## **Algorithms and Data Structures**

# Big O Introduction to Big O

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Notation	Description
O(1)	constant
$\mathcal{O}(\log(n))$	logarithmic
$\mathcal{O}((\log(n))^c)$	polylogarithmic
$\mathcal{O}(n)$	linear
$\mathcal{O}(n^2)$	square
$\mathcal{O}(n^c)$	polynomial
$\mathcal{O}(\boldsymbol{c}^n)$	exponential

#### Learning goals

- Runtime behavior
- Definition of Big O
- Classes of functions

#### **EFFICIENCY OF ALGORITHMS**

We are interested in the **efficiency** of algorithms. Efficiency can be associated with different attributes such as

- CPU runtime
- Memory usage
- Memory usage on the hard drive

We will mainly focus on the runtime behavior of algorithms.

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### THE BIG O NOTATION

- When we are interested in the complexity of an algorithm, we are **not** interested in the exact number of operations, but rather in the relationship of the number of operations to the size of the problem.
- Usually one is interested in the **worst case**: what is the maximum number of operations for a given problem size?
- The Big O notation (also called Bachmann-Landau notation) is used in mathematics and computer science to classify algorithms according to how their run time or space requirements grow as the input size grows.

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#### **INPUT SIZES**

An analysis of complexity depends on how you specify the input size of a problem.

Typical input sizes are:

- Number of elements of a list
- Number of bits of a number
- Number of nodes in a graph
- Number of rows / columns of a matrix

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#### INTRODUCTORY EXAMPLE

```
isElement = function(xs, el) {
  for (x in xs) {
    if (identical(x, el))
      return(TRUE)
  }
  return(FALSE)
}
```

## expr mean
## 1 isElement(1:1000, 1000L) 308.286
## 2 isElement(1:2000, 2000L) 626.519
## 3 isElement(1:5000, 5000L) 1684.067
## 4 isElement(1:10000, 10000L) 3137.450

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#### INTRODUCTORY EXAMPLE / 2

- The input size of the problem is *n* being the length of vector *xs*.
- The order of the function is  $\mathcal{O}(n)$  (worst case).
- That is:

If we were to evaluate the function for different *xs* and visualize the runtime in a graph, it would show that the runtime depends linearly on the number of elements in *xs*.

• For example, if we always consider the vector xs = 1:n and test for the number 1, our function would obviously be much faster than  $\mathcal{O}(n)$ .

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#### **INTRODUCTORY EXAMPLE / 3**





In the best case, we always access the first element of the list. The runtime is constant. In the worst case we access the *n*-th element of the list - so *n* elements have to be evaluated. On average  $\frac{n}{2}$  evaluations are needed.

#### **INTRODUCTORY EXAMPLE / 4**

- In general, the Big-O notation is used to describe the **worst case** and thus represents an upper bound.
- Another common performance measure is the **average case** runtime.
- Many algorithms have poor worst-case performance, but good average-case performance and are therefore quite practicable depending on the application.
- Less common is the best case performance, i.e. the behavior of the algorithm under optimal conditions.

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Let  $f, g: \mathbb{R} \to \mathbb{R}$  be two functions.

We define

 $f(x)\in \mathcal{O}(g(x)) \quad ext{for } x o\infty$ 

if and only if 2 positive real numbers M and  $x_0$  exist, such that

 $|f(x)| \leq M \cdot |g(x)|$  for all  $x > x_0$ .

Intuition: *f* does not grow faster than *g*.

**Comment:** Often the above definition is abbreviated by  $f \in O(g)$ .

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**Example:** We consider the function  $f(x) = 3x^3 + x^2 + 100 \sin(x)$ .



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For large x, f(x) is well above  $1 \cdot g(x) = 1 \cdot x^3$ 





We are now looking at the relationship between f(x) and  $M \cdot x^3$  for M = 1, 2, 3, ... In the graph below we can see that f(x) runs entirely **beneath**  $4 \cdot x^3$  for x values greater than  $\approx 3$ ,. This means f grows cubic:  $f \in \mathcal{O}(x^3)$ .

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Mathematical derivation:

$$\begin{aligned} |f(x)| &= |3x^3 + x^2 + 100\sin(x)| \le 3 \cdot |x|^3 + x^2 + 100 \underbrace{|\sin(x)|}_{\le 1} \\ &\le 3 \cdot |x|^3 + \underbrace{x^2}_{\le |x|^3 \text{ for } x > 1} + 100 \\ &\le 4|x|^3 + 100 \text{ for } x > 1. \end{aligned}$$

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Since  $100 \le 4|x|^3$  for  $x > \sqrt[3]{25} \approx$  2.9 it follows

$$|f(x)| \le 4|x^3|$$
 for  $x > x_0 := \sqrt[3]{25}$ ,

or in short  $f \in \mathcal{O}(x^3)$ , which corresponds to our graphical derivation.

For functions  $f, g: X \to \mathbb{R}$ ,  $X \subset \mathbb{R}$  you can also use this notation to examine the behavior of the function f at a certain point  $a \in X$  (often a = 0):

$$f(x) \in \mathcal{O}(g(x))$$
 for  $x o a \in \mathbb{R}$ 

if 2 positive real numbers M and d exist, such that

 $|f(x)| \leq M \cdot |g(x)|$  for |x-a| < d.

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If g(x) is not equal to 0 and is close enough to *a* for values of *x*, then both definitions can be expressed using the limes superior:

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#### NOTATION

• When we talk about the order of a function, we write

$$f \in \mathcal{O}(n^2)$$

• A second, more commonly used notation is

$$f = \mathcal{O}(n^2)$$

although it is formally incorrect:  $n^2 = O(n^2)$  and  $n^2/2 = O(n^2)$ , but  $n^2 \neq n^2/2$ 

• In this context, the "=" is not intended to be a sign of equality, but a simple "is"



#### **CLASSES OF FUNCTIONS**

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The table is sorted from slow to fast growing for c > 1

#### CLASSES OF FUNCTIONS / 2



