Review of Big-O Notation

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1 Big-O Notation

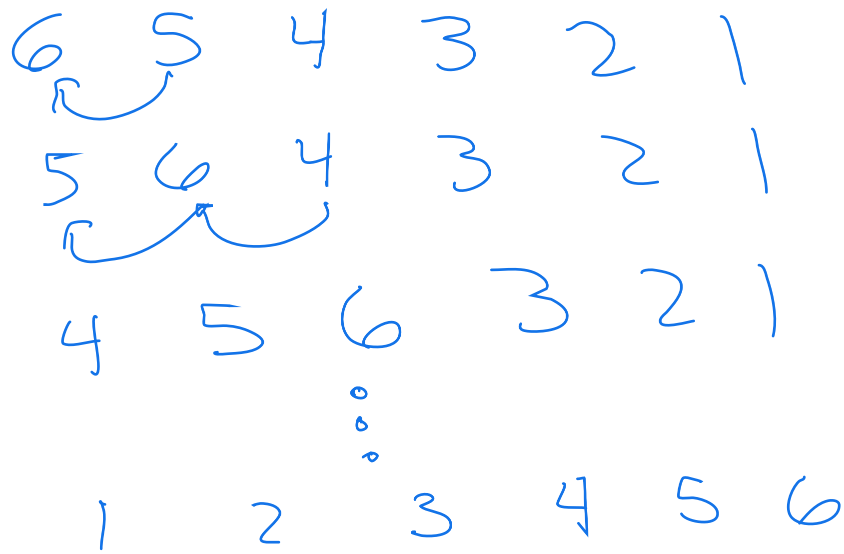
Big-O notation is useful for making statements about the growth of a function $f(n)$, n a natural number, whose values may seem difficult or impossible to compute. The statements we care most about are those that state upper and/or lower bounds on f's growth. Although we may not know the exact bounds (since we may not know the exact values of f), we may be able to determine meaningful ones in case we know the following two things:

1. the rule, call it $g(n)$, for the fastest growing term (ignoring constants) of the bounding function, and
2. that there exists a constant $c > 0$ such that, $cg(n)$ provides a bound for f, for sufficiently large n.

Example 1.1. Carol has programmed the `Insertion Sort` algorithm to run on her laptop. What upper bound can she provide on the elapsed time $t(n)$ that will occur on her laptop clock after `Insertion Sort` has sorted an integer array of size n? She knows that the worst case occurs when the input array is sorted in reverse order, and in this case a total of

$$\frac{n(n-1)}{2} = \frac{n^2}{2} - \frac{n}{2}$$

comparisons and swaps must be performed in order to sort such an array. In this case, the rule for the fastest growing term of the upper-bounding function is $g(n) = n^2$. Also, she knows that each comparison and swap requires at most two machine instructions, and that each machine instruction requires at most 10^{-8} seconds to execute. Therefore, there is a $c > 0$ such that $cg(n)$ is an upper bound for the elapsed time. □



$$1 + 2 + \cdots + 5 = \frac{(6)(5)}{2}$$

$$1 + 2 + \cdots + n-1 = \frac{(n-1)n}{2}$$

Let $f(n)$ and $g(n)$ be functions from the set of nonnegative integers to the set of nonnegative real numbers. Then

Big-O $f(n) = \mathrm{O}(g(n))$ iff there exist constants $c > 0$ and $k \geq 1$ such that $f(n) \leq cg(n)$ for every $n \geq k$.

Big-Ω $f(n) = \Omega(g(n))$ iff there exist constants $c > 0$ and $k \geq 1$ such that $f(n) \geq cg(n)$ for every $n \geq k$.

Big-Θ $f(n) = \Theta(g(n))$ iff $f(n) = \mathrm{O}(g(n))$ and $f(n) = \Omega(g(n))$.

little-o $f(n) = \mathrm{o}(g(n))$ iff $\lim_{n\to\infty} \frac{f(n)}{g(n)} = 0$.

little-ω $f(n) = \omega(g(n))$ iff $\lim_{n\to\infty} \frac{f(n)}{g(n)} = \infty$.

Example 1.2. From the above discussion we have $f(n) = 3.5n^2 + 4n + 36 = \Theta(n^2)$ since

$C_1 =$

$$3.5n^2 \leq f(n) = 3.5n^2 + 4n + 36 \leq 3.5n^2 + 4n^2 + 36n^2 = 43.5n^2,$$

is true for all $n \geq 1$. And so $f(n) = \Theta(n^2)$, where $c_1 = 3.5$ and $c_2 = 43.5$ are the respective lower and upper-bound constants. □

Definition 1.3. The following table shows the most common kinds of rules for $g(n)$ that are used within big-O notation.

Function	**Type of Growth**
1	constant growth
$\log n$	logarithmic growth
$\log^k n$, for some integer $k \geq 1$	polylogarithmic growth
n^k for some positve $k < 1$	sublinear growth
n	linear growth
$n \log n$	log-linear growth
$n \log^k n$, for some integer $k \geq 1$	polylog-linear growth
$n^j \log^k n$, for some integers $j, k \geq 1$	polylog-polynomial growth
n^2	quadratic growth
n^3	cubic growth
n^k for some integer $k \geq 1$	polynomial growth
$2^{\log^c n}$, for some $c > 1$	quasi-polynomial growth
$\omega(n^k)$, for all integers $k \geq 1$	superpolynomial growth
a^n for some $a > 1$	exponential growth

Example 1.4. Returning to Example 1.1, using big-O notation Carol can say that, when running `Insertion Sort` on her laptop with an input of size n, the elapsed time equals $O(n^2)$ seconds. Also, since `Insertion Sort` requires at least n comparisons for any input, she may also say that its running time equals $\Omega(n)$ seconds. □

Theorem 1.5. The following are all true statements.

