## **Relative Rates of Growth**

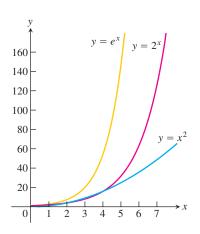
It is often important in mathematics, computer science, and engineering to compare the rates at which functions of x grow as x becomes large. Exponential functions are important in these comparisons because of their very fast growth, and logarithmic functions because of their very slow growth. In this section we introduce the *little-oh* and *big-oh* notation used to describe the results of these comparisons. We restrict our attention to functions whose values eventually become and remain positive as  $x \to \infty$ .

#### **Growth Rates of Functions**

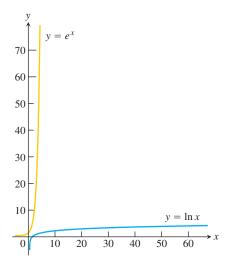
You may have noticed that exponential functions like  $2^x$  and  $e^x$  seem to grow more rapidly as x gets large than do polynomials and rational functions. These exponentials certainly grow more rapidly than x itself, and you can see  $2^x$  outgrowing  $x^2$  as x increases in Figure 7.14. In fact, as  $x \to \infty$ , the functions  $2^x$  and  $e^x$  grow faster than any power of x, even  $x^{1,000,000}$  (Exercise 19).

To get a feeling for how rapidly the values of  $y=e^x$  grow with increasing x, think of graphing the function on a large blackboard, with the axes scaled in centimeters. At x=1 cm, the graph is  $e^1\approx 3$  cm above the x-axis. At x=6 cm, the graph is  $e^6\approx 403$  cm  $\approx 4$  m high (it is about to go through the ceiling if it hasn't done so already). At x=10 cm, the graph is  $e^{10}\approx 22,026$  cm  $\approx 220$  m high, higher than most buildings. At x=24 cm, the graph is more than halfway to the moon, and at x=43 cm from the origin, the graph is high enough to reach past the sun's closest stellar neighbor, the red dwarf star Proxima Centauri:

$$e^{43} \approx 4.73 \times 10^{18} \, \mathrm{cm}$$
  
=  $4.73 \times 10^{13} \, \mathrm{km}$   
 $\approx 1.58 \times 10^{8} \, \mathrm{light\text{-}seconds}$  In a vacuum, light travels at 300,000 km/sec.  
 $\approx 5.0 \, \mathrm{light\text{-}years}$ 



**FIGURE 7.14** The graphs of  $e^x$ ,  $2^x$ , and  $x^2$ .



**FIGURE 7.15** Scale drawings of the graphs of  $e^x$  and  $\ln x$ .

The distance to Proxima Centauri is about 4.22 light-years. Yet with x = 43 cm from the origin, the graph is still less than 2 feet to the right of the y-axis.

In contrast, logarithmic functions like  $y = \log_2 x$  and  $y = \ln x$  grow more slowly as  $x \to \infty$  than any positive power of x (Exercise 21). With axes scaled in centimeters, you have to go nearly 5 light-years out on the x-axis to find a point where the graph of  $y = \ln x$  is even y = 43 cm high. See Figure 7.15.

These important comparisons of exponential, polynomial, and logarithmic functions can be made precise by defining what it means for a function f(x) to grow faster than another function g(x) as  $x \to \infty$ .

#### **DEFINITION** Rates of Growth as $x \to \infty$

Let f(x) and g(x) be positive for x sufficiently large.

1. f grows faster than g as  $x \to \infty$  if

$$\lim_{x \to \infty} \frac{f(x)}{g(x)} = \infty$$

or, equivalently, if

$$\lim_{x \to \infty} \frac{g(x)}{f(x)} = 0.$$

We also say that g grows slower than f as  $x \to \infty$ .

2. f and g grow at the same rate as  $x \to \infty$  if

$$\lim_{x \to \infty} \frac{f(x)}{g(x)} = L$$

where *L* is finite and positive.

