

ASYMPTOTIC NOTATIONS

Outline of Lecture 3:

- ✓ **Formal Definition** of Individual Asymptotic Notation
- ✓ Geometrical Interpretation of each Asymptotic Notation
- ✓ Examples to understand the corresponding notation
- ✓ Properties of Big Oh Asymptotic Notation
- ✓ Calculation of Big Oh of an Algorithm

Contents

- What is an asymptote?
- What do you mean by the run time $T_A(n)$ of an algorithm?
- Why we need to know asymptotic behavior for analyzing an algorithm?
- What are the different types of asymptotic notations?
- Big Oh: An Asymptotic Upper Bound
 - ✓ Definition
 - ✓ Geometrical Interpretation
 - ✓ Examples
 - ✓ Properties
 - ✓ How Big Oh help us to calculate the time complexity of an algorithm?

Contents (Contd...)

- Small oh: An Asymptotic Loose upper bound
 - ✓ Definition
 - ✓ Geometrical Interpretation
 - ✓ Examples
- Big -Omega: An Asymptotic Lower Bound
 - ✓ Definition
 - ✓ Geometrical Interpretation
 - ✓ Examples
- Small -omega: An Asymptotic lose Lower Bound
 - ✓ Definition
 - ✓ Geometrical Interpretation
 - ✓ Examples
- Theta Notation
 - ✓ Definition
 - ✓ Geometrical Interpretation
 - ✓ Examples

What is an asymptote?

