

CS 315 - Day 08, Asymptotics

First, let's watch this (there is a pedagogical reason!): https://www.youtube.com/watch?v=P4Mpt_7g6U0

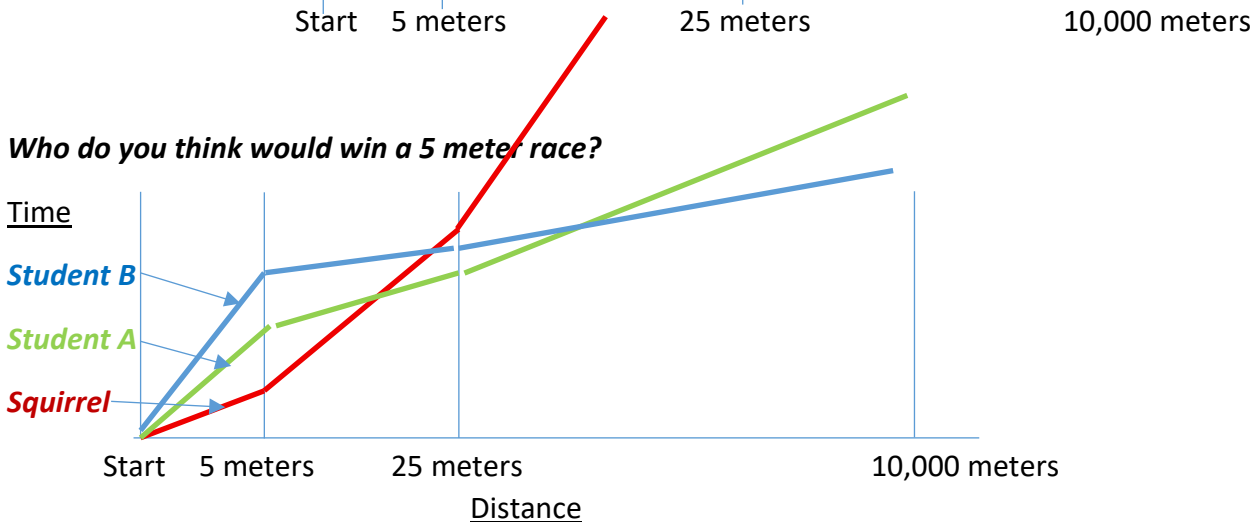
This is one of my favorites in this genre of ads (there really is no pedagogical reason to watch this): https://www.youtube.com/watch?v=m_MaJDK3VNE

So, back to algorithms... Let's picture a race, Student A, Student B on a bike, and a squirrel.

Student A

Student B on a bike

Squirrel



It depends on how long the race is. The Squirrel would dominate very short races, the running Student would dominate the middle distances, and then after a certain point, the bike riding Student would win all the races. When we get those arbitrarily large distances, where the ordering of the finishes is set, we are observing **asymptotic** behavior.

So when we describe functions which represent the running time of algorithms, we are interested in their asymptotic behavior, which means their behavior on large problem sizes.

We use **bounds** for the functions representing running time, since we're worried about the asymptotic effects and it wouldn't be worth the extra effort to calculate the exact function.

The notation we use: θ , O , Ω actually represent **sets** of functions.

Applications:

When is our first exam?

- "Sometime after next week" \rightarrow lower bound.
- "Sometime before December 1" \rightarrow upper bound.
- "On {**actual date here**}." \rightarrow tight bound.

What are the following in asymptotic notation? Remember we only look at the highest order term, and disregard coefficients.

So, yes, there might be a bit of algebra involved.

Oh, and usually on a closed expression we can pick a tight bound.

$$\frac{k(k+1)}{2} = \frac{k^2+k}{2} = \frac{k^2}{2} + \frac{k}{2} \rightarrow \theta(k^2)$$

$\frac{N(N+1)(2N+1)}{6}$ here, it's pretty obvious that the highest order term would be something involving N^3 , so we can jump to $\theta(N^3)$.

So, the “punch line” is that:

$$\sum_{i=1}^k i = \theta(k^2)$$
$$\sum_{k=1}^N k^2 = \theta(N^3)$$

We skipped over the closed formulas, and went directly from the sigma notation to the asymptotic notation.

Note that we also stayed consistent, using the variables provided, and not the “dummy”/loop control variables. We will generate closed formulas when we analyze code.

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So, back to algorithms... Let's picture a race, Student A, Student B on a bike, and a squirrel.

Student A

Student B on a bike

Squirrel

Start 5 meters 25 meters 10,000 meters

Who do you think would win a 5 meter race?

