

# Discrete Structures

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# Text book

Discrete Mathematics and Its Application, 7<sup>th</sup> Edition  
Kenneth H. Rosen

# References

## Chapter 5

1. Discrete Mathematics and Its Application, 7<sup>h</sup> Edition

By Kenneth H. Rose

2. Discrete Mathematics with Applications

By Thomas Koshy

These slides contain material from the above resources.

# The Growth of Combinations of Functions

**Theorem** Suppose that  $f_1(x)$  is  $O(g_1(x))$  and that  $f_2(x)$  is  $O(g_2(x))$ . Then  $(f_1 + f_2)(x)$  is  $O(\max(|g_1(x)|, |g_2(x)|))$ .

**Corollary** Suppose that  $f_1(x)$  and  $f_2(x)$  are both  $O(g(x))$ . Then  $(f_1 + f_2)(x)$  is  $O(g(x))$ .

**Theorem** Suppose that  $f_1(x)$  is  $O(g_1(x))$  and  $f_2(x)$  is  $O(g_2(x))$ . Then  $(f_1 f_2)(x)$  is  $O(g_1(x)g_2(x))$ .

**Example** Give a big-O estimate for  $f(n) = 3n \log(n!) + (n^2 + 3) \log n$ , where  $n$  is a positive integer.

## Solution:

$$f(n) = 3n \log(n!) + (n^2 + 3) \log n$$

$$\log(n!) = O(n \log n)$$

$$3n = O(n)$$

Suppose that  $f_1(x)$  is  $O(g_1(x))$  and  $f_2(x)$  is  $O(g_2(x))$ . Then  $(f_1 f_2)(x)$  is  $O(g_1(x)g_2(x))$ .

$$\Rightarrow 3n \log(n!) \text{ is } O(n^2 \log n).$$

$$(n^2 + 3) \log n?$$

Because  $(n^2 + 3) < 2n^2$  when  $n > 2$ , it follows that

$$n^2 + 3 \text{ is } O(n^2).$$

$$\Rightarrow (n^2 + 3) \log n \text{ is } O(n^2 \log n).$$

**Theorem** Suppose that  $f_1(x)$  is  $O(g_1(x))$  and that  $f_2(x)$  is  $O(g_2(x))$ .  
Then  $(f_1 + f_2)(x)$  is  $O(\max(|g_1(x)|, |g_2(x)|))$ .