- ✓ Definition
- ✓ Consider a curve say $y = 1 / x$

x	1	2	3	4	5	100	1000	10000
y	1	0.5	0.33	0.25	0.2	0.01	0.001	0.0001

X=1

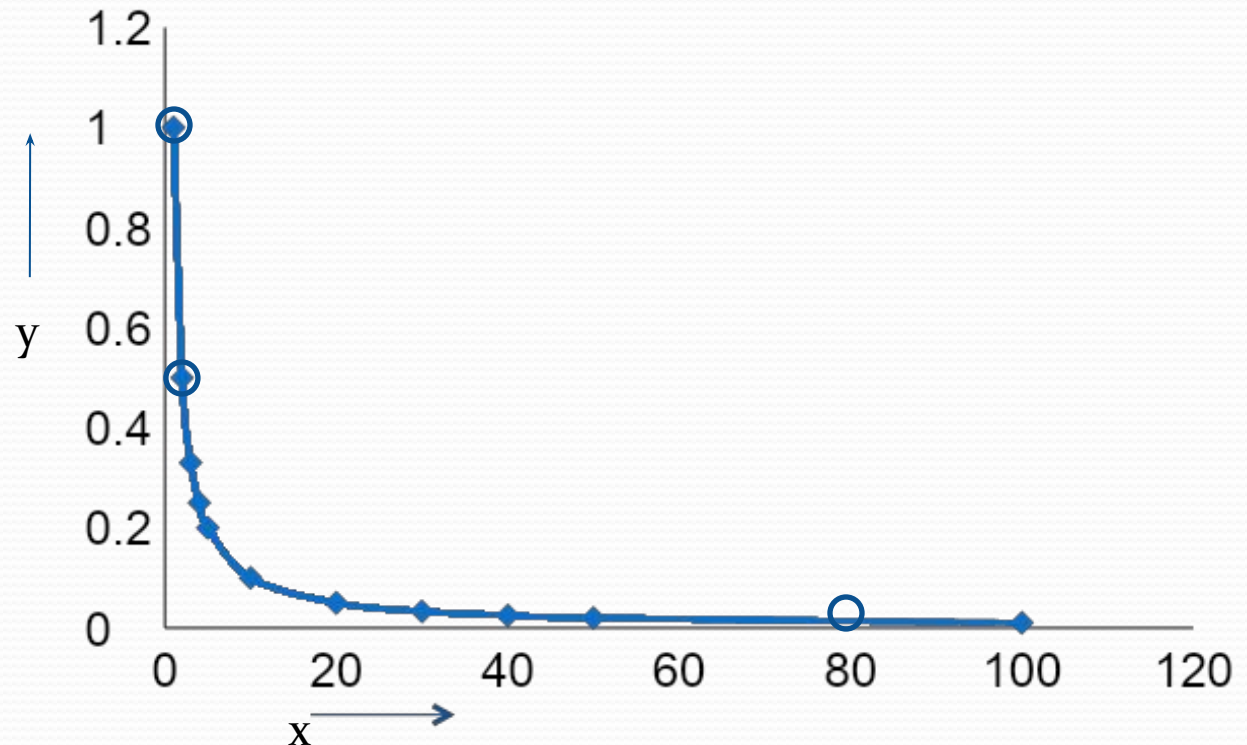
y=1

X=2

y=0.5

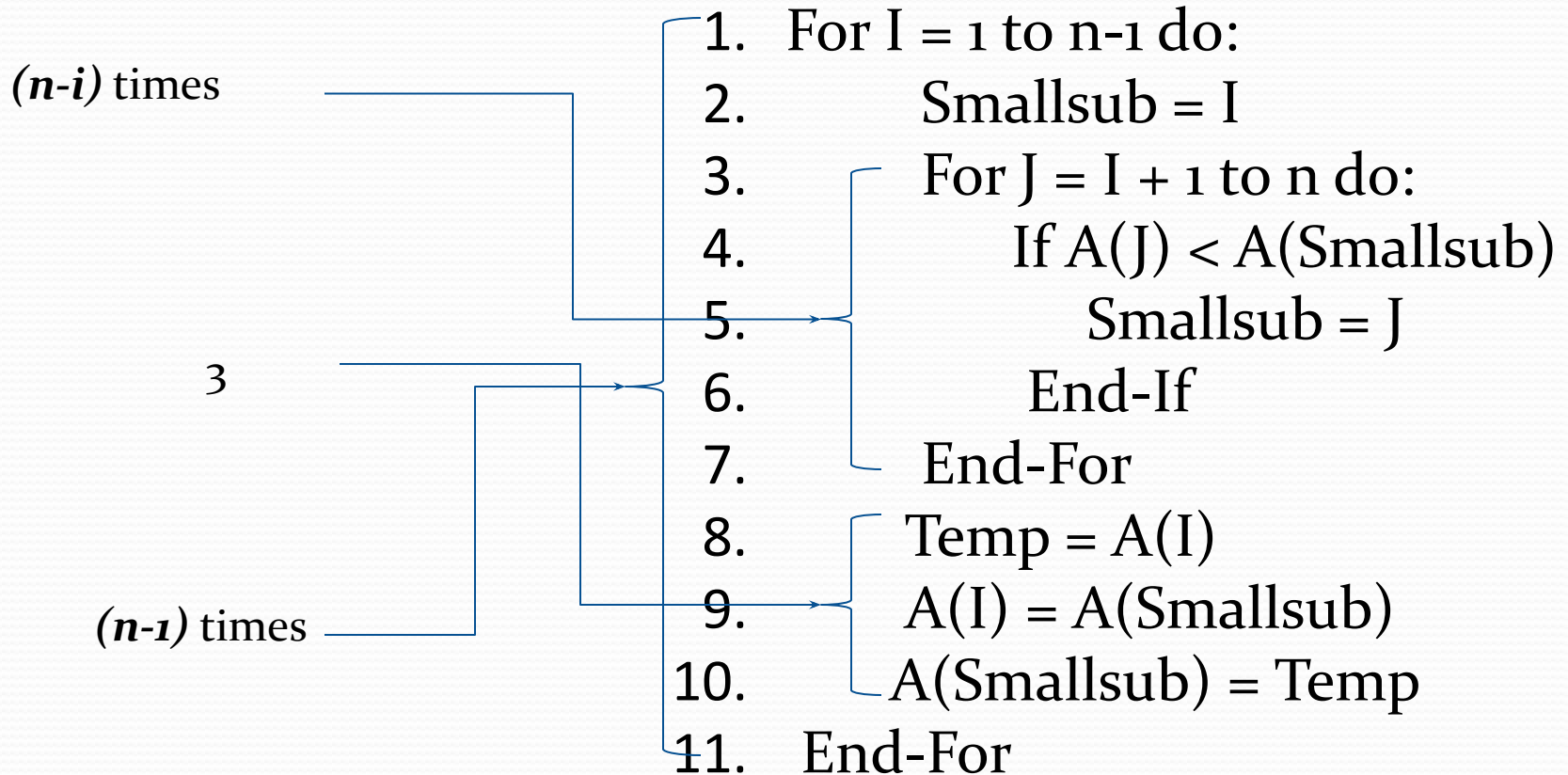
X=100

y=0.01



Calculation of Run time $T_A(n)$ of an Algorithm

Selection Sort(A)



$$T_A(n) = \sum \{2 * (n - i) + 3\} \text{ where } i = 1, 2, \dots, n - 1$$

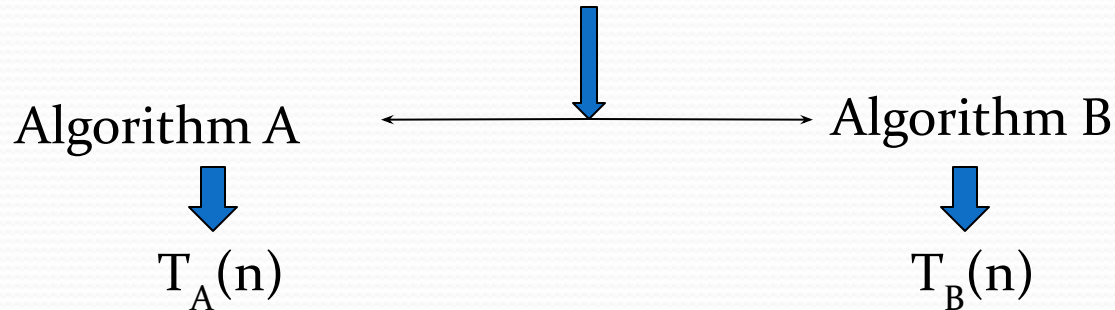
$$\begin{aligned}
 T_A(n) &= ((2 * (n - 1) + 3) + (2 * (n - 2) + 3) + (2 * (n - 3) + 3) + \dots + (2 * 1 + 3)) \\
 &= (2 * ((n - 1) * n / 2) + 3 * (n - 1)) = n * (n - 1) + 3 * (n - 1) = \mathbf{n^2 + 2n - 3}.
 \end{aligned}$$

Calculation of Run time $T_A(n)$ of an Algorithm: Assumption involved

- All operations have been considered as taking same time.
- Time taken by a particular instruction depends on the architecture.
- For example, multiplication operation takes longer than addition operation.

