Asymptotic Notation and Mathematical Induction

K. Subramani

Department of Computer Science and Electrical Engineering,
West Virginia University,
Morgantown, WV
ksmani@csee.wvu.edu

1 Asymptotic Notation

The following list of notations is used to simplify the specification of algorithm complexity.

Definition: 1.1 $O(g(n)) = \{f(n) | \exists c, n_0 > 0, \text{ such that } f(n) \leq c.g(n) \forall n \geq n_0 \}$ i.e. g(n) sits above f(n) when their graphs are drawn, after some point n_0 . Refer Figure (1).

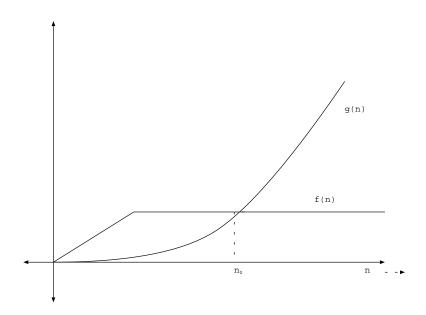


Figure 1: Growth of functions

Definition: 1.2 $\Omega(\mathbf{g}(\mathbf{n})) = \{f(n) | \exists c, n_0 > 0, \text{ such that } f(n) \geq c.g(n) \forall n \geq n_0 \}$ i.e. g(n) sits below f(n) when their graphs are drawn, after some point n_0 .

Definition: 1.3 $\Theta(\mathbf{g}(\mathbf{n})) = \{f(n) | \exists c_1, c_2, n_0 > 0, \text{ such that } c_1.g(n) \leq f(n) \leq c_2.g(n) \forall n \geq n_0 \}$ i.e. f(n) is sandwiched by g(n) for appropriately chosen constants c_1 and c_2 , when their graphs are drawn, after some point n_0 .

Definition: 1.4 $o(g(n)) = \{f(n) | \lim_{n \to \infty} \frac{f(n)}{g(n)} = 0\}$ i.e. g(n) grows asymptotically faster than f(n)

Definition: 1.5 $\omega(\mathbf{g}(\mathbf{n})) = \{f(n) | \lim_{n \to \infty} \frac{g(n)}{f(n)} = 0\}$ i.e. f(n) grows asymptotically faster than g(n)

Remark: 1.1 The asymptotic notation denotes a relationship and not a function i.e. the correct style is $f(n) \in O(g(n))$ and not f(n) = O(g(n)); however, over the years Computer Scientists have preferred the later notation scheme. But never forget that although we use equality it is actually a set inclusion symbol.

Lemma: 1.1 f(n) = O(g(n)) if and only if $g(n) = \Omega(f(n))$

Lemma: 1.2 f(n) = o(g(n)) if and only if $g(n) = \omega(f(n))$

Lemma: 1.3 $f(n) = \Theta(g(n))$ if and only if f(n) = O(g(n)) and $f(n) = \Omega(g(n))$.

1.1 How to compare two polynomial functions

First, we can always write a polynomial in the form

$$a_d \cdot n^d + a_{d-1} \cdot n^{d-1} + \dots a_0$$

as $\Theta(n^d)$. Note that a constant function is denoted by O(1). Further, $O(1) \in O(n) \in O(n^2) \in O(n^3) \dots$; Likewise $\dots \in \Omega(n^d) \in \Omega(n^{d-1}) \in \dots \cap \Omega(1)$.

2 Laws of exponents

For all real $a \neq 0, m$ and n, we have

$$a^0 = 1. (1)$$

$$a^1 = a. (2)$$

$$a^{-1} = 1/a. (3)$$

$$(a^m)^n = a^{m \cdot n}. (4)$$

$$(a^m)^n = (a^n)^m. (5)$$

$$a^m.a^n = a^{m+n}. (6)$$

Remark: 2.1 Exponential functions grow at a much faster rate than any polynomial. Observe that, given a > 1 and b,

$$\lim_{n \to \infty} \frac{n^b}{a^n} = 0,\tag{7}$$

by L'Hospital's rule. Hence, $n^b = o(a^n)$.