Time

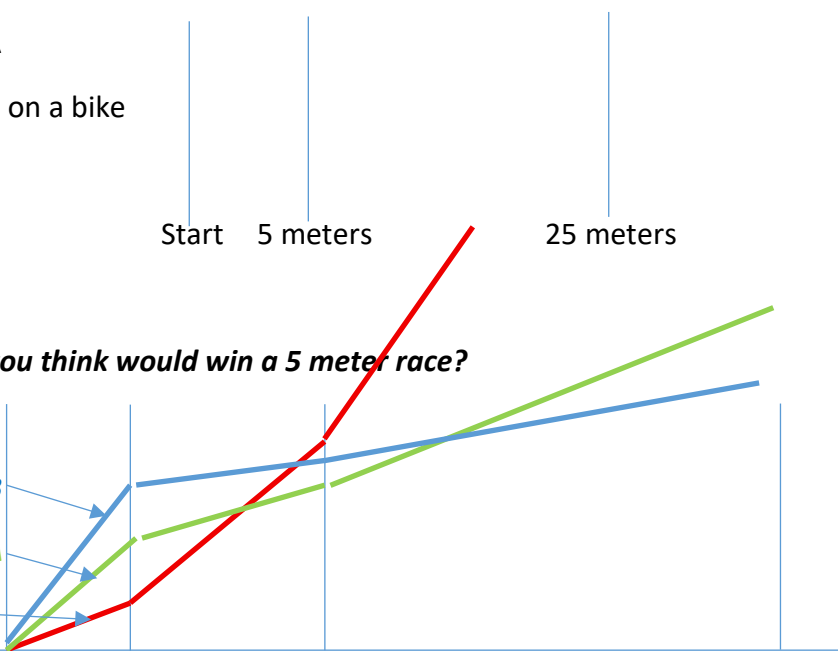
Student B

Student A

Squirrel

Start 5 meters 25 meters 10,000 meters

Distance



It depends on how long the race is. The Squirrel would dominate very short races, the running Student would dominate the middle distances, and then after a certain point, the bike riding Student would win all the races. When we get those arbitrarily large distances, where the ordering of the finishes is set, we are observing **asymptotic** behavior.

So when we describe functions which represent the running time of algorithms, we are interested in their asymptotic behavior, which means their behavior on large problem sizes.

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The notation we use: θ , O , Ω actually represent sets of functions.

O -notation

O -notation characterizes an *upper bound* on the asymptotic behavior of a function: it says that a function grows *no faster* than a certain rate. This rate is based on the highest order term.

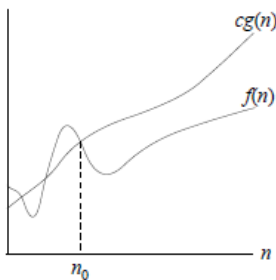
For example, $f(n) = 7n^3 + 100n^2 - 20n + 6$ is $O(n^3)$, since the highest order term is $7n^3$, and therefore the function grows no faster than n^3 .

The function $f(n)$ is also $O(n^5)$, $O(n^6)$, and $O(n^c)$ for any constant $c \geq 3$.

$O(g(n)) = \{f(n) : \text{there exist positive constants } c \text{ and } n_0 \text{ such that } 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0\}$.

$g(n)$ is an *asymptotic upper bound* for $f(n)$.

If $f(n) \in O(g(n))$, we write $f(n) = O(g(n))$ (will precisely explain this soon).



Example

$2n^2 = O(n^3)$, with $c = 1$ and $n_0 = 2$.

Examples of functions in $O(n^2)$:

n^2
 $n^2 + n$
 $n^2 + 1000n$
 $1000n^2 + 1000n$
 Also,
 n

Ω -notation

Ω -notation characterizes a *lower bound* on the asymptotic behavior of a function: it says that a function grows *at least as fast* as a certain rate. This rate is again based on the highest-order term.

For example, $f(n) = 7n^3 + 100n^2 - 20n + 6$ is $\Omega(n^3)$, since the highest-order term, n^3 , grows at least as fast as n^3 .

The function $f(n)$ is also $\Omega(n^2)$, $\Omega(n)$, and $\Omega(n^c)$ for any constant $c \leq 3$.

Ω -notation

$\Omega(g(n)) = \{f(n) : \text{there exist positive constants } c \text{ and } n_0 \text{ such that } 0 \leq cg(n) \leq f(n) \text{ for all } n \geq n_0\}$.

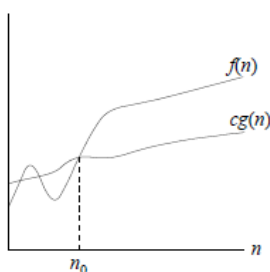
$g(n)$ is an *asymptotic lower bound* for $f(n)$.

Example

$\sqrt{n} = \Omega(\lg n)$, with $c = 1$ and $n_0 = 16$.

Examples of functions in $\Omega(n^2)$:

n^2
 $n^2 + n$
 $n^2 - n$
 $1000n^2 + 1000n$
 $1000n^2 - 1000n$
 Also,
 n^3



Can a function be in both O and Ω ?