1. $1 = o(\log n)$
2. $\log n = o(n^{\epsilon})$ for any $\epsilon > 0$
3. $\log^k n = o(n^{\epsilon})$ for any $k > 0$ and $\epsilon > 0$
4. $n^a = o(n^b)$ if $a < b$, and $n^a = \Theta(n^b)$ if $a = b$.
5. $n^k = o(2^{\log^c n})$, for all $k > 0$ and $c > 1$.
6. $2^{\log^c n} = o(a^n)$ for all $a, c > 1$.
7. For nonnegative functions $f(n)$ and $g(n)$,
$$(f+g)(n) = \Theta(\max(f,g)(n)).$$
8. If $f(n) = \Theta(h(n))$ and $g(n) = \Theta(k(n))$, then $(fg)(n) = \Theta((hk)(n))$.
9. If $f(n) = o(g(n))$ then $f(n) = \mathrm{O}(g(n))$.
10. If $f(n) = \omega(g(n))$ then $f(n) = \Omega(g(n))$.

Example 1.6. For each of the following, state whether $f(n) = O(g(n))$, $f(n) = \Omega(g(n))$, or both, i.e. $f(n) = \Theta(g(n))$.

1. $f(n) = 3n + 5$, $g(n) = 10n + 6\log n$.
2. $f(n) = \sqrt{n} \cdot \log^2 n$, $g(n) = \sqrt[3]{n}\log^3 n$.
3. $f(n) = 10\log n$, $g(n) = 50\log n^2$.
4. $f(n) = n^2/\log n$, $g(n) = n\log^2 n$.
5. $f(n) = n2^n$, $g(n) = 3^n$.

2 Advanced Results

Log Ratio Test. Suppose f and g are continuous functions over the interval $[1, \infty)$, and

$$\lim_{n\to\infty} \log(\frac{f(n)}{g(n)}) = \lim_{n\to\infty} \log(f(n)) - \log(g(n)) = L.$$

Then

1. If $L = \infty$ then
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = \infty.$$
2. If $L = -\infty$ then
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = 0.$$
3. If $L \in (-\infty, \infty)$ is a constant then
$$\lim_{n\to\infty} \frac{f(n)}{g(n)} = 2^L.$$

Integral Theorem. Let $f(x) > 0$ be an increasing or decreasing Riemann-integrable function over the interval $[1, \infty)$. Then

$$\sum_{i=1}^{n} f(i) = \Theta(\int_1^n f(x)dx),$$

if f is decreasing. Moreover, the same is true if f is increasing, provided $f(n) = O(\int_1^n f(x)dx)$.

Proof of Integral Theorem. We prove the case when f is decreasing. The case when f is increasing is left as an exercise. The quantity $\int_1^n f(x)dx$ represents the area under the curve of $f(x)$ from 1 to n. Moreover, for $i = 1, \ldots, n-1$, the rectangle R_i whose base is positioned from $x = i$ to $x = i+1$, and whose height is $f(i+1)$ lies under the graph. Therefore,

$$\sum_{i=1}^{n-1} \text{Area}(R_i) = \sum_{i=2}^{n} f(i) \leq \int_1^n f(x)dx.$$

Adding $f(1)$ to both sides of the last inequality gives

$$\sum_{i=1}^{n} f(i) \leq \int_1^n f(x)dx + f(1).$$

Now, choosing $C > 0$ so that $f(1) = C\int_1^n f(x)dx$ gives

$$\sum_{i=1}^{n} f(i) \leq (1 + C)\int_1^n f(x)dx,$$

which proves $\sum_{i=1}^{n} f(i) = \mathrm{O}(\int_1^n f(x)dx)$.

Now, for $i = 1, \ldots, n-1$, consider the rectangle R'_i whose base is positioned from $x = i$ to $x = i+1$, and whose height is $f(i)$. This rectangle covers all the area under the graph of f from $x = i$ to $x = i+1$. Therefore,

$$\sum_{i=1}^{n-1} \text{Area}(R'_i) = \sum_{i=1}^{n-1} f(i) \geq \int_1^n f(x)dx.$$

Now adding $f(n)$ to the left side of the last inequality gives

$$\sum_{i=1}^{n} f(i) \geq \int_1^n f(x)dx,$$

which proves $\sum_{i=1}^{n} f(i) = \Omega(\int_1^n f(x)dx)$.

Therefore,

$$\sum_{i=1}^{n} f(i) = \Theta(\int_1^n f(x)dx).$$

3 Big-O Notation within the Context of Algorithms

Given a problem L, and an algorithm $\mathcal{A}$ that solves L, big-O notation finds its use in the study of algorithms as a means for describing bounds on the number of steps and the amount of memory required by $\mathcal{A}$ as a function of the **size parameters** of L, i.e. the parameters used to indicate the number of bits required to represent an instance of L.

Example 3.1. The following are examples of how big-O notation arises in the study of data structures and algorithms.

1. Inserting an item into a balanced tree of size n requires $\mathrm{O}(\log n)$ insertions.
2. It has been proven that, sorting n numbers using pairwise comparisons requires $\Omega(n \log n)$ comparisions.
3. The Fast Fourier Transform algorithm has a running time of $\Theta(m \log m)$, where m is the degree of the input polynomial.
4. Two b-bit integers may be recursively added/subtracted in $\mathrm{O}(b)$ steps and recursively multiplied/divided in $\mathrm{O}(b^2)$.

It is also common to see big-O notation used within an arithmetic expression, such as $n^2 + o(n)$, and $n^{\mathrm{O}(1)}$.