

Section 3.2

The Growth of Functions

We quantify the concept that g *grows at least as fast as* f .

What really matters in comparing the complexity of algorithms?

- We only care about the behavior for *large* problems.
 - Even bad algorithms can be used to solve small problems.
 - Ignore implementation details such as loop counter incrementation, etc. We can straight-line any loop.
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The Big-O Notation

Definition: Let f and g be functions from \mathbb{N} to \mathbb{R} . Then g *asymptotically dominates* f , denoted f is $O(g)$ or ' f is big-O of g ,' or ' f is order g ,' iff

$$\exists k \in \mathbb{N} \exists C > 0 \forall n [n > k \implies |f(n)| \leq C |g(n)|]$$

Note:

- Choose k
- Choose C ; it may depend on your choice of k
- Once you choose k and C , you must prove the truth of the implication (often by induction)

An alternative for those with a calculus background:

Definition: if $\lim_n \frac{f(n)}{g(n)} = 0$ then f is $o(g)$ (called *little-o* of g)

Theorem: If f is $o(g)$ then f is $O(g)$.

Proof: by definition of limit as n goes to infinity, $f(n)/g(n)$ gets arbitrarily small.

That is for any $\epsilon > 0$, there must be an integer N such that when $n > N$, $|f(n)/g(n)| < \epsilon$.

Hence, choose $C = 1/\epsilon$ and $k = N$.

Q. E. D.

It is usually easier to prove f is $o(g)$

- using the theory of limits
- using L'Hospital's rule
- using the properties of logarithms

etc.

Example:

$$3n + 5 \text{ is } O(n^2)$$

Proof: It's easy to show $\lim_n \frac{3n + 5}{n^2} = 0$ using the theory of limits.

Hence $3n + 5$ is $o(n^2)$ and so it is $O(n^2)$.

Q. E. D.

We will use induction later to prove the result from scratch.

Also note that $O(g)$ is a set called a

complexity class.

It contains all the functions which g dominates.

$$f \text{ is } O(g) \text{ means } f \in O(g).$$

Properties of Big-O

- f is $O(g)$ iff $O(f) \subseteq O(g)$
- If f is $O(g)$ and g is $O(f)$ then $O(f) = O(g)$

Proof of ii): There is a k_1 and C_1 such that

$$1. f_1(n) < C_1 g_1(n)$$

when $n > k_1$.

There is a k_2 and C_2 such that

$$2. f_2(n) < C_2 g_2(n)$$

when $n > k_2$.

We must find a k_3 and C_3 such that

$$3. f_1(n)f_2(n) < C_3 g_1(n)g_2(n)$$

when $n > k_3$.

We use the inequality

$$\text{if } 0 < a < b \text{ and } 0 < c < d \text{ then } ac < bd$$

to conclude that

$$f_1(n)f_2(n) < C_1 C_2 g_1(n)g_2(n)$$

as long as $k > \max\{k_1, k_2\}$ so that both inequalities 1 and 2. hold at the same time.

Therefore, choose

$$C_3 = C_1 C_2$$

and

$$k_3 = \max\{k_1, k_2\}.$$

Q. E. D.

Important Complexity Classes

$$\begin{array}{cccccc} O(1) & O(\log n) & O(n) & O(n \log n) & O(n^2) & \\ & O(n^j) & O(c^n) & O(n!) & & \end{array}$$

where $j > 2$ and $c > 1$.

Example:

Find the complexity class of the function

$$(nn! + 3^{n+2} + 3n^{100})(n^n + n2^n)$$

Solution:

This means to simplify the expression.

Throw out stuff which you know doesn't grow as fast.

We are using the property that if f is $O(g)$ then $f + g$ is $O(g)$.

- Eliminate the $3n^{100}$ term since $n!$ grows much faster.

- Eliminate the 3^{n+2} term since it also doesn't grow as fast as the $n!$ term.

Now simplify the second term:

Which grows faster, the n^n or the $n2^n$?

- Take the log (base 2) of both.

Since the log is an increasing function whatever conclusion we draw about the logs will also apply to the original functions (why?).

- Compare $n \log n$ or $\log n + n$.

- $n \log n$ grows faster so we keep the n^n term

The complexity class is

$$O(n n! n^n)$$

If a flop takes a nanosecond, how big can a problem be solved (the value of n) in

a minute?

a day?

a year?

for the complexity class $O(n n! n^n)$.

Note: We often want to compare algorithms in the same complexity class

Example:

Suppose

Algorithm 1 has complexity $n^2 - n + 1$

Algorithm 2 has complexity $n^2/2 + 3n + 2$

Then both are $O(n^2)$ but Algorithm 2 has a smaller leading coefficient and will be faster for large problems.

Hence we write

Algorithm 1 has complexity $n^2 + O(n)$

Algorithm 2 has complexity $n^2/2 + O(n)$
