CM0889 Analysis of Algorithms Algorithm Analysis

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Semester 2020-2

Conventions

- The number assigned to chapters, examples, exercises, figures, sections, or theorems on these slides correspond to the numbers assigned in the textbook [Skiena 2012].
- The source code examples are in course's repository.

The **computational complexity** of an algorithm is the amount of resources (e.g. time and space) required to execute it.

Definition

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For us 'the complexity of an algorithm' means the time computational complexity of the algorithm.

Introduction

Two abstractions

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For the analysis of algorithms we required two abstractions:

- (i) Where do the algorithms run? In a theoretical computer, i.e., we are interested in machineindependent algorithms.
- (ii) Which complexity are we interested? We are interested in **asymptotic complexity**, i.e., we are interested in the behaviour of the algorithm for large values of the input.

The RAM Model of Computation

See Skiena's lecture slides: Asymptotic Notation

The running time function

If the running time of an algorithm depends of the input then it usually means it depends of the size of the input.

So, we shall use a function

$$T(n):\mathbb{N}\to\mathbb{R}^{\geq 0}$$

which will denote the running time of an algorithm on inputs of size n.

Example

For a sorting algorithm the size of the input is the number of elements to sort.

There complexity functions

Given an input of size n we can think in three complexity functions: best-case complexity, worst-case complexity and average-case complexity.

See Skiena's lecture slides: Asymptotic Notation

Let $g: \mathbb{N} \to \mathbb{R}^{\geq 0}$ be a function. We define the set of functions **big** O of g(n), denoted by O(g(n)), by

$$O(g(n)) := \{ f : \mathbb{N} \to \mathbb{R}^{\geq 0} \mid \text{there exist positive constants } c \in \mathbb{R}^+ \\ \text{and } n_0 \in \mathbb{Z}^+ \text{ such that } f(n) \leq cg(n) \\ \text{for all } n \geq n_0 \}.$$

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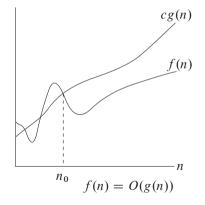
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Notation

Both 'f(n) = O(g(n))' and 'f(n) is O(g(n))' mean that $f(n) \in O(g(n))$.

Definition (continuation)

If $f(n) \in O(g(n))$ then function g(n) is an upper bound on the growth rate of the function f(n).*



*Figure source: Cormen, Leiserson, Rivest and Stein [2009, Fig. 3.1b]. Algorithm Analysis

Example

Let $T(n) = 3n^2 - 100n + 6$. The function T(n) is $O(n^2)$ because choosing $n_0 = 1$ and c = 3 we have that

$$3n^2 - 100n + 6 \le cn^2, \quad \text{for all } \mathsf{n} \ge \mathsf{n}_0,$$

that is,

$$3n^2 - 100n + 6 \le 3n^2$$
, for all $n \ge 1$.

Exercise

Let $T(n) = (n+1)^2$. To prove that $T(n) \in O(n^2)$. Hint: Choose $n_0 = 1$ and c = 4.

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Question

If $T(n) \in O(n^2)$ then $T(n) \in O(n^3)$? What about $O(n^4)$?

Example

Let $T(n) = 6n^2$. The function T(n) is not O(n) because

 $6n^2 > cn$, when n > c.

Theorem

Let d be a natural number and T(n) a polynomial function of degree d, that is,

$$T:\mathbb{N}
ightarrow\mathbb{R}$$
 $T(n)=\sum_{i=0}^d c_i n^i, \quad ext{with } c_i\in\mathbb{R} ext{ and } c_d
eq 0.$

If $c_d > 0$ then $T(n) \in O(n^d)$.*

Algorithm Analysis

^{*}See, e.g. [Cormen, Leiserson, Rivest and Stein 2009].

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Example

$$T(n) = 42n^3 + 1523n^2 + 45728n$$
 is $O(n^3)$.

Algorithm Analysis

^{*}See, e.g. [Cormen, Leiserson, Rivest and Stein 2009].

Example

Since any constant is a polynomial of degree 0, any constant function is $O(n^0)$, i.e. O(1).

Remark

Note the missing variable in O(1).*

^{*}We could use the λ -calculus notation, i.e. $O(\lambda n.1)$.

Example

Let $T(n) = \lg(7n^2 + 4n)$. To prove that: (i) T(n) is $O(\lg n)$.

(ii) T(n) is $O(\log_b n)$, for any real number b > 1.

Adapted from [Vrajitoru and Knight 2014, Example 3.3.2.(c)].

Proof

i) Since

$$lg(7n^{2} + 4n) < lg(7n^{2} + 4n^{2})$$

= lg(11n^{2})
= lg 11 + 2 lg n
< lg n + 2 lg n, for $n \ge 12$
= 3 lg n

then T(n) is $O(\lg n)$ by choosing $n_0 = 12$ and c = 3.