3 Laws of Logarithms

For all a > 0, b > 0, c > 0 and n

$$a = b^{\log_b a} \tag{8}$$

$$\log(ab) = \log a + \log b \tag{9}$$

$$\log a^n = n \cdot \log a \tag{10}$$

$$\log_b a = \frac{1}{\log_a b} = \frac{\log_c a}{\log_c b} \tag{11}$$

$$a^{\log_b n} = n^{\log_b a} \tag{12}$$

3.1 Abbreviations

- $lg n = log_2 n$
- $ln \ n = \log_e n$
- $\log^k n = (\log n)^k$
- $\log \log n = \log(\log n)$
- Iterated log:

$$\log^{i} n = n, \quad \text{if } i = 0,$$

$$= \log(\log^{(i-1)} n), \quad \text{if } i > 0 \quad \text{and } \log^{(i-1)} n > 0.$$
(13)

Then, we define

$$\log^* n = \min\{i \ge 0 : \log^{(i)} n \le 1\},\tag{15}$$

(14)

as the iterated log function. In other words, $\log^* n$ is the smallest integer i, such that after applying the log function i times repeatedly, the resultant quantity sinks below 1. The iterated log function has the smallest growth rate other than a constant function (remember that the constant function f(n) = c does not grow at all!). When $n = 2^{65536}$, $\log^* n = 5$!!

Remark: 3.1 Substitute $\lg n$ for n and 2^a for a in Equation (7), we get

$$\lim_{n \to \infty} \frac{\lg^b n}{2^{a \cdot \lg n}} = \lim_{n \to \infty} \frac{\lg^b n}{n^a} = 0 \tag{16}$$

Thus, we have

$$\lg^b n = o(n^a),$$

for any a > 0 i.e. the log function does not grow as fast as polynomial functions. (Make sure that you can derive this equality).

You now have the machinery to compare function growth rates.

4 Mathematical Induction

Mathematical induction is a general purpose tool of testing out a hyopothesis. The drawback of this technique is that the hypothesis must be supplied!

For example, let us say that we want a closed form representation of the sum

$$S_n = 1 + 2 + \dots = \sum_{i=1}^n i \tag{17}$$

Further assume that some good samaritan gave us the hypothesis that the closed form function is $\frac{n \cdot (n+1)}{2}$. We need to check that the samaritan is not deceiving us.

So our Proposition is:

$$P(n): S_n = \frac{n.(n+1)}{2}, \forall n = 1, 2, ...$$

Induction proceeds by two steps:

- 1. Step 1: The base case. Is P(1) true? The Left Hand Side (LHS) is $S_1 = 1$ and the RHS is $\frac{1.(1+1)}{2}$, which is 1. Thus, LHS = RHS and P(1) is true. Thus, the samaritan is correct at least when n = 1. This step is called base confirmation.
- 2. Step 2: The Inductive step: Here we assume that the samaritan is correct when n = k i.e P(k) is true and show that the formula must also hold for n = k + 1 i.e. P(k + 1). Thus, we want to show that

$$P(k) \Rightarrow P(k+1)$$

In our case, assuming that P(k) is true gives $S_k = \frac{k \cdot (k+1)}{2}$. What is P(k+1)? On the LHS it is

$$S_{k+1} = 1 + 2 + \dots + (k+1)$$

 $\Rightarrow S_{k+1} = (1 + 2 + \dots + k) + (k+1)$
 $\Rightarrow S_{k+1} = S_k + (k+1)$

Since P(k) is true by assumption, we can set $S_k = \frac{k \cdot (k+1)}{2}$

$$\Rightarrow S_{k+1} = \frac{k \cdot (k+1)}{2} + (k+1)$$
$$\Rightarrow S_{k+1} = \frac{(k+1) \cdot (k+2)}{2}$$

which is exactly what we would obtain by substituting (k+1) in the samaritan's formula (= RHS). Thus we have,

$$P(k) \Rightarrow P(k+1)$$
.

Since P(1) is true, we can then conclude that P(2) is true and hence P(3) is true and P(n) is true for all n. Thus the samaritan was good after all.

Remark: 4.1 Show that

$$\sum_{i=1}^{n} i^2 = \frac{n.(n+1).(2.n+1)}{6}$$