CS 441: Growth Rates

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Today's topics

- Growth rates of functions
 - Big-O notation and its relation to CS
 - Growth rates of combined functions
 - Big-Omega and Big-Theta notations



Let's define this "big-O notation" that you've probably heard of (and maybe used)

Definition: Let f and g be functions from the set of integers (or real numbers) to the set of real numbers. We say that f(x) is O(g(x)) if there are constants C and k such that $|f(x)| \le C|g(x)|$ whenever $x \ge k$.

• *C* and *k* are referred to as witnesses which prove the relationship

Formally, O(g(x)) is a set of functions: $O(g(x)) = \{f \mid \exists k, C \forall x(x > k \to |f(x)| \le C |g(x)|)\}$

When considering positive values only, we will often drop the absolute value

- $2x^2$ is $O(x^2)$ because of witnesses C = 3 and k = 1: $2x^2 \le 3x^2$ whenever $x \ge 1$
- 3x + 5 is O(x) because of witnesses C = 4 and k = 5: $3x + 5 \le 4x$ when $x \ge 5$

Examples:



$$f(x)$$
 is $O(g(x))$

The part of the graph f(x) that satisfies f(x) < C g(x) is shown in color.

Why does this matter to computing?

This notation predates its use in computer science by ~70 years!

Consider the intuition behind the math: "The growth of f(x) is bounded above by some multiple of g(x)."

• What does this tell us, if *f*(*x*) describes an algorithm's cost to solve an instance of size *x*?

Big-O notation is used in algorithm analysis to group algorithms together

- Simple growth rate is more important than exact runtime
- Algorithm analysis describes how algorithms scale to larger and larger problem instances

How to find witnesses to prove a big-O relationship

When f(x) is O(g(x)), there are infinite witnesses

- e.g., if k works, then any k' > k also works
- but, we only need to identify one pair (k, C) to prove the relationship

Simple key idea: Round up

- To prove that $2x^2 + 3x + 2$ is $O(x^2)$, "round up" each term to a multiple of x^2
- $2x^2 + 3x + 2 \le 2x^2 + 3x^2 + 2x^2 = 7x^2$, whenever $x \ge 1$
- So, let C = 7 and k = 1

In general: Pick a threshold where it is easy to calculate an upper bound for f(x) in terms of g(x)

But wait, doesn't this mean that any greater g(x) would also work?

In fact, yes!

• $2x^2$ is $O(x^2)$, but also $O(2x^2)$, $O(10x^2)$, $O(x^3)$, and $O(x^4)$...

However, it is most useful to state the most specific or descriptive relationship that you can prove

- Multiplicative constants can be anything and are generally left out
- O(x²) is a proper subset of O(x³), so stating f(x) is in the former also implies it is in the latter, but not vice-versa

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- If we know it is $O(x^2)$, then stating it is $O(x^3)$ leaves out information unnecessarily
- Nobody cares that f(x) is $O(x^{x^{x^{x}}})$ unless you really can't prove something more specific!

How do we know when we can't use a smaller bound?

Let's see by example: Prove that x^2 is not O(x)

- We need to prove that there is no choice of *C* and *k* that satisfy the constraints. Let's use contradiction.
- Suppose there is a *C* and *k* where $x^2 \leq Cx$ whenever $x \geq k$
- When x > 0, we can divide both sides by x to see $x \le C$
- However, we cannot pick *C* that satisfies this, since there is no *C* that is greater than any (arbitrarily large) integer
- This contradiction proves that C and k do not exist where $x^2 \leq Cx$ whenever $x \geq k$

Therefore, x^2 is not O(x)!

• That is, x has a strictly smaller rate of growth than x^2

A heuristic for growth rates of polynomials: Drop multiplicative constants and lower-order terms

Theorem: Let $f(x) = a_n x^n + a_{n-1} x^{n+1} + \dots + a_1 x + a_0$, where each a_i is a real number. Then, f(x) is $O(x^n)$.

- In other words, every *n*-degree polynomial is $O(x^n)$
- See §3.2.3 for a proof

This means that we can calculate growth rates without explicitly finding witnesses

- Drop lower-order terms: $3x^3 + 6x^2 3x + 9$ becomes $3x^3$
- Drop multiplicative constants: $3x^3$ becomes x^3
- Thus, $3x^3 + 6x^2 3x + 9$ is $O(x^3)$

This informal approach matches our goals with algorithm analysis

- Highest-order term will dominate at scale
- Multiplicative constants are equivalent to hardware choice



Growth rates of combined functions

Theorem: If $f_1(x)$ is $O(g_1(x))$ and $f_2(x)$ is $O(g_2(x))$, then $(f_1 + f_2)(x)$ is O(g(x)), where $g(x) = \max(g_1(x), g_2(x))$ for all x.

In other words, the sum of two functions has a growth rate equal to the max of their individual growth rates

Examples:

- $x^3 + x \log x$ is $O(x^3)$
- $\log x + (\log x)^2$ is $O(\log^2 x)$

Note that this is a generalization of the previous theorem regarding polynomials

Growth rates of combined functions

Theorem: If $f_1(x)$ is $O(g_1(x))$ and $f_2(x)$ is $O(g_2(x))$, then $(f_1f_2)(x)$ is $O(g_1(x)g_2(x))$.

In other words, the product of two functions has a growth rate equal to the product of their individual growth rates

Examples:

- $(x^2 + x)(x + 5)$ is $O(x^3)$
- $(\log x + \log \log x)(8 + \log x)$ is $O(\log^2 x)$

This is especially useful for analyzing nested loops in algorithm analysis

• As we'll see next time!

Related notations to big-O

Definition: Let f and g be functions from the set of integers (or real numbers) to the set of real numbers. We say that f(x) is $\Omega(g(x))$ if there are constants C and k such that $|f(x)| \ge C|g(x)|$ whenever $x \ge k$.

- If big-O represents an asymptotic upper bound, big-Omega represents an asymptotic lower bound
- (Asymptotic = at scale, as x increases toward infinity)

Examples:

- $2x^2$ is $\Omega(x^2)$, $\Omega(x)$, and $\Omega(1)$
 - In addition to being $O(x^2)$, $O(x^3)$, $O(x^4)$, ...

When f(x) is both O(g(x)) and $\Omega(g(x))$, we say it is $\Theta(g(x))$, so $2x^2$ is $\Theta(x^2)$

"Big theta"

In-class exercises

On Top Hat

Final thoughts

- Growth rates are commonly expressed using big-O and related notations
- These notations were not developed for computing, but fit well for algorithm analysis
- Next time:
 - Algorithm analysis (Section 3.3)