Proof (continuation)

(ii) Case b < 2

Since $\lg n < \log_b n$ then T(n) is $O(\log_b n)$ because it is $O(\lg n)$.

Proof (continuation)

(ii) Case b > 2

Because $\log_b n < \lg n$ we can not use the fact that T(n) is $O(\lg n)$ like in the case b < 2. Now, since for $n \ge 12$,

$$\lg(7n^2 + 4n) \le 3\lg n \quad \text{and} \quad \lg n = \lg b \cdot \log_b n,$$

then T(n) is $O(\log_b n)$ by choosing $n_0 = 12$ and $c = 3 \cdot \lceil \lg b \rceil$.

Let $g: \mathbb{N} \to \mathbb{R}^{\geq 0}$ be a function. We define the set of functions **big** Ω of g(n), denoted by $\Omega(g(n))$, by

$$\begin{split} \Omega(g(n)) &:= \{ f : \mathbb{N} \to \mathbb{R}^{\geq 0} \mid \text{there exist positive constants } c \in \mathbb{R}^+ \\ & \text{and } n_0 \in \mathbb{Z}^+ \text{ such that } f(n) \geq cg(n) \\ & \text{ for all } n \geq n_0 \, \}. \end{split}$$

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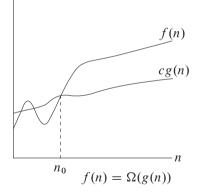
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Notation

Both ' $f(n) = \Omega(g(n))$ ' and 'f(n) is $\Omega(g(n))$ ' mean that $f(n) \in \Omega(g(n))$.

Definition (continuation)

If $f(n) \in \Omega(g(n))$ then function g(n) is a lower bound on the growth rate of the function f(n).*



*Figure source: Cormen, Leiserson, Rivest and Stein [2009, Fig. 3.1c]. Algorithm Analysis

Let $g: \mathbb{N} \to \mathbb{R}^{\geq 0}$ be a function. We define the set of functions **big** Θ of g(n), denoted by $\Theta(g(n))$, by

$$\Theta(g(n)) := \{ f : \mathbb{N} \to \mathbb{R}^{\geq 0} \mid \text{there exist positive constants } c_1, c_2 \in \mathbb{R}^+ \\ \text{and } n_0 \in \mathbb{Z}^+ \text{ such that} \\ c_1 g(n) \leq f(n) \leq c_2 g(n) \text{ for all } n \geq n_0 \}.$$

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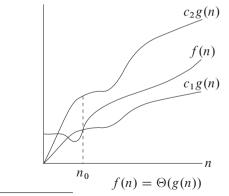
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Asymptotic Notations: Big Θ

Definition (continuation)

If $f(n) \in \Theta(g(n))$ then function g(n) is a lower bound and an upper bound on the growth rate of the function f(n).*



*Figure source: Cormen, Leiserson, Rivest and Stein [2009, Fig. 3.1a]. Algorithm Analysis

Growing rates of some functions

Each operation takes one nanosecond (10^9 seconds). Figure 2.4 in the textbook.

n f(n)	$\lg n$	n	$n \lg n$	n^2	2^n	n!
10	$0.003~\mu{ m s}$	$0.01~\mu{ m s}$	$0.033~\mu{ m s}$	$0.1 \ \mu s$	$1 \ \mu s$	$3.63 \mathrm{ms}$
20	$0.004 \ \mu s$	$0.02~\mu{ m s}$	$0.086~\mu{ m s}$	$0.4 \ \mu s$	1 ms	77.1 years
30	$0.005~\mu { m s}$	$0.03~\mu{ m s}$	$0.147~\mu{ m s}$	$0.9 \ \mu s$	$1 \mathrm{sec}$	$8.4 \times 10^{15} \text{ yrs}$
40	$0.005 \ \mu s$	$0.04 \ \mu s$	$0.213~\mu{ m s}$	$1.6 \ \mu s$	$18.3 \min$	
50	$0.006 \ \mu s$	$0.05~\mu{ m s}$	$0.282~\mu { m s}$	$2.5 \ \mu s$	$13 \mathrm{days}$	
100	$0.007 \ \mu s$	$0.1 \ \mu s$	$0.644~\mu{ m s}$	$10 \ \mu s$	$4 \times 10^{13} \text{ yrs}$	
1,000	$0.010 \ \mu s$	$1.00~\mu{ m s}$	$9.966~\mu{ m s}$	1 ms		
10,000	$0.013~\mu s$	$10 \ \mu s$	$130 \ \mu s$	100 ms		
100,000	$0.017 \ \mu s$	$0.10 \mathrm{\ ms}$	$1.67 \mathrm{\ ms}$	$10 \mathrm{sec}$		
1,000,000	$0.020 \ \mu s$	$1 \mathrm{ms}$	$19.93 \mathrm{\ ms}$	$16.7 \min$		
10,000,000	$0.023 \ \mu s$	$0.01 \sec$	$0.23 \sec$	1.16 days		
100,000,000	$0.027 \ \mu s$	$0.10 \sec$	$2.66 \sec$	115.7 days		
1,000,000,000	$0.030~\mu{ m s}$	$1 \mathrm{sec}$	$29.90 \sec$	31.7 years		