YES!

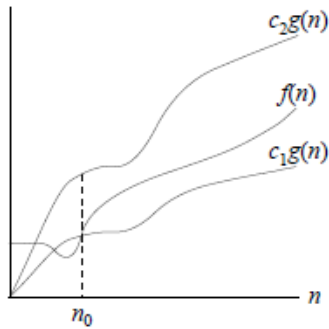
Θ -notation

Θ -notation characterizes a *tight bound* on the asymptotic behavior of a function: it says that a function grows *precisely* at a certain rate, again based on the highest-order term.

If a function is both $O(f(n))$ and $\Omega(f(n))$, then a function is $\Theta(f(n))$.

Θ -notation

$\Theta(g(n)) = \{f(n) : \text{there exist positive constants } c_1, c_2, \text{ and } n_0 \text{ such that } 0 \leq c_1 g(n) \leq f(n) \leq c_2 g(n) \text{ for all } n \geq n_0\}$.



$g(n)$ is an *asymptotically tight bound* for $f(n)$.

Example

$n^2/2 - 2n = \Theta(n^2)$, with $c_1 = 1/4$, $c_2 = 1/2$, and $n_0 = 8$.

Theorem

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

So, if you can show that a function is both O and Ω , then it is automatically θ .

Note that $f(n) = \theta(n^2)$ really means that $f(n) \in \theta(n^2)$, and remember that in a mathematical expression, leading constants and low-order terms don't matter.

A constant factor can be expressed as $\theta(1)$ or $O(1)$, since it's within a constant factor of 1.

For example, the worst-case running time for insertion sort is $O(n^2)$, $\Omega(n^2)$, and $\Theta(n^2)$; all are correct. Prefer to use $\Theta(n^2)$ here, since it's the most precise. The best-case running time for insertion sort is $O(n)$, $\Omega(n)$, and $\Theta(n)$; prefer $\Theta(n)$.

But *cannot* say that the running time for insertion sort is $\Theta(n^2)$, with "worst-case" omitted. Omitting the case means making a blanket statement that covers *all* cases, and insertion sort does *not* run in $\Theta(n^2)$ time in all cases.

Can make the blanket statement that the running time for insertion sort is $O(n^2)$, or that it's $\Omega(n)$, because these asymptotic running times are true for all cases.

For merge sort, its running time is $\Theta(n \lg n)$ in all cases, so it's OK to omit which case.

Computer scientists typically mis-use notation, referring to something using O , but intending it to be a tight bound, which is θ . They cover by saying “the best” O bound.

Bounding functions asymptotics:

- “Tight Bound” $\theta(g(n)) = \{f(n) : \exists \text{ positive constants } c_1, c_2, \text{ and } n_0 \text{ such that } 0 \leq c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n) \quad \forall n \geq n_0\}$
- “Upper Bound” $O(g(n)) = \{f(n) : \exists \text{ positive constants } c \text{ and } n_0 \text{ such that } 0 \leq f(n) \leq c \cdot g(n) \quad \forall n \geq n_0\}$
- “Lower Bound” $\Omega(g(n)) = \{f(n) : \exists \text{ positive constants } c \text{ and } n_0 \text{ such that } 0 \leq c \cdot g(n) \leq f(n) \quad \forall n \geq n_0\}$

So, $\sum_{i=1}^n i = \frac{n(n+1)}{2} = \frac{1}{2}n^2 + \frac{1}{2}n$ is $\theta(n^2)$. But let’s take a deep dive and plug this into the definition.

$$0 \leq c_1 n^2 \leq \frac{1}{2}n^2 + \frac{1}{2}n \leq c_2 n^2, \quad \forall n_0 > n$$

We need to find c_1 , c_2 , and n_0 .

$$c_1 n^2 \leq \frac{1}{2}n^2 + \frac{1}{2}n \leq c_2 n^2$$

$$c_1 \leq \frac{1}{2} + \frac{1}{2n} \leq c_2$$

We can just “guess and check” or inspect a graph, to determine which values of c_1 , c_2 , and n_0 would work.

(Hint: just try “easy” values).

$$c_1 = \frac{1}{2}$$

$$c_2 = 1$$

$$n_0 = 1$$

Next, let’s show $\frac{1}{2}n + 14$ is $O(n^2)$ by plugging into the definition.

$$0 \leq \frac{1}{2}n + 14 \leq cn^2$$

Pick n_0 then find c

or

Pick c then find n_0

$$n_0 = 10$$

$$c = 1$$

$$\frac{1}{2}10 + 14 \leq c10^2$$

$$\frac{1}{2}n + 14 \leq n^2$$

$$19 \leq c10^2$$

$$\frac{1}{2} + \frac{14}{n} \leq n$$

$$0.19 \leq c, \text{ so use } c = 0.20$$

$$n_0 = 10 \text{ should work}$$