

Algorithm analysis

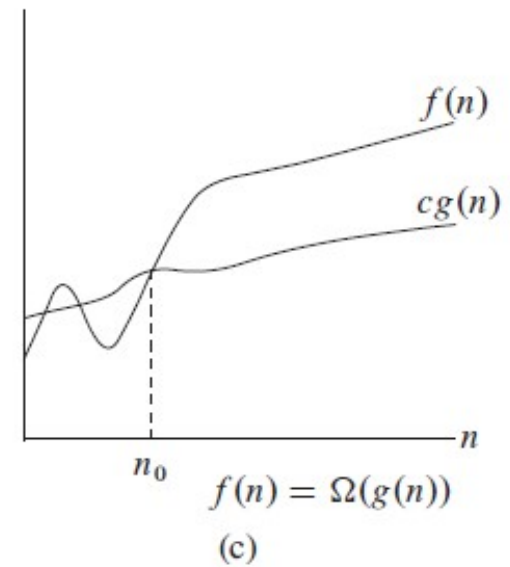
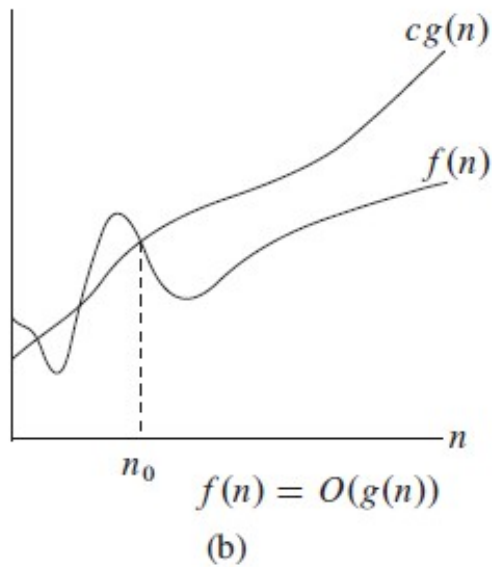
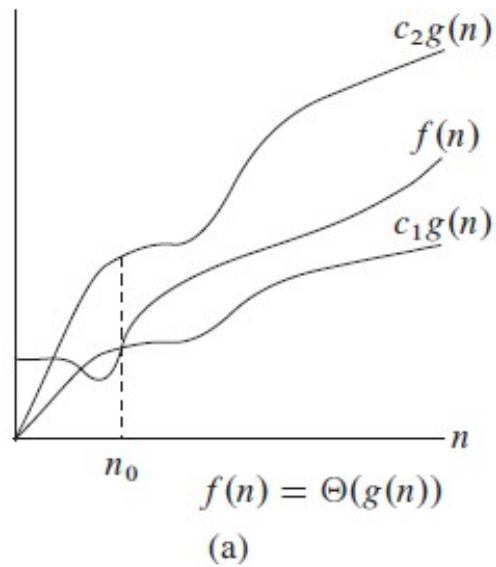
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Presentation by Antonio-Gabriel Sturzu

- Asymptotic notation
- Examples
- Substitution method
- Recursion tree method
- Master Theorem
- ➡ Examples

Big O, Θ and Ω notation



- In practice we are mainly interested in a tight upper bound for the worst case scenario and this is where the big O notation comes to the rescue
- $O(g(n)) = \{ f(n) : \text{there exist constants } c > 0 \text{ and } n_0 > 0 \text{ such that } 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \}$
- $\Omega(g(n)) = \{ f(n) : \text{there exist constants } c > 0 \text{ and } n_0 > 0 \text{ such that } 0 \leq cg(n) \leq f(n) \text{ for all } n \geq n_0 \}$
- $\Theta(g(n)) = O(g(n)) \cap \Omega(g(n))$

- In all the examples when we say $f(n)=O(g(n))$ we actually mean $f(n)\in O(g(n))$ because O is a set
- $2n^2= O(n^3)$ ($c=1, n_0=2$)
- $\log_2 n= O(\log_3 n)$ ($c=\log_2 3, n_0=2$)
- $n^2=\Omega(n)$ ($c=1, n_0=1$)
- $2^{n+10}= \Theta(2^n)$ ($c=2^{10}, n_0=1$)

- A nice trick is that in practice we can ignore the lower order terms of an asymptotically positive function because for a sufficient larger n they will get dominated by the highest order term
- Also the coefficient of the highest order term can be ignored because it will only modify by a constant factor the c constant in the big O notation

