CMP_SC 3050: Asymptotic growth of functions

Rohit Chadha

September 3, 2014

Announcements

Homework 1 is on Blackboard. Due, September 9, 2014 at 12:29:29 pm.

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Email: akvhxd@mail.missouri.edu

Office: 303 EBN

Office hours: Friday, 3:00 pm - 5:00 pm

Teaching Assistant: Eric C. Gaudiello

Office: 239 EBW

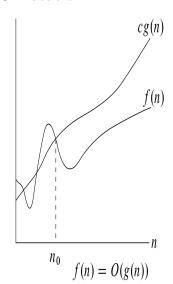
Email: ecgprc@mail.missouri.edu

Office hours: Tuesday, Thursday 3:30 pm - 4:30 pm

Asymptotic analysis

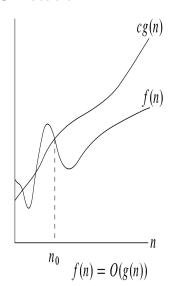
- Running times are functions of sizes of input
- Our focus is on how the running time grows as input size grows
- Such kind of analysis is called asymptotic analysis (analysis in the limit)
- In this analysis, we can ignore low-order terms and constant factors of functions
- ullet The Θ notation is an example of this analysis (compares functions)
- The other example that you have seen in CMP_SC 2050 is the O (big-oh) notation

O-notation



Informal: Asymptotically, a function f(n) is said to be O(g(n)) if in the limit f(n) is smaller than some constant times g(n)

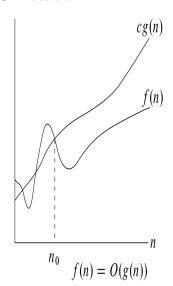
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 $O \approx \le$: Useful to think of O-notation as saying that the function f is less than the function g

• 2n is O(n)

- 2n is O(n)
- 2n is also $O(n^2)$

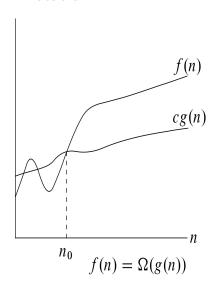
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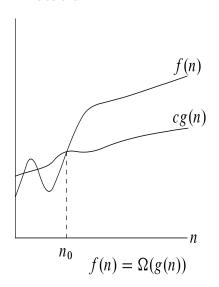
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Ω -notation



Informal: Asymptotically, a function f(n) is said to be O(g(n)) if in the limit f(n) is bigger than some constant times g(n)

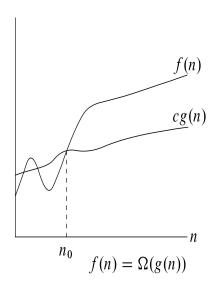
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 $\Omega \approx \geq$: Useful to think of Ω -notation as saying that the function f is bigger than the function g

• 2n is $\Omega(n)$

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- 2n is NOT $\Omega(n^2)$ but n^2 is $\Omega(2n)$

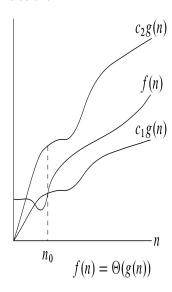
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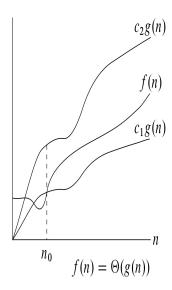
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Θ-notation



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Θ -notation



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 $\Theta \approx =:$ Useful to think of Θ notation as saying the function f behaves like the function g

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Reflexivity

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Transitivity

- If f(n) is O(g(n)) and g(n) is O(h(n)) then f(n) is O(h(n))
- If f(n) is $\Omega(g(n))$ and g(n) is $\Omega(h(n))$ then f(n) is $\Omega(h(n))$
- If f(n) is $\Theta(g(n))$ and g(n) is $\Theta(h(n))$ then f(n) is $\Theta(h(n))$

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Symmetry

- If f(n) is $\Theta(g(n))$ then g(n) is $\Theta(f(n))$
- Not true for O and Ω

Reflexivity

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- Not true for O and Ω

Transpose Symmetry

• f(n) is O(g(n)) if and only if g(n) is $\Omega(f(n))$

A non-property

There are functions f(n) and g(n) which cannot be compared in asymptotic notation

That is neither f(n) is O(g(n)) nor f(n) is $\Omega(g(n))$

An example is $n^{1+\sin n}$ since $1+\sin n$ oscillates between 0 and 2

Asymptotic bounds for polynomial functions

As we shall continue, we shall be interested primarily in finding upper bound on running times (that is the *O*-notation) It will be useful to know bounds for some common functions

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 where $a_d > 0$.

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- The function f is $\Theta(n^d)$ and hence $O(n^d)$
- Also, note that f is $O(n^{d+1})$ but not $\Theta(O^{d+1})$

Asymptotic bounds for logarithmic function

Logarithms: Recall $\log_b n$ (logarithm of n to the base b) is the number y such that $b^y = n$

• Base does not matter. That is for each b > 1, the function

$$\log_b n$$
 is $\Theta(\log_2 n)$

From now on, we shall just write $\log n$ and ignore the base

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• For each x > 0, the function

$$\log_b n$$
 is $O(n^x)$

• For each x > 0, the function

$$\log_b n$$
 is NOT $\Theta(n^x)$.

In other words, $\log_b n$ grows much slowly than n^x



Asymptotic bounds for exponential function

Exponential:

• For each r > 1 and x > 0, the function

$$r^n$$
 is $\Omega(n^x)$

• For each r > 1 and x > 0, the function

$$r^n$$
 is **NOT** $\Theta(n^x)$.

In other words, r^n grows much faster than n^x

By an O(f(n)) algorithm, we shall mean an algorithm whose worst-case running time is O(f(n))

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- $O(\log n)$: Example: Binary search

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- $O(n \log n)$: Example: Merge Sort

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- Quadratic Time: These are algorithms whose worst case behavior is $O(n^2)$. Examples: Insertion sort, selection sort
- $O(\log n)$: Example: Binary search
- $O(n \log n)$: Example: Merge Sort
- Cubic time: These are algorithms whose worst case behavior is $O(n^3)$

Summary

Study asymptotic behavior of running times (Chapter 3 of the book)

$$O \approx <$$

$$\Omega \approx \geq$$

$$\Rightarrow \approx =$$

 While we will focus mainly on running times, we can also analyze the extra space used by an algorithm using the same asymptotic notation