**Corollary** Suppose that  $f_1(x)$  and  $f_2(x)$  are both  $O(g(x))$ .  
Then  $(f_1 + f_2)(x)$  is  $O(g(x))$ .

$$\because f(n) = 3n \log(n!) + (n^2 + 3) \log n$$

$$\Rightarrow 3n \log(n!) \text{ is } O(n^2 \log n).$$

$$\Rightarrow (n^2 + 3) \log n \text{ is } O(n^2 \log n).$$

**Corollary** Suppose that  $f_1(x)$  and  $f_2(x)$  are both  $O(g(x))$ .  
Then  $(f_1 + f_2)(x)$  is  $O(g(x))$ .

$$\because (f_1 + f_2)(x) = O(n^2 \log n)$$

**Example:** Let  $f(n) = 6n^2 + 5n + 7\lg n!$  Estimate the growth of  $f(n)$



## Solution:

$$f(n) = 6n^2 + 5n + 7\lg n!$$

$$6n^2 = O(n^2)$$

$$5n = O(n)$$

$$\because (f_1 + f_2)(x) \text{ is } O(\max(|g_1(x)|, |g_2(x)|))$$

$$6n^2 + 5n = O(n^2)$$

$$7 = O(1)$$

$$\lg n! = O(n \lg n)$$

$$\because (f_1 f_2)(x) \text{ is } O(g_1(x) g_2(x))$$

$$7 \lg n! = O(1 \cdot n \lg n) = O(n \lg n)$$

$$\because (f_1 + f_2)(x) \text{ is } O(\max(|g_1(x)|, |g_2(x)|))$$

$$6n^2 + 5n + 7\lg n! \text{ is } O(\max(n^2, n \lg n)) = O(n^2)$$

# big-Omega ( $\Omega$ )

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

**$|f(x)| \geq C|g(x)|$**  whenever  **$x > k$** . [This is read as “ $f(x)$  is big-Omega of  $g(x)$ .”]

**Note:** There is a strong connection between big-O and big-Omega notation. In particular,  **$f(x)$  is  $\Omega(g(x))$**  if and only if  **$g(x)$  is  $O(f(x))$**

**Example** The function  $f(x) = 8x^3 + 5x^2 + 7$  is  $\Omega(g(x))$ , where  $g(x)$  is the function  $g(x) = x^3$ .

## Solution

$$f(x) = 8x^3 + 5x^2 + 7$$

$$|f(x)| \geq C|g(x)| \text{ whenever } x > k.$$

$$\because f(x) = 8x^3 + 5x^2 + 7 \geq 8x^3 \text{ for all positive real numbers } x.$$

This is equivalent to saying that  $g(x) = x^3$  is  $O(8x^3 + 5x^2 + 7)$ , which can be established directly by turning the inequality around.

# big-Theta( $\Theta$ )

- Let  $f$  and  $g$  be functions from the set of integers or the set of real numbers to the set of real numbers. We say that  $f(x)$  is  $\Theta(g(x))$  if  $f(x)$  is  $O(g(x))$  and  $f(x)$  is  $\Omega(g(x))$ . When  $f(x)$  is  $\Theta(g(x))$  we say that “ $f$  is big-Theta of  $g(x)$ ”, that  $f(x)$  is of order  $g(x)$ , and that  $f(x)$  and  $g(x)$  are of the same order.
- When  $f(x)$  is  $\Theta(g(x))$ , it is also the case that  $g(x)$  is  $\Theta(f(x))$ . Also note that  $f(x)$  is  $\Theta(g(x))$  if and only if  $f(x)$  is  $O(g(x))$  and  $g(x)$  is  $O(f(x))$ .
- $f(x)$  is  $\Theta(g(x))$  if and only if there are real numbers  $C_1$  and  $C_2$  and a positive real number  $k$  such that  $C_1|g(x)| \leq |f(x)| \leq C_2|g(x)|$  whenever  $x > k$ . The existence of the constants  $C_1$ ,  $C_2$ , and  $k$  tells us that  $f(x)$  is  $\Omega(g(x))$  and that  $f(x)$  is  $O(g(x))$ , respectively

**Example** Show that  $3x^2 + 8x \log x$  is  $\Theta(x^2)$ .

**Solution:**

$$C_1 |g(x)| \leq |f(x)| \leq C_2 |g(x)| \text{ whenever } x > k$$

**For O:**

$$|f(x)| \leq C_2 |g(x)| \quad \text{whenever } x > k.$$

$$0 \leq 3x^2 + 8x \log x \leq 3x^2 + 8x^2 \leq 11x^2 \quad \text{whenever } x > 1$$

$$3x^2 + 8x \log x \leq 11x^2$$

$$3x^2 + 8x \log x \leq Cg(x) \quad \text{whenever } x > 1$$

$$C_2 = 11, k = 1$$

**Note:**  $C_2$  and  $k$  are constants, whereas  $k$  is a positive real number and  $C$  is a real number

**For  $\Omega$ :**

$$|f(x)| \geq C_1 |g(x)| \quad \text{whenever } x > k.$$

$$3x^2 + 8x \log x \geq 3x^2 \quad \text{whenever } x > 1.$$

$$3x^2 + 8x \log x \geq C_2 |g(x)|$$

$$C_1 = 3, k = 1$$

**Note:  $C_1$  and  $k$  are constants, whereas  $k$  is a positive real number and  $C$  is a real number**

$$3x^2 + 8x \log x \text{ is } \Theta(x^2).$$



**Theorem** Let  $f(x) = a_n x^n + a_{n-1} x^{n-1} + \dots + a_1 x + a_0$ , where  $a_0, a_1, \dots, a_n$  are real numbers with  $a_n \neq 0$ . Then  $f(x)$  is of order  $x^n$ .