Why do we need to know asymptotic behavior for analyzing an algorithm?

A given problem



□ Compare the two functions and determine which algorithm is *the best*.

□ $T_A(n_o) < T_B(n_o)$ where n_o denotes the known problem size.

□ No prior knowledge of the problem size.

$$T_A(n) \leq T_B(n), \text{ for all } n > 0$$

□ One of the functions is less than or equal to the other over the entire range of problem sizes.

✓ $T_A(n) = 2 * n + 20, T_B(n) = n^2$

✓ Can we conclude whether

$T_A(n) \leq T_B(n)$ or $T_A(n) > T_B(n)$?

✓ $T_A(n_0) = 32, T_B(n_0) = 36$ where $n_0 = 6$

✓ $T_A(n) < T_B(n) \forall n \geq 6$

✓ $T_A(n) > T_B(n) \forall n \leq 5$

✓ So how do we compare these two functions $T_A(n)$ and $T_B(n)$

✓ Algorithm A is better than algorithm B (As we think that the problem input size n as large as possible)

What are the different types of asymptotic notations?

- ✓ Big Oh (O)
- ✓ Small oh (o)
- ✓ Big Omega (Ω)
- ✓ Small omega (ω)
- ✓ Theta (Θ)

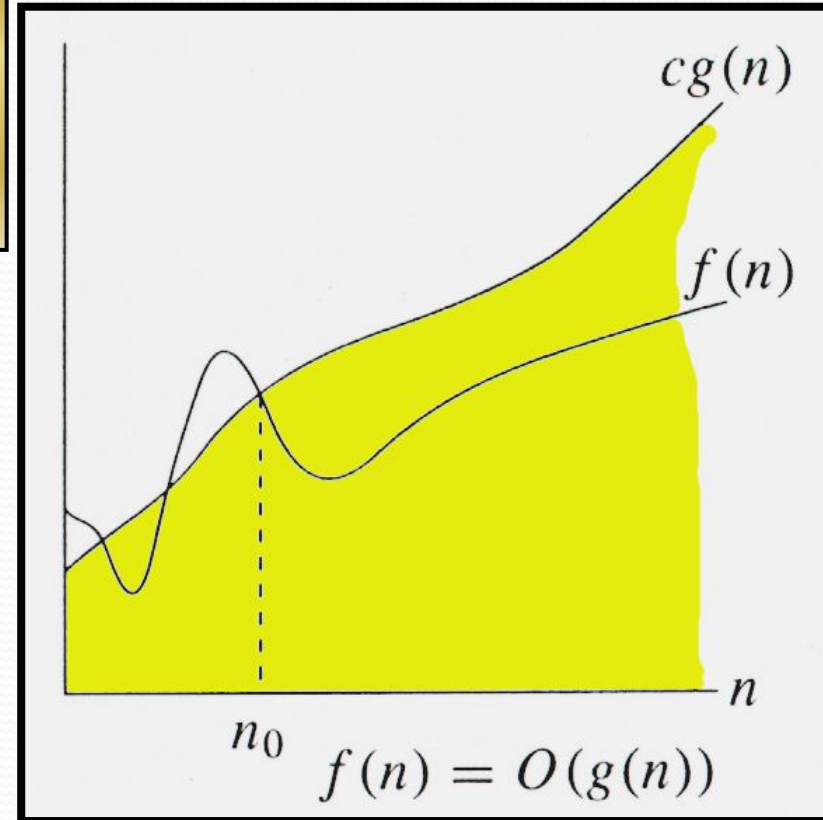
Big Oh Notation

$O(g(n)) = \{f(n) :$
 \exists positive constants c and
positive integer n_0 , such that $\forall n$
 $\geq n_0$, we have $0 \leq f(n) \leq cg(n) \}$

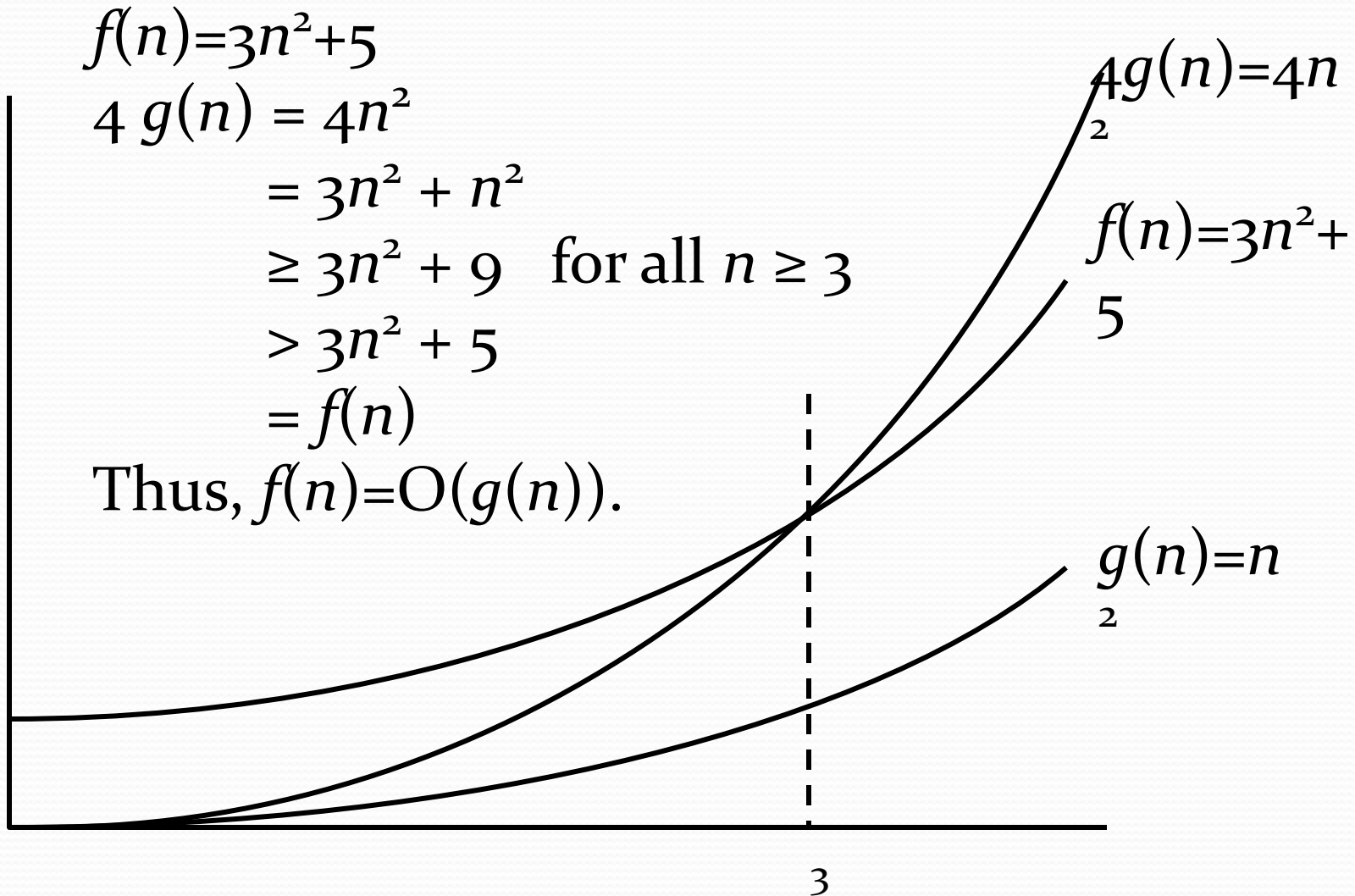
- ✓ We write $f(n) = O(g(n))$.
- ✓ $g(n)$ is an *asymptotic upper bound* for $f(n)$.
- ✓ $f(n) = O(g(n))$ iff

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = l$$

where l is finite.

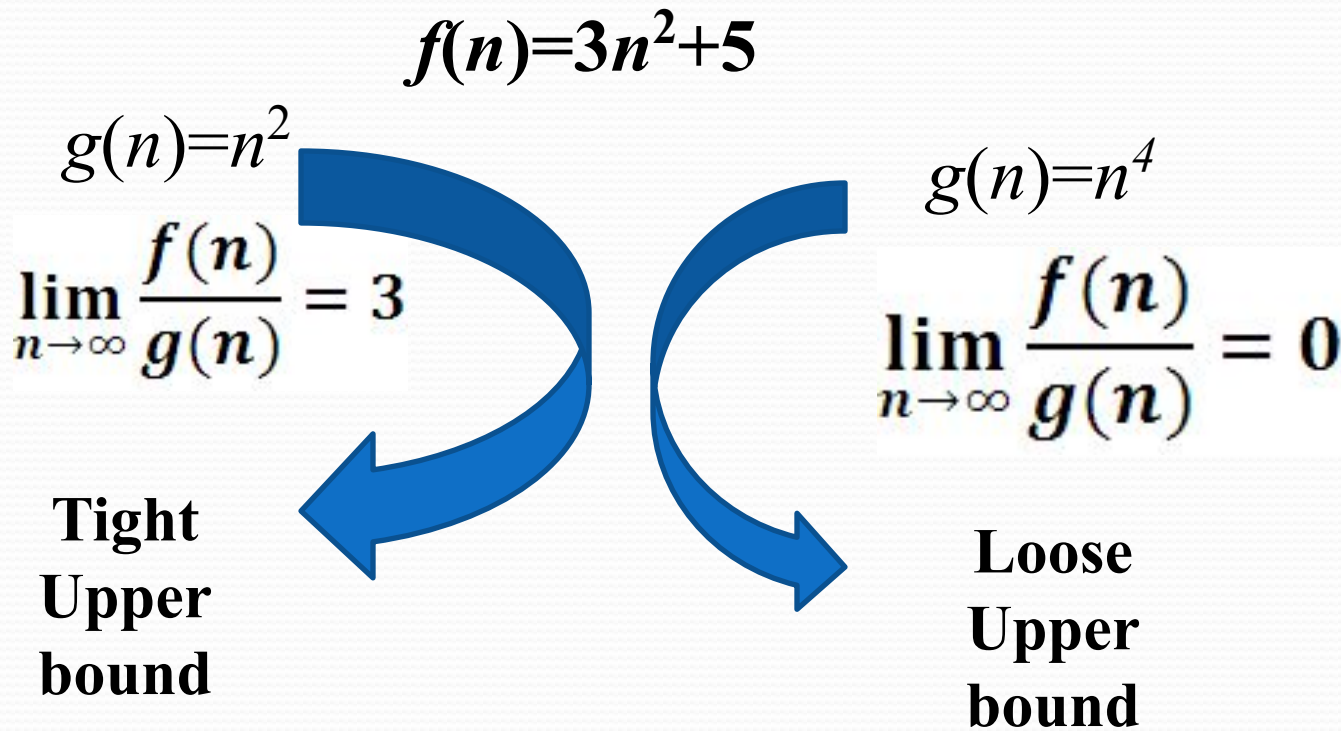


Example of Asymptotic Upper Bound



Loose and Tight Upper Bounds

The upper bound given by Big Oh may be loose or tight upper bound:



Properties of Big Oh

Property 1

If $f(n) = a_m n^m + a_{m-1} n^{m-1} + \dots + a_1 n + a_0$, Then $f(n) = O(n^m)$

Proof: $f(n) = a_m n^m + a_{m-1} n^{m-1} + \dots + a_1 n + a_0$

$$\Rightarrow f(n) \leq \sum_{i=0}^m |a_i| n^i \text{ [since } |x + y| \leq |x| + |y| \text{ and } |xy| = |x||y| \text{]}$$

$$\Rightarrow f(n) \leq \sum_{i=0}^m |a_i| n^m \text{ [Since } n^i \leq n^m \text{ as } i = 0, 1, 2, \dots, m \text{]}$$

$$\Rightarrow f(n) \leq n^m \sum_{i=0}^m |a_i|$$

$$\Rightarrow f(n) \leq c n^m \forall n \geq 1 \text{ where } c = \sum_{i=0}^m |a_i| + 1$$

$$\Rightarrow f(n) = O(n^m)$$

So, the Big Oh of a polynomial function is the highest power of the variable in the function.

Properties of Big Oh (contd.)

Property 2

If $f(n) = c_1g(n)$, then $f(n) = O(g(n))$

Proof: $f(n) = c_1g(n)$

$$\Rightarrow |f(n)| = |c_1g(n)|$$

$$\Rightarrow |f(n)| \leq c |g(n)| \text{ where } n \geq 1 \text{ and } c = (|c_1| + 1)$$

$$\Rightarrow f(n) = O(g(n))$$

Properties of Big Oh(contd.)

Property 3

*If $f(n) = f_1(n) + f_2(n)$
and $f_1(n) \leq f_2(n)$ for all values of n
Then $f(n) = O(f_2(n))$*

Proof: $f(n) = f_1(n) + f_2(n)$

$$\Rightarrow f(n) \leq f_2(n) + f_2(n) \quad \forall n$$

$$\Rightarrow f(n) \leq 2f_2(n) \quad \forall n$$

$$\Rightarrow f(n) = O(f_2(n)) \quad \forall n$$

So, we only consider the fastest growing function out of all the functions making up function $f(n)$ in order to find the Big Oh of function $f(n)$.

Properties of Big Oh(contd.)

Property 4

Prove that $O(\log_a n) = O(\log_b n)$.

Or

Prove that all \log functions grows in the same fashion in terms of Big Oh.

Proof: $O(\log_a n) = O(\log_a b \cdot \log_b n) = O(\log_b n)$
as $c = \log_a b$ is a positive constant.

Example of Calculation of Big Oh using Properties

Sample Code:

Block 1:

$$c_1 n \log n \left\{ \begin{array}{l} \{..... \\ \} \end{array} \right. \quad \begin{array}{l} T(n) = c_1 n \log n + c_2 n^2 \\ \end{array}$$

Solution:

Considering only the fastest growing term, we get:

Block 2:

$$c_2 n^2 \left\{ \begin{array}{l} \{..... \\ \\ \} \end{array} \right. \quad \begin{array}{l} T(n) = c_1 n \log n + c_2 n^2 \\ T(n) \leq c_1 n^2 + c_2 n^2 \text{ [since, } n^2 \geq n \log n \forall n] \\ T(n) \leq cn^2 \text{ where } c = |c_1| + |c_2| + 1 \\ \text{So, } T(n) = O(n^2) \end{array}$$

Example of Calculation of Big Oh using Properties

Sample Code:

```

for(i = 1; i <= n; i++)
{
    ....c1 instructions
    for(j = 1; j <= n; j++)
    {
        ....c2 instructions
        for(k = 1; k <= n; k++)
        {
            ....c3 instructions
        }
    }
    .....c4 instructions
    for(i = 1; i <= n; i++)
    {....c5 instructions
        for(j = 1; j ≤ n; j++)
        {.....c6 instructions
        }
    }
}
    
```

$$\begin{aligned}
 T(n) &= ((c_3n + c_2)n + c_1)n + c_4 + (c_6n + c_5)n \\
 &= c_3n^3 + c_2n^2 + c_1n + c_4 + c_6n^2 + c_5n \\
 &= c_3n^3 + (c_2 + c_6)n^2 + (c_1 + c_5)n + c_4
 \end{aligned}$$

Method 1:

Considering only the fastest growing term, we get $T(n) = O(c_3n^3)$ [using property 3]
 So, $T(n) = O(n^3)$ [using property 2]

Method 2:

Considering only the term having highest power of the variable in the polynomial, we get:

$$T(n) = O(n^3) \text{ using property 1}$$

Small Oh: An Asymptotic Loose Upper Bound

$$o(g(n)) = \{f(n) : \forall c > 0 \exists n_0 > 0 \text{ such that } \forall n \geq n_0 \\ 0 \leq f(n) < cg(n)\}$$

- ✓ We write $f(n)=o(g(n))$
- ✓ Small- oh notation is used to denote an **upper bound** that is **not asymptotically tight**.
- ✓ $f(n)=o(g(n))$ iff

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = 0$$

Differences between Big Oh and Small oh

Big Oh

- $O(g(n)) = \{f(n) :$
 \exists positive constants c and n_0 ,
 such that $\forall n \geq n_0$,
 $0 \leq f(n) \leq cg(n) \}$
- The bound $0 \leq f(n) \leq cg(n)$
holds for some value of
constant $c > 0$

Small oh

- $o(g(n)) =$
 $\{f(n) : \forall c > 0 \exists n_0 > 0 \text{ such}$
 that $\forall n \geq n_0$,
 $0 \leq f(n) < cg(n)\}$
- The bound $0 \leq f(n) < cg(n)$
some holds for all value of
constants $c > 0$

Example of Small-oh

$$2n = o(n^2)$$

Since, for all values of $c > 0$, $cn^2 > 2n$

$$2n^2 \neq o(n^2)$$

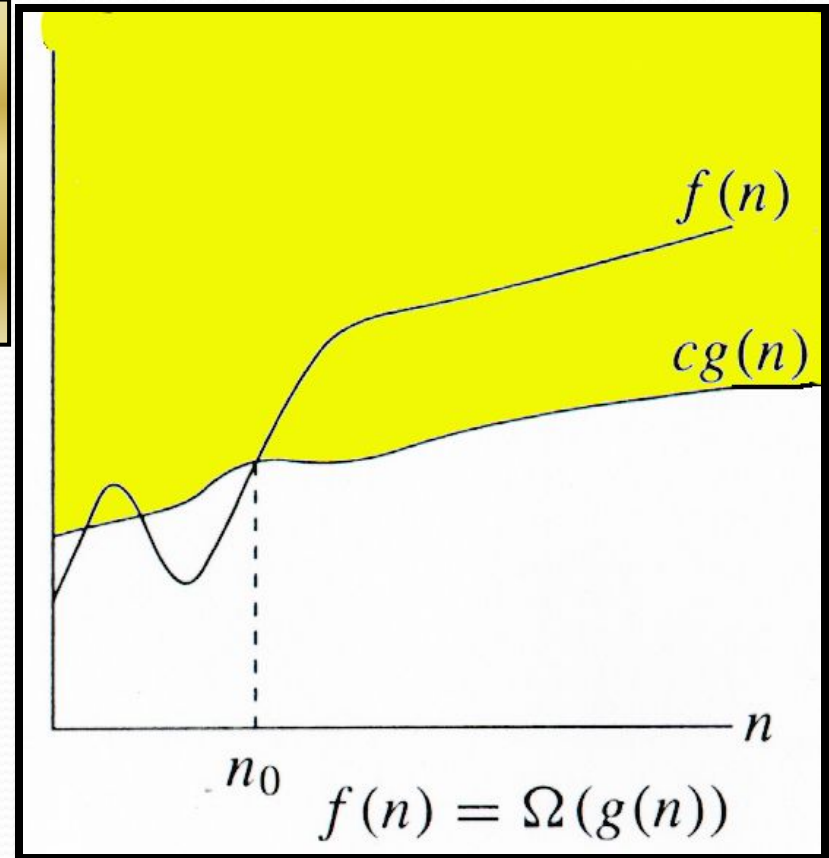
Since, for $c=1$, $cn^2 < 2n$

Big Omega: An Asymptotic Lower Bound

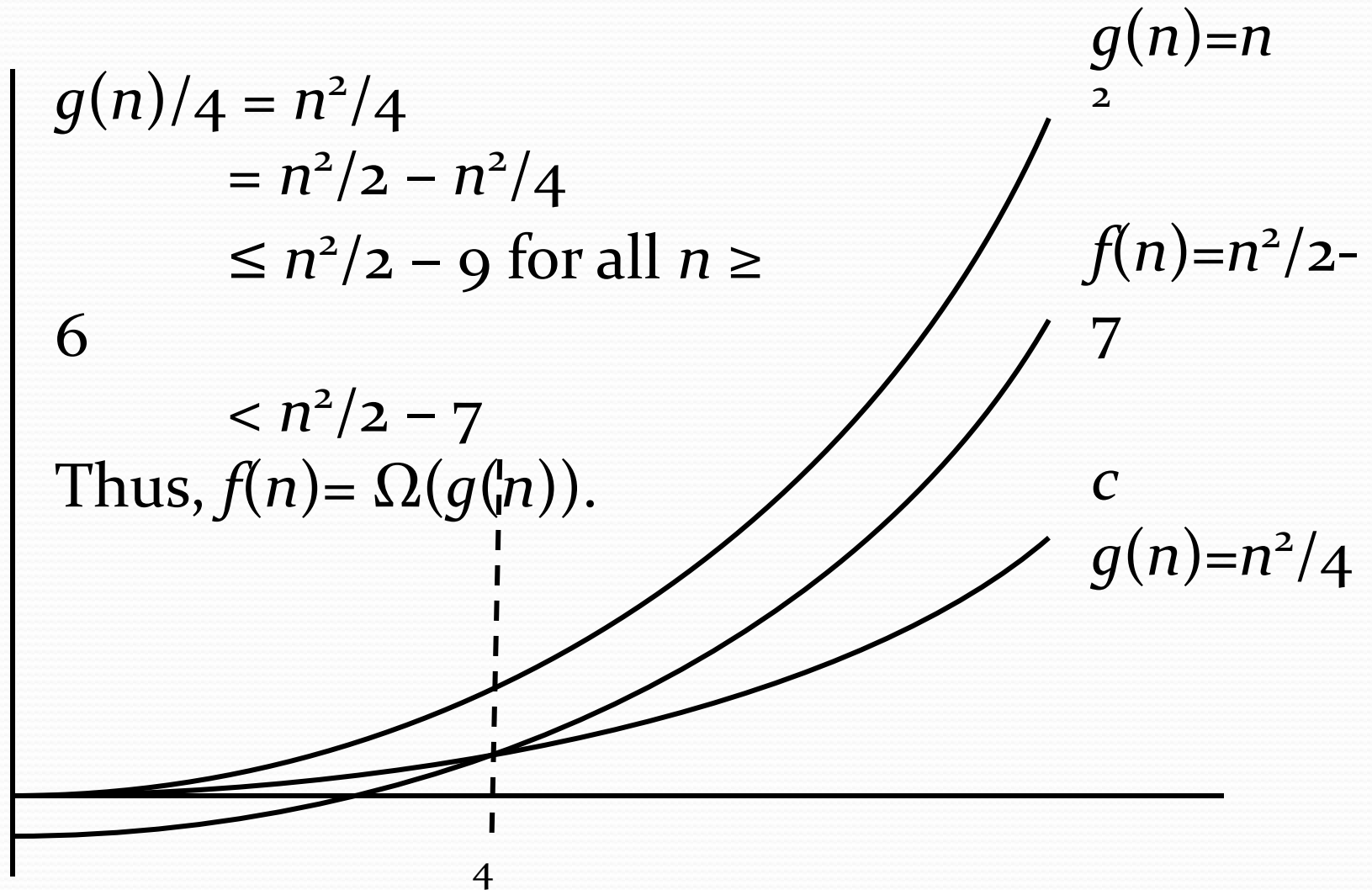
$\Omega(g(n)) = \{f(n) :$
 \exists positive constants c and n_0 ,
such that $\forall n \geq n_0$,
we have $0 \leq cg(n) \leq f(n)\}$

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

We write $f(n) = \Omega(g(n))$

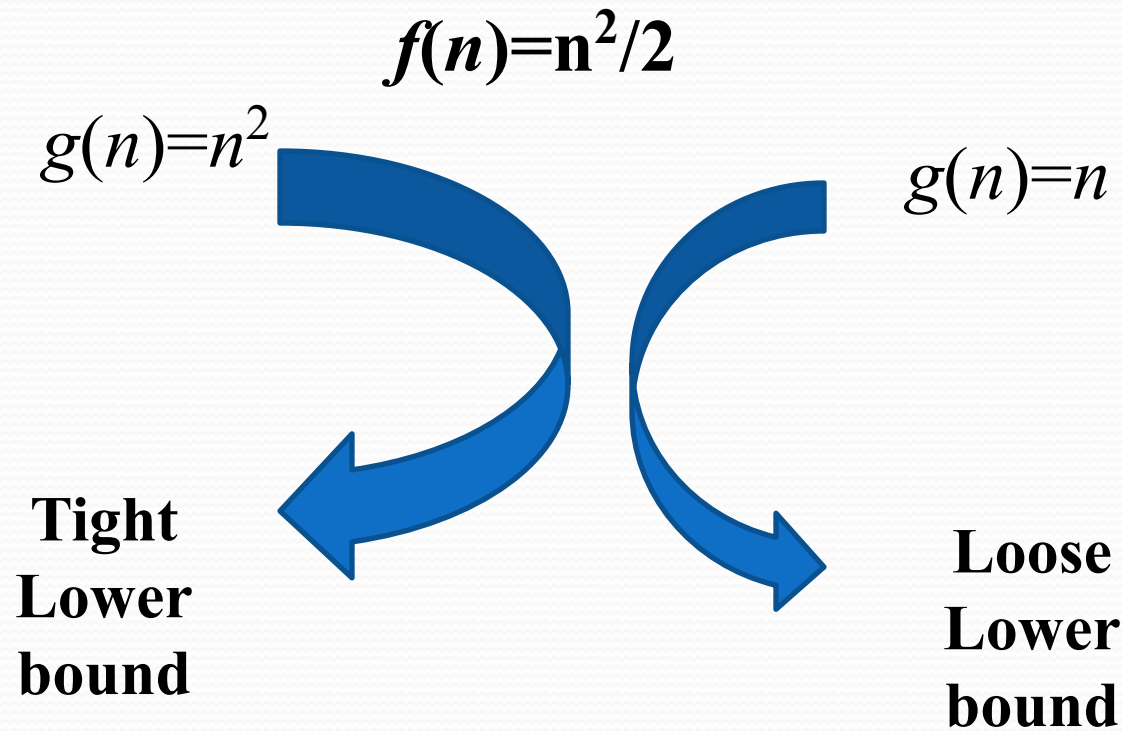


Example of Asymptotic Lower Bound (Big Omega)



Loose and Tight Lower Bounds

The lower bound given by Big Oh may be loose or tight lower bound:



Small Omega: An Asymptotic Loose Lower Bound

$$\omega(g(n)) = \{ f(n) : \forall c > 0, \exists n_0 > 0 \text{ such that} \\ \forall n \geq n_0, \text{ we have } 0 \leq cg(n) < f(n) \}.$$

- ✓ We write $f(n) = \omega(g(n))$
- ✓ Small- omega notation is used to denote a **lower bound** that is **not asymptotically tight**.
- ✓ $f(n) = \omega(g(n))$ iff

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \infty$$

Differences between Big Omega and Small Omega

Big Omega

- $\Omega(g(n)) = \{f(n) : \exists \text{ positive constants } c \text{ and } n_0 \text{ such that } \forall n \geq n_0, \text{ we have } 0 \leq cg(n) \leq f(n)\}$
- The bound $0 \leq cg(n) \leq f(n)$ holds for some value of constant $c > 0$.

Small omega

- $\omega(g(n)) = \{f(n) : \forall c > 0, \exists n_0 > 0 \text{ such that } \forall n \geq n_0, \text{ we have } 0 \leq cg(n) < f(n)\}$.
- The bound $0 \leq cg(n) < f(n)$ holds for all value of constants $c > 0$.

Example of Small Omega

$$n^2/2 = \omega(n)$$

Since, for all values of $c > 0$ $(n^2/2) > cn$

$$n^2/2 \neq \omega(n^2)$$

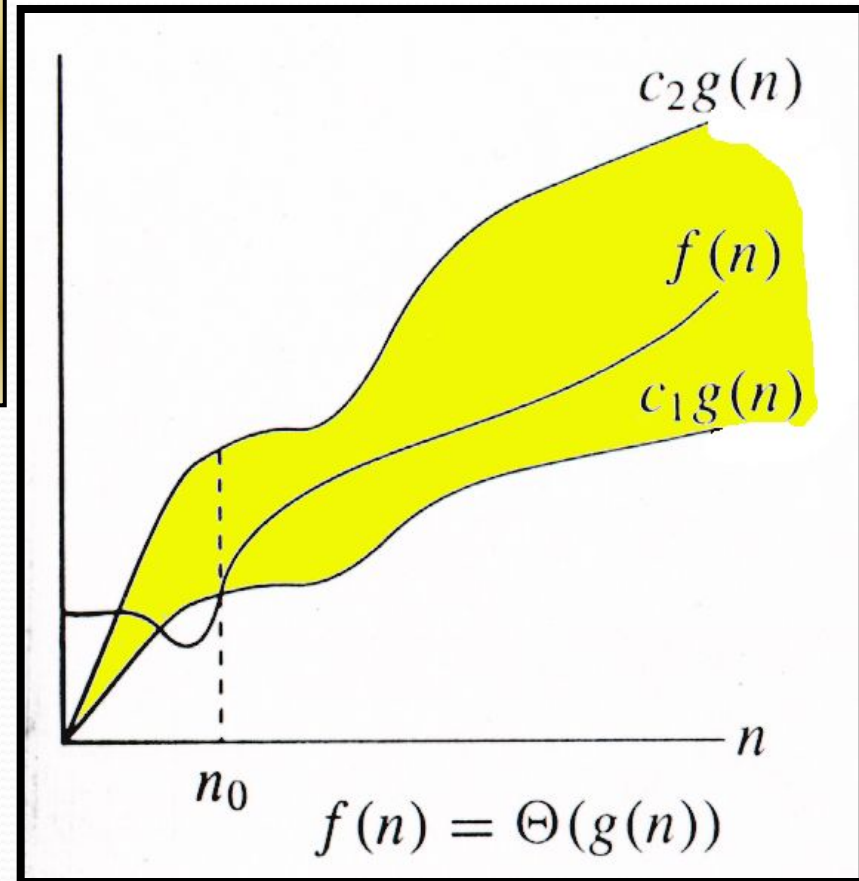
Since, for $c > 1/2$, $(n^2/2) < cn$

Theta Notation

$\Theta(g(n)) = \{f(n) :$
 \exists positive constants c_1, c_2 , and
 n_0 , such that $\forall n \geq n_0$,
we have $0 \leq c_1 g(n) \leq f(n) \leq c_2 g(n)$
 $\}$

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

We write $f(n) = \Theta(g(n))$



Example of Theta

Let $f(n) = \frac{1}{2}n^2 - 3n$

We must find c_1, c_2, n_0 such that:

$$c_1 n^2 \leq \frac{1}{2}n^2 - 3n \leq c_2 n^2, \forall n \geq n_0$$

For right hand inequality:

$$n \geq 1, c_2 = 1/2$$

For left hand inequality:

$$\text{So, taking } n \geq 7, c_1 = 1/14$$

$$n_0 = 7 = \max\{n_1, n_2\} = \{1, 7\}$$

$$c_1 = 1/14,$$

$$c_2 = 1/2$$

$$\text{Hence, } c_1 n^2 \leq \frac{1}{2}n^2 - 3n \leq c_2 n^2, \forall n \geq n_0$$

$$f(n) = \theta(n^2)$$