Supercomputers

Machines from: www.top500.org (last updated: September 2020) PetaFLOP (PFLOP): 10^{15} floating-point operations per second

Date	Machine	PFLOPs
2020-06	Fugaku	415.53
2019-06	Summit	148.60
2018-11	Summit	143.50
2018-06	Summit	122.30
2016-06	Sunway TaihuLight	93.01
2013-06	Tianhe-2	33.86
2012-06	Blue Gene/Q	16.32
2011-06	K computer	8.16

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The problem was proposed in Karp's 21 NP-complete problems [Karp 1972].

Improvements on the time complexity of 3-SAT deterministic algorithmic *

 $O(1.32793^n)$ Liu [2018]

- $O(1.3303^n)$ Makino, Tamaki and Yamamoto [2011, 2013]
- $O(1.3334^n)$ Moser and Scheder [2011]
- $O(1.439^n)$ Kutzkov and Scheder [2010]
- $O(1.465^n)$ Scheder [2008]
- $O(1.473^n)$ Brueggemann and Kern [2004]
- $O(1.481^n)$ Dantsin, Goerdt, Hirsch, Kannan, Kleinberg, Papadimitriou, Raghavan and Schöning [2002]

(continued on next slide)

*Main sources: Hertli [2011, 2015]. Last updated: July 2020.

Algorithm Analysis

Improvements on the time complexity of 3-SAT deterministic algorithmic (continuation)

- $O(1.497^n)$ Schiermeyer [1996]
- $O(1.505^n)$ Kullmann [1999]
- $O(1.6181^n)$ Monien and Speckenmeyer [1979, 1985]
- $O(2^n)$ Brute-force search

3-SAT simulation

Running 3-SAT times on different supercomputers using the faster deterministic algorithm, i.e. $T(1.32793^n)$.

Date	Machine	PFLOPs	n = 150	n = 200	n = 400
2020-06	Fugaku	415.53	$7.2 \sec$	120.2 days	$1.4 \times 10^{24} \text{ yrs}$
2019-06	Summit	148.60	20.1 sec	$336.1 \mathrm{~days}$	$4.0 \times 10^{24} \text{ yrs}$
2018-11	Summit	143.50	20.8 sec	$348.1 \mathrm{~days}$	$4.1 \times 10^{24} \text{ yrs}$
2018-06	Summit	122.30	24.5 sec	$1.1 \mathrm{\ yrs}$	$4.8 \times 10^{24} \text{ yrs}$
2016-06	Sunway	93.01	32.2 sec	$1.5 { m yrs}$	$6.4 \times 10^{24} \text{ yrs}$
	TaihuLight				
2013-06	Tianhe-2	33.86	$1.5 \min$	$4.1 \mathrm{\ yrs}$	$1.7 \times 10^{25} \text{ yrs}$
2012-06	Blue	16.32	$3.1 \mathrm{min}$	$8.4 \ \mathrm{yrs}$	$3.6 \times 10^{25} \text{ yrs}$
	Gene/Q				
2011-06	K computer	8.16	$6.1 \min$	$16.8 \ \mathrm{yrs}$	$7.3 \times 10^{25} \text{ yrs}$

3-SAT simulation

Running 3-SAT times for different deterministic algorithms using the faster supercomputer, i.e. $415.53~\mbox{PFLOPs}.$

Complexity	n = 150	n = 200	n = 400
$\overline{T(1.32793^n)}$	$7.2 \sec$	120.2 days	$1.4 \times 10^{24} \text{ yrs}$
$T(1.3303^{n})$	$9.4 \sec$	$172.0 \mathrm{~days}$	$2.9 imes 10^{24} \text{ yrs}$
$T(1.3334^{n})$	13.3 sec	$273.5 \mathrm{~days}$	$7.3 imes 10^{24} m \ yrs$
$T(1.439^{n})$	$14.2 \mathrm{~days}$	3.1×10^6 yrs	$1.3 \times 10^{38} \text{ yrs}$
$T(1.465^{n})$	$209.1 \mathrm{~days}$	1.1×10^8 yrs	1.7×10^4 yrs
$T(2^n)$	$1.1 \times 10^{20} \text{ yrs}$	$1.3 \times 10^{35} \text{ yrs}$	$2.0 \times 10^{95} \text{ yrs}$

Example (informal)

See

http://science.slc.edu/~jmarshall/courses/2002/spring/cs50/BigO/.

Let f and g two functions. The function f **dominates** the function g, denoted $f \gg g$, iff g(n) becomes insignificant relative to f(n) as n approaches infinity, that is, $\lim_{n\to\infty} g(n)/f(n) = 0$.

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Example

$$n! \gg 2^n \gg n^3 \gg n^2 \gg n \log n \gg n \gg \log n \gg 1.$$

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