**Example** The polynomials

$$3x^8 + 10x^7 + 221x^2 + 1444,$$

$$x^{19} - 18x^4 - 10,112,$$

and

$$-x^{99} + 40,001x^{98} + 100,003x$$

are of orders  $x^8$ ,  $x^{19}$ , and  $x^{99}$ , respectively.

# Complexity of Algorithms

Questions such as these involve the **computational complexity** of the algorithm.

- An analysis of the **time** required to solve a problem of a particular size involves the **time complexity** of the algorithm.
- An analysis of the **computer memory** required involves the **space complexity** of the algorithm.

**TABLE 1** Commonly Used Terminology for the Complexity of Algorithms.

<i>Complexity</i>	<i>Terminology</i>
$\Theta(1)$	Constant complexity
$\Theta(\log n)$	Logarithmic complexity
$\Theta(n)$	Linear complexity
$\Theta(n \log n)$	Linearithmic complexity
$\Theta(n^b)$	Polynomial complexity
$\Theta(b^n)$ , where $b > 1$	Exponential complexity
$\Theta(n!)$	Factorial complexity

# Induction and Recursion

Many **mathematical statements** assert that a property is true for all **positive integers**.

**Examples** of such statements are that for every positive integer  $n$ :

- $n! \leq n^n$
- $n^3 - n$  is divisible by 3
- A set with  $n$  elements has  $2^n$  subsets
- The sum of the first  $n$  positive integers is  $n(n + 1)/2$ .

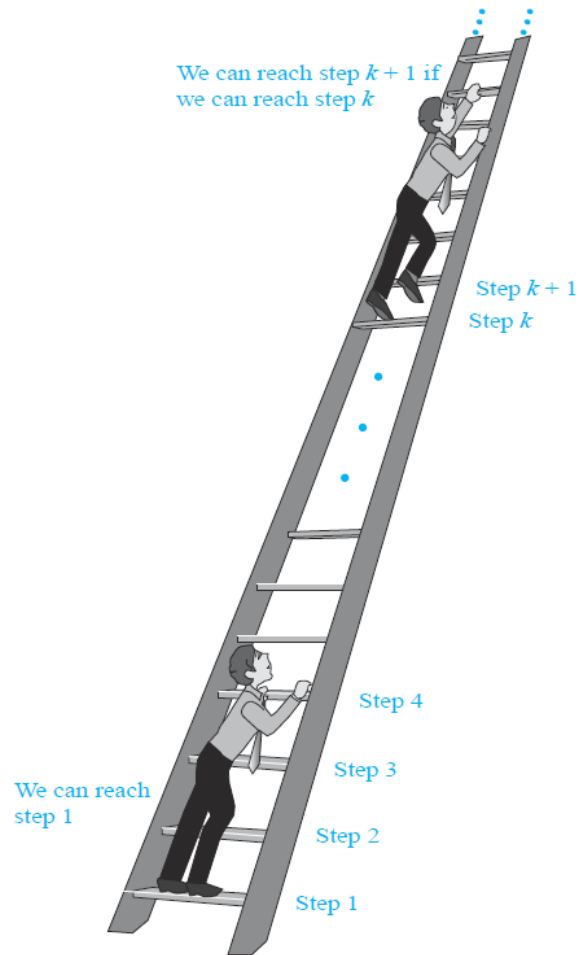
Proofs using mathematical induction have two parts.

First, they show that the statement holds for the **positive integer 1**.

**Second**, they show that if the statement holds for a **positive integer** then it must also hold for the **next larger integer**.

**Mathematical induction** is based on the **rule of inference** that tells us that if  **$P(1)$**  and  **$\forall k(P(k) \rightarrow P(k + 1))$**  are true for the domain of positive integers, then  **$\forall P(n)$**  is true.

# Mathematical Induction



**FIGURE 1** Climbing an Infinite Ladder.

# Mathematical Induction

Introduction: Suppose that we have an **infinite ladder**, as shown in **Figure 1** , and we want to know whether we can reach every step on this ladder.

We know two things:

- 1 . We can reach the **first rung** of the ladder.
2. If we can reach a particular **rung of the ladder**, then we can reach **the next rung**.



# Mathematical Induction

- Can we conclude that we can reach every rung? By (1), we know that we can reach the first rung of the ladder.
- Moreover, because we can reach the first rung, by (2), we can also reach the second rung; it is the next rung after the first rung. Applying (2) again, because we can reach the second rung, we can also reach the third rung.
- Continuing in this way, we can show that we can reach the fourth rung, the fifth rung, and so on.

# Mathematical Induction

- For example, after 100 uses of (2), we know that we can reach the 101<sup>st</sup> rung. But can we conclude that we are able to reach every rung of this infinite ladder?
- The **answer is yes**, something we can verify using an important proof technique called **mathematical induction**. That is, we can show that  **$P(n)$**  is true for **every positive integer**  $n$ , where  $P(n)$  is the statement that we can reach the  $n$ th rung of the ladder.

# Principle of Mathematical Induction

To prove that  $P(n)$  is true for all positive integers  $n$ , where  $P(n)$  is a propositional function, we complete two steps:

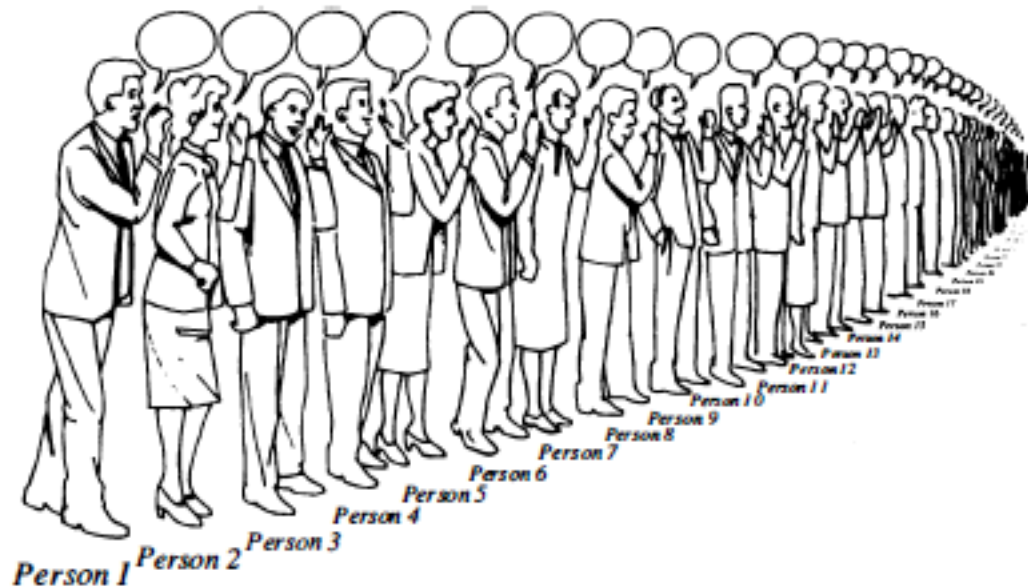
**Basis Step:** We verify that  $P(1)$  is true.

**Inductive Step:** We show that the conditional statement  $P(k) \rightarrow P(k + 1)$  is true for all positive integers  $k$ .

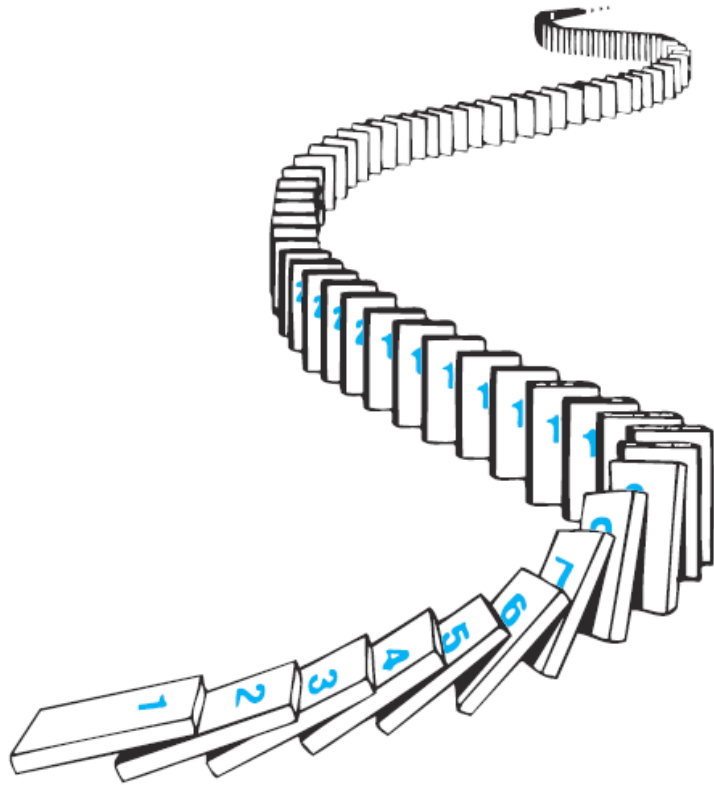
Expressed as a **rule of inference**, this proof technique can be stated as

$(P(1) \wedge \forall k (P(k) \rightarrow P(k + 1))) \rightarrow \forall n P(n)$ , when the domain is the set of positive integers.

# WAYS TO REMEMBER HOW MATHEMATICAL INDUCTION WORKS



# WAYS TO REMEMBER HOW MATHEMATICAL INDUCTION WORKS



**FIGURE 2** Illustrating How Mathematical Induction Works Using Dominoes.

# Mathematical induction: Example 1

**Example** Show that if  $n$  is a positive integer, then

$$1 + 2 + \cdots + n = \frac{n(n+1)}{2}.$$

## Solution

$$1 + 2 + \cdots + n = \frac{n(n+1)}{2}.$$

$$\text{Let } P(n) = \frac{n(n+1)}{2}$$

**Basis Step:**  $P(1)$  is true

$$\because 1 = \frac{1(1+1)}{2} = 1$$

**Inductive Step:** Let it will be true  $n = k$

$$1 + 2 + \dots + k = \frac{k(k+1)}{2}$$

Under this assumption, it must be shown that  **$P(k + 1)$**  is true

Adding  $k+1$  on both sides

$$1 + 2 + \dots + k + k + 1 = \frac{k(k+1)}{2} + k + 1$$

$$1 + 2 + \dots + k + k + 1 = \frac{k(k+1) + 2(k+1)}{2}$$

$$1 + 2 + \dots + k + k + 1 = \frac{(k+1)(k+2)}{2}$$

$$1 + 2 + \dots + k + \overline{k+1} = \frac{(\overline{k+1})(\overline{k+1}+1)}{2}$$

It true for  $n = k+1$



We have completed the **basis step** and the **inductive step**, so by mathematical induction we know that  **$P(n)$**  is true for all positive integers  $n$ .

That is, we have proven that

$$1 + 2 + \dots + n = n(n + 1)/2 \text{ for all positive integers } n.$$

# Suggested Readings

## 5.1 Mathematical Induction