- A clear example that proves this is that given $f(n) = a_p n^p + a_{p-1} n^{p-1} + \dots + a_1 n + a_0$, $a_p > 0$ and all the coefficients are constant then $f(n) = \theta(n^p)$
- In practice a constant will be expressed by $\theta(1)$ or $O(1)$ since it is a degree 0 polynomial
- The above notation could also mean a constant function

Substitution method for solving recurrences



- Guess the form of the solution
- Verify by mathematical induction
- Solve for constants

Substitution method for solving recurrences

- Example:
- $T(n) = 4T(n/2) + n$ (we assume that $T(1) = 1$)
- We guess that the upper bound is $O(n^3)$
- Now begins the induction phase
- First we prove the base case
- The base case is that $T(1) = O(n^3)$
- It is easy to see that the inductive assumption holds for $c \geq 1$

Substitution method for solving recurrences

- The general case is to prove that $T(n) \leq cn^3$
- We use the inductive hypothesis that $T(m) \leq cm^3$ for $m < n$
- Using this we have $T(n) = 4T(n/2) + n \leq 4c(n/2)^3 + n$
- Then $T(n) \leq (c/2)n^3 + n \leq cn^3$
- From here we get the condition $(c/2)n^3 - n \geq 0$ and for any $n \geq 1$ we have $(c/2)n^2 \geq 1$ and from here $c \geq 2/n^2$
- We can choose $c=2$ and $n_0=1$ and the proof is complete

Substitution method for solving recurrences

- Sometimes the upperbound that we guess isn't tight enough
- We guess that $T(n)=O(n^2)$
- First we try to prove the base case $T(1)=O(n^2)$ for $c \geq 1$
- We will try to prove that $T(n) \leq cn^2$
- The inductive hypothesis is $T(k) \leq ck^2$, $k < n$
- $T(n)=4T(n/2)+n \leq 4c(n/2)^2+n= cn^2+n=O(n^2)$

Substitution method for solving recurrences

- The proof is wrong because we are trying to prove that $T(n) \leq cn^2$
- From the inductive hypothesis we have that $T(n) \leq cn^2 + n$
- If we impose $cn^2 + n \leq cn^2$ it implies that $n \leq 0$ which is false !
- So we need to make a different inductive assumption in order to prove that $T(n) = O(n^2)$

Substitution method for solving recurrences

- We assume that $T(k) \leq ck^2 - k$, $c > 0$, $k < n$
- $T(n) = 4T(n/2) + n \leq 4c(n/2)^2 - 4n/2 + n = cn^2 - n \leq cn^2$ for every $c > 0$ and $n > 0$
- We choose $c=2$ and $n_0=1$
- All that is left to do is to prove the base case $T(1) \leq 2 \cdot 1 = 2$ which holds and the proof is complete

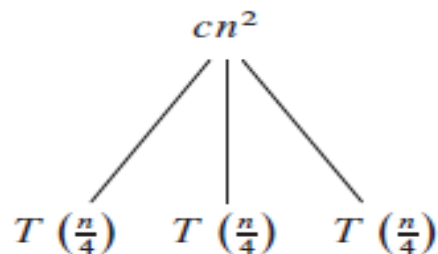
Substitution method for solving recurrences



