = c_bench.times / 1e6 # times in milliseconds
using Statistics
m,  = minimum(t), std(t)

histogram(t, bins=500,
    xlim=(m - 0.01, m + ),
    xlabel="milliseconds", ylabel="count", label="")
```

Out[5]:



1.2 Next: python's built-in `sum`

In [6]:
```
using PyCall

# Call a low-level PyCall function to get a Python list, because
# by default PyCall will convert to a NumPy array instead (we benchmark NumPy below):

apy_list = PyCall.array2py(a, 1, 1)

# get the Python built-in "sum" function:
pysum = pybuiltin("sum")

pysum(a)

pysum(a)  sum(a)

py_list_bench = @benchmark $pysum($apy_list)

d["Python built-in"] = minimum(py_list_bench.times) / 1e6
d
```

Out[6]:
```
Dict{Any,Any} with 2 entries:
  "C"               => 4.41494
  "Python built-in" => 54.7549
```

1.3 Next: python's numpy `sum`

Takes advantage of hardware "SIMD", but only works when it works.

`numpy` is an optimized C library, callable from Python. It may be used within Julia as follows:

```
In [7]: using Conda

        numpy_sum = pyimport("numpy")["sum"]
        apy_numpy = PyObject(a) # converts to a numpy array by default

        py_numpy_bench = @benchmark $numpy_sum($apy_numpy)

        numpy_sum(apy_list) # python thing

        numpy_sum(apy_list)  sum(a)

        d["Python numpy"] = minimum(py_numpy_bench.times) / 1e6
        d
```

```
Out[7]: Dict{Any,Any} with 3 entries:
          "C"                => 4.41494
          "Python numpy"     => 4.6328
          "Python built-in" => 54.7549
```

1.4 Next: python hand-written

We could try and see how our hand-written implementation performs:

```
In [8]: py"""
        def py_sum(a):
            s = 0.0
            for x in a:
                s = s + x
            return s
        """

        sum_py = py"py_sum"

        py_hand = @benchmark $sum_py($apy_list)

        sum_py(apy_list)

        sum_py(apy_list)  sum(a)

        d["Python hand-written"] = minimum(py_hand.times) / 1e6
        d
```

```
Out[8]: Dict{Any,Any} with 4 entries:
          "C"                    => 4.41494
```

```
 "Python numpy"         => 4.6328
 "Python hand-written" => 284.278
 "Python built-in"     => 54.7549
```

1.5 julia built-in

`julias` library is written entirely in julia! No `C` at all! you can easily look at the code by typing

```
In [9]: @which sum(a)
```

```
Out[9]: sum(a::AbstractArray) in Base at reducedim.jl:645
```

```
In [10]: j_bench = @benchmark sum($a)

         d["Julia built-in"] = minimum(j_bench.times) / 1e6
         d
```

```
Out[10]: Dict{Any,Any} with 5 entries:
           "C"                   => 4.41494
           "Python numpy"        => 4.6328
           "Python hand-written" => 284.278
           "Python built-in"     => 54.7549
           "Julia built-in"      => 4.48438
```

1.6 julia hand-written

```
In [11]: function mysum(A)
             s = 0.0  # s = zero(eltype(A))
             for a in A
                 s += a
             end
             s
         end

         j_bench_hand = @benchmark mysum($a)

         d["Julia hand-written"] = minimum(j_bench_hand.times) / 1e6
         d
```

```
Out[11]: Dict{Any,Any} with 6 entries:
           "C"                   => 4.41494
           "Python numpy"        => 4.6328
           "Julia hand-written"  => 9.74541
           "Python hand-written" => 284.278
           "Python built-in"     => 54.7549
           "Julia built-in"      => 4.48438
```

1.7 R built-in

In [12]:
```
using RCall

r_bench = @benchmark R"sum($a)"
d["R built-in"] = minimum(r_bench.times) / 1e6
```

```
Info: Recompiling stale cache file /Users/florian.oswald/.julia/compiled/v1.0/RCall/8GFyb.ji 
@ Base loading.jl:1190
```

Out[12]:
```
48.683041
```

1.8 Summary

In [13]:
```
for (key, value) in sort(collect(d), by=x->x[2])
    println(rpad(key, 20, "."), lpad(round(value,digits= 2), 10, "."))
end
```

```
C...4.41
Julia built-in...4.48
Python numpy...4.63
Julia hand-written...9.75
R built-in...48.68
Python built-in...54.75
Python hand-written...284.28
```

1.8.1 Take aways (on my computer!):

1. `C` is fastest
2. built-in julia checks out very close to `C`, and ex-equo with the numpy
3. Hand written julia gets compiled to very efficient machine code in this example.
4. Python and R built-in sums are roughly 10 times slower than `C`, `julia` and `numpy`
5. Hand writing python code without any optimizations performs poorly in this instance.

In [ ]: