# Advanced R Programming - Lecture 6 Computational complexity

Krzysztof Bartoszek (slides based on Leif Jonsson's and Måns Magnusson's)

Linköping University krzysztof.bartoszek@liu.se

29 IX, 1 X 2020 (Zoom)

- Optimizing code
- Performant Code
- Computational complexity
- Classes of problems
- Big Oh notation
- Determining complexity

# Questions since last time?

Programmers waste enormous amounts of time thinking about, or worrying about, the speed of noncritical parts of their programs, and these attempts at efficiency actually have a strong negative impact when debugging and maintenance are considered.

- Donald F Knuth

#### Performance

#### Depends on many things

- 1. Code
- 2. Complexity
- 3. Compiler
- 4. Hardware
- 5. Language

If you don't measure, you don't optimize!



#### How to optimize

- 0. Choose optimal algorithm
- 1. Write code that works with accompanying test suite
- 2. Profile your code for bottlenecks
- 3. Try to eliminate the bottle necks
- 4. Redo 2-3 until fast enough

proc.time() is a basic starting tool



#### Profiling (code below is deprecated, see RprofEx.R)

```
Rprof(tmp <- tempfile(),</pre>
  line.profiling = TRUE,
  memory.profiling = TRUE)
test_data <- pxweb::get_pxweb_data(</pre>
   nr1 =
     "http://api.scb.se/OV0104/v1/doris/sv/ssd/BE/BE0101
                     /BE0101A/BefolkningNy",
   dims = list(Region = c('*').
     Civilstand = c('*),
     Alder = c('*'),
     Kon = c('*').
     ContentsCode = c('*'),
     Tid = as.character(1970),
   clean = TRUE)
Rprof()
summaryRprof(tmp, lines = "show", memory = "both")
```

\$by.self

	self.time	self.pct	total.time	total.pct	mem.total	
get_pxweb_data.R#102	1.96	39.2	1.96	39.2	579.2	
get_pxweb_data_internal.R#42	1.16	23.2	1.16	23.2	405.0	
get_pxweb_data.R#56	0.52	10.4	0.52	10.4	31.3	
get_pxweb_data.R#80	0.38	7.6	0.38	7.6	29.1	
get_pxweb_data.R#82	0.32	6.4	0.32	6.4	40.7	
get_pxweb_data_internal.R#48	0.26	5.2	0.26	5.2	73.2	
get_pxweb_data_internal.R#74	0.26	5.2	0.26	5.2	29.8	
get_pxweb_data.R#83	0.08	1.6	0.08	1.6	17.2	
api_catalogue.R#75	0.02	0.4	0.02	0.4	0.0	
get_pxweb_data_internal.R#44	0.02	0.4	0.02	0.4	12.6	
get pxweb data internal.R#71	0.02	0.1	0.02	0.1	16.0	

#### **Improvements**

- 0. Optimal data structure and algorithm
- 1. Look for existing solutions
- 2. Do less work
- Vectorise
- 0. Optimal data structure and algorithm
- 4. Parallelize
- 0. Optimal data structure and algorithm
- Avoid copies



Speed is important! (do not forget memory)

Speed is important! (do not forget memory)

Time to write code

Speed is important! (do not forget memory)

Time to write code
Time to maintain (understand) code

Speed is important! (do not forget memory)

Time to write code
Time to maintain (understand) code
Time to execute code

# Old Adage About Software

"You can have it Good, Fast, Cheap. Pick any two."

#### Performance

- 1. Performance
- 2. Complexity

Complexity affects performance

#### Computational complexity

Theoretical worst case (but what about average case?)

Big-Oh notation

Basic operations

Relationship: operations to problem size



#### Types of complexity

Time complexity

Space (memory) complexity

Worst case complexity

Average case complexity



Matrix (dataframe, list)

List (**NOT** in R sense, but with pointers), FIFO, LIFO

Sets (no particular order of elements, cannot index)

Graphs (vertex, edge): vertex adjacency matrix, vertex adjacency list

**Decision problems** answer is yes or no, e.g. is x a prime number **Optimization problems** find an object that satisfies a certain property, e.g. largest prime number smaller than x+1Non-algorithmic problems cannot be solved by an algorithm,

e.g. halting problem does a given algorithm end in finite time or fall into an infinite loop?

Presumably nonalgorithmic problems no algorithm is known but we do not know if non-algorithmic e.g. Collatz problem repeat {

```
if (k\%2==0)\{k=k/2\} else\{k=3*k+1\}
    if (k==1){break}
}
```

Does it halt for every k?

#### Classes of problems

**Non-polynomial problems** cannot be solved by an algorithm whose running time is bounded by a polynomial of its input's size e.g. generate all permumations of an n element set. n!**Polynomial problems** can be solved by an algorithm whose running time is bounded by a polynomial of its input's size e.g. sorting *n* elements

Non-polynomial problems cannot be solved by an algorithm whose running time is bounded by a polynomial

P class polynomial problems



**NP class** *Nondeterministic polynomial* class of problems, there exists a polynomial time procedure that verifies if something is an admissable solution, e.g. check if graph colouring is admissable

$$P \subset NP$$
 but  $P \stackrel{???}{=} NP$ 

NP-complete every problem in NP can be reduced to it in polynomial time

e.g. bin packing, knapsack, longest common subsequence, chromatic number of graph,

TSP ( $\mathbb{N}$ ), multiprocessor scheduling (some) satisfiability (SAT): is there a way to assign TRUE, FALSE values so that a logical statement is TRUE?

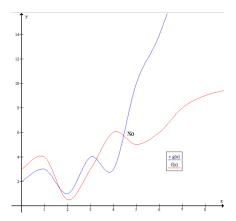
**NP-hard**: if it can be solved in polynomial time, then  $SAT \in P$ 

"How fast does a function grow?"

$$f(n) = O(g(n))$$
 or  $f(n) \in O(g(n))$  
$$\exists_{C>0} \exists_{N_0 \in \mathbb{N}} \forall_{\mathbb{N} \ni n > N_0} |f(n)| \le C * |g(n)|$$
 or 
$$\limsup_{n \to \infty} \frac{|f(n)|}{|g(n)|} < \infty$$

number of operations f(n) does not (up to a scaling constant) grow faster than g(n)

#### Big Oh



https://en.wikipedia.org/wiki/Big\_O\_notation

#### Example

$$f(n) = n^2 + 100n + 100$$

#### Example

$$f(n) = n^2 + 100n + 100$$
  
 $f(n) = O(n^2)$ 

$$f = o(g) \quad \forall_{C>0} \exists_{N_0 \in \mathbb{N}} \forall_{\mathbb{N} \ni n > N_0} | f(n) | \leq C | g(n) | \quad \lim_{n \to \infty} \frac{|f(n)|}{|g(n)|} = 0$$

$$f = O(g) \quad \exists_{C>0} \exists_{N_0 \in \mathbb{N}} \forall_{\mathbb{N} \ni n > N_0} | f(n) | \leq C | g(n) | \quad \lim_{n \to \infty} \sup_{n \to \infty} \frac{|f(n)|}{|g(n)|} < \infty$$

$$f = \omega(g) \quad \forall_{C>0} \exists_{N_0 \in \mathbb{N}} \forall_{\mathbb{N} \ni n > N_0} | f(n) | \geq C | g(n) | \quad \lim_{n \to \infty} \frac{|f(n)|}{|g(n)|} = \infty$$

$$f = \Omega(g) \quad \exists_{C>0} \exists_{N_0 \in \mathbb{N}} \forall_{\mathbb{N} \ni n > N_0} f(n) \geq C | g(n) | \quad \lim_{n \to \infty} \frac{f(n)}{|g(n)|} > 0$$

$$f = \Theta(g) \quad f = O(g) \text{ and } f = \Omega(g)$$

$$f \sim g \quad \lim_{n \to \infty} \frac{f(n)}{g(n)} = 1$$

26/39

# Complexities (the data size is a lower bound)

Name	Example, optimal
constant	assignments, $O(1)$
logarithmic	binary search (sorted input), $O(\log N)$
linear	max., $O(N)$
log–linear	sorting, $O(N \log N)$
quadratic	naive vector-matrix mult., preprocessing
cubic	naive matrix inversion, $O(n^{2.373})$
cubic	naive matrix-matrix mult., $O(n^{2.373})$
polynomial	
exponential	brute force cracking of password, ???
	constant logarithmic linear log-linear quadratic cubic cubic polynomial

Quicksort:  $O(N^2)$  worst case, but  $O(N \log N)$  on average



```
statement 1
statement 2
                        O(1)
statement c
```

```
if(a)
  statement a
else
  statement b
```

```
for(i in 1:N)
  statement i
```

```
for(i in 1:N)
  for (j in 1:M)
                     0?
    statement i,j
```

```
for(i in 1:N)
                     O(N * M)
  for (j in 1:M)
    statement i,j
```

$$g(n) = O(n^2)$$
$$O(n^3)$$

```
naïve sorting: O(n^2)
merge sort: O(n \log n) but large number of copies
"merge sorted lists of two into four, then those and so on"
sort()
quicksort: average (uniform) O(n \log n), worst O(n^2), low overhead
radix sort: O(n \cdot k), sorts numbers on k digits, by using the digits
shell sort: O(n^{4/3}) sorts in-place by swapping elements
```

#### Analysis of recursive algorithms (mergesort)

```
mergesort <-function(L){
## assume n=2^k
n<-length(L)
if (n==1){return(L)}
else{
    L1 \leftarrow mergesort(L[1:(n/2)])
    L2 \leftarrow mergesort(L[(n/2+1):n])
    ## merge is done in O(n) time
    return(merge(L1,L2)))
}}
```

$$T(n) \le \begin{cases} c_1 & n = 1 \\ 2T(n/2) + c_2 n & n > 1 \end{cases}$$

# Analysis of recursive algorithms (Master Theorem)

A function f is multiplicave if f(xy) = f(x)f(y)Let a, b, c > 0,  $k \in \mathbb{N}$  and d(n) be a multiplicative function. Then the solution to the recurrence equation

$$T(n) = \begin{cases} \Theta(1) & n = 1 \\ aT(n/b) + d(n) & n = b^k \end{cases}$$

is

$$T(n) = \Theta(a^k) + \sum_{j=0}^{k-1} a^j d(b^{k-j})$$

with asymptotic behaviour

$$T(n) = \begin{cases} \Theta(n^{\log_a d(b)}) & a < d(b) \\ \Theta(n^{\log_b a} \log n) & a = d(b) \\ \Theta(n^{\log_b a}) & a > d(b) \end{cases}$$

 $c_n n$  is not multiplicative so take  $T(n) = c_2 \tilde{T}(n)$ , then

$$ilde{T}(1) = T(1)/c_2 = c_1/c_2 = c$$
 $T(n) = 2T(n/2) + c_2n$  becomes  $c_2\tilde{T}(n) = 2c_2\tilde{T}(n/2) + c_2n$ 

Consider

$$U(n) = \begin{cases} c & n = 1 \\ 2U(n/2) + n & n > 1 \end{cases}$$

n is multiplicative and using the Master Theorem we obtain

$$U(n) = \Theta(n \log n)$$
 and hence  $U(n) \ge T(n) = O(n \log n)$ .

Actually  $T(n) = \Theta(n \log n)$ .



#### Approximate algorithms

If we cannot solve a hard problem let us approximate its solution. Let  $S_{opt}$  be the optimal solution and  $S_{approx}$  the approximate one

$$k$$
-absolute approximate algorithm if  $|S_{opt} - S_{approx}| \le k$ 

$$k$$
–(relative) approximate algorithm if  $s \leq k$ , where

$$s = \max(S_{opt}/S_{approx}, S_{approx} - S_{opt})$$

LAB: knapsack problem