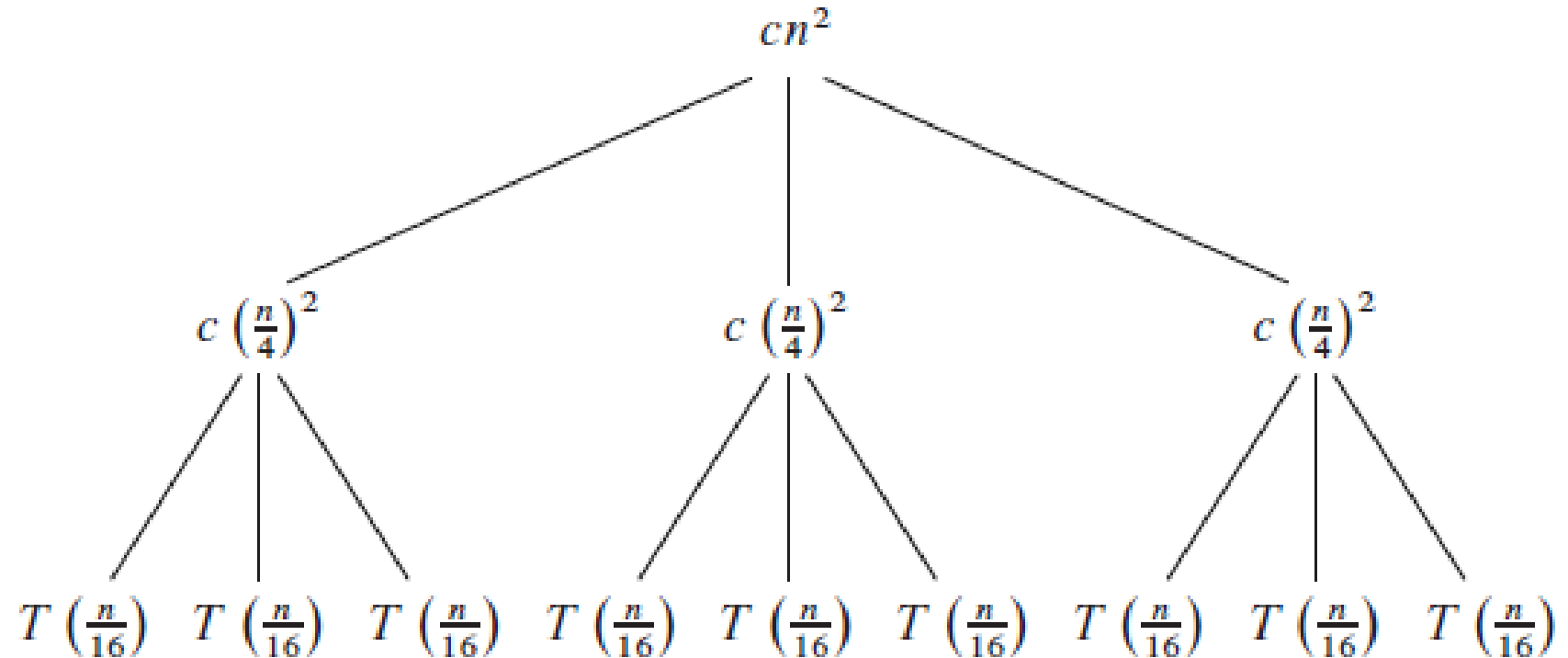
- Sometimes if the base case doesn't hold we can take advantage of the Big O definition that says that we can prove the inequality for $n \geq n_0$ which we can conveniently choose

- Models the cost of a recursive algorithm
- Is intuitive but sometimes it can be somewhat imprecise
- Each node in the tree represents the cost of a subproblem in the recursive invocation of the algorithm
- Can be used as a guess for the substitution method if we were sloppy in the recursion tree method

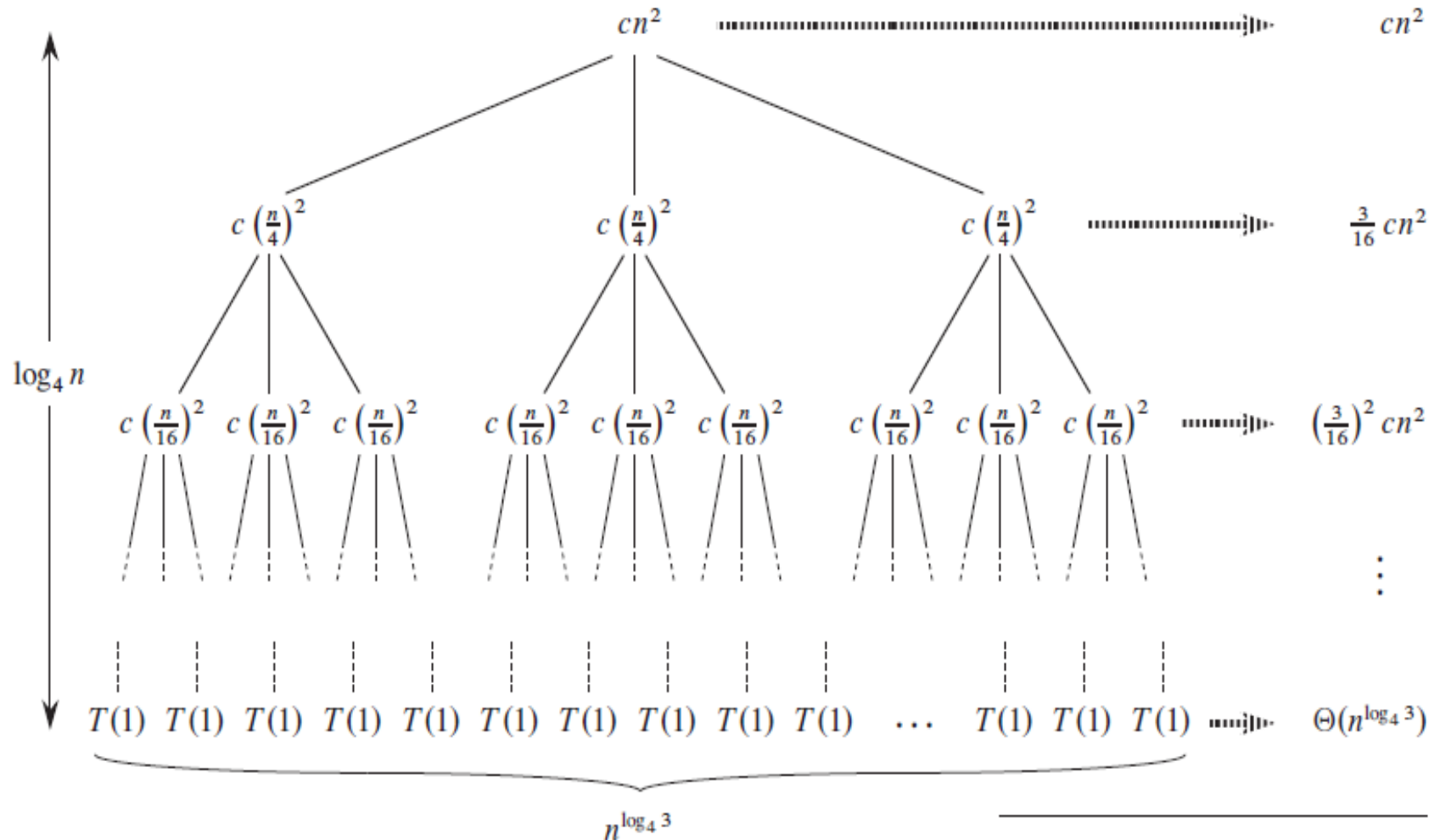
- Example
- $T(n) = 3T(n/4) + \Theta(n^2)$
- First we write $T(n) = 3T(n/4) + cn^2$
- In the first recursive invocation of the algorithm the tree looks like this:



- In the next recursive call the tree looks like this:



Recursion tree method



- The number of subproblems at level j is 3^j
- The work done by a subproblem at level j is $c(n/4^j)^2$ which is equivalent to $cn^2(1/16)^j$
- The total work done at level j will be $cn^2(3/16)^j$
- At the last level the number of nodes is $3^{\log_4(n)}$ which is equivalent to $n^{\log_4(3)}$

- Therefore the total work done will be

$$\begin{aligned} cn^2 \sum_{i=0}^{\log_4 n - 1} \left(\frac{3}{16} \right)^i + \theta(n^{\log_4 3}) &< cn^2 \sum_{i=0}^{\infty} \left(\frac{3}{16} \right)^i + \theta(n^{\log_4 3}) \\ &= \frac{1}{1 - \frac{3}{16}} cn^2 + \theta(n^{\log_4 3}) = \frac{16}{13} cn^2 + \theta(n^{\log_4 3}) = O(n^2) \end{aligned}$$

- Let $a \geq 1$ and $b > 1$ be constants and let $f(n)$ be a nonnegative function with $T(n) = aT(n/b) + f(n)$
- Then $T(n)$ has the following asymptotic bounds:
 1. If $f(n) = O(n^{\log_b a - \epsilon})$ for some constant $\epsilon > 0$, then $T(n) = \Theta(n^{\log_b a})$.
 2. If $f(n) = \Theta(n^{\log_b a})$, then $T(n) = \Theta(n^{\log_b a} \lg n)$.
 3. If $f(n) = \Omega(n^{\log_b a + \epsilon})$ for some constant $\epsilon > 0$, and if $af(n/b) \leq cf(n)$ for some constant $c < 1$ and all sufficiently large n , then $T(n) = \Theta(f(n))$. ■

- $T(n) = 2T(n/2) + n$
- We have $a=2$, $b=2$, $f(n)=n$ and we are in case 2
- So $T(n) = \theta(n \lg n)$
- $T(n) = 8T(n/2) + n^2$
- We have $a=8$, $b=2$, $f(n)=n^2$ and we are in case 1
- So $T(n) = \theta(n^3)$
- $T(n) = 3T(n/4) + n \lg n$
- We have $a=3$, $b=4$, $f(n)=n \lg n$ and we are in case 3
- So $T(n) = \theta(n \lg n)$

- A more tricky example
- $T(n) = 2T(\sqrt{n}) + \log_2 n$
- The idea is to make a change of variable
- Consider $m = \log_2 n$ then the recurrence becomes
- $T(2^m) = 2T(2^{m/2}) + m$
- Let $S(m) = T(2^m)$. The relation becomes $S(m) = 2S(m/2) + m$
- The time complexity will be $\theta(\lg n \lg(\lg n))$