According to these definitions, y = 2x does not grow faster than y = x. The two functions grow at the same rate because

$$\lim_{x \to \infty} \frac{2x}{x} = \lim_{x \to \infty} 2 = 2,$$

which is a finite, nonzero limit. The reason for this apparent disregard of common sense is that we want "f grows faster than g" to mean that for large x-values g is negligible when compared with f.

#### **EXAMPLE 1** Several Useful Comparisons of Growth Rates

(a)  $e^x$  grows faster than  $x^2$  as  $x \to \infty$  because

$$\lim_{\substack{x \to \infty \\ \infty / \infty}} \frac{e^x}{x^2} = \lim_{\substack{x \to \infty \\ \infty / \infty}} \frac{e^x}{2x} = \lim_{x \to \infty} \frac{e^x}{2} = \infty.$$
 Using l'Hôpital's Rule twice

**(b)**  $3^x$  grows faster than  $2^x$  as  $x \to \infty$  because

$$\lim_{x \to \infty} \frac{3^x}{2^x} = \lim_{x \to \infty} \left(\frac{3}{2}\right)^x = \infty.$$

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$$\lim_{x \to \infty} \frac{x^2}{\ln x} = \lim_{x \to \infty} \frac{2x}{1/x} = \lim_{x \to \infty} 2x^2 = \infty.$$
 l'Hôpital's Rule

(d)  $\ln x$  grows slower than x as  $x \to \infty$  because

$$\lim_{x \to \infty} \frac{\ln x}{x} = \lim_{x \to \infty} \frac{1/x}{1}$$
 l'Hôpital's Rule
$$= \lim_{x \to \infty} \frac{1}{x} = 0.$$

## **EXAMPLE 2** Exponential and Logarithmic Functions with Different Bases

(a) As Example 1b suggests, exponential functions with different bases never grow at the same rate as  $x \to \infty$ . If a > b > 0, then  $a^x$  grows faster than  $b^x$ . Since (a/b) > 1,

$$\lim_{x \to \infty} \frac{a^x}{b^x} = \lim_{x \to \infty} \left(\frac{a}{b}\right)^x = \infty.$$

**(b)** In contrast to exponential functions, logarithmic functions with different bases a and b always grow at the same rate as  $x \to \infty$ :

$$\lim_{x \to \infty} \frac{\log_a x}{\log_b x} = \lim_{x \to \infty} \frac{\ln x / \ln a}{\ln x / \ln b} = \frac{\ln b}{\ln a}.$$

The limiting ratio is always finite and never zero.

If f grows at the same rate as g as  $x \to \infty$ , and g grows at the same rate as h as  $x \to \infty$ , then f grows at the same rate as h as  $x \to \infty$ . The reason is that

$$\lim_{x \to \infty} \frac{f}{g} = L_1 \qquad \text{and} \qquad \lim_{x \to \infty} \frac{g}{h} = L_2$$

together imply

$$\lim_{x \to \infty} \frac{f}{h} = \lim_{x \to \infty} \frac{f}{g} \cdot \frac{g}{h} = L_1 L_2.$$

If  $L_1$  and  $L_2$  are finite and nonzero, then so is  $L_1L_2$ .

# **EXAMPLE 3** Functions Growing at the Same Rate

Show that  $\sqrt{x^2 + 5}$  and  $(2\sqrt{x} - 1)^2$  grow at the same rate as  $x \to \infty$ .

**Solution** We show that the functions grow at the same rate by showing that they both grow at the same rate as the function g(x) = x:

$$\lim_{x \to \infty} \frac{\sqrt{x^2 + 5}}{x} = \lim_{x \to \infty} \sqrt{1 + \frac{5}{x^2}} = 1,$$

$$\lim_{x \to \infty} \frac{(2\sqrt{x} - 1)^2}{x} = \lim_{x \to \infty} \left(\frac{2\sqrt{x} - 1}{\sqrt{x}}\right)^2 = \lim_{x \to \infty} \left(2 - \frac{1}{\sqrt{x}}\right)^2 = 4.$$

### **Order and Oh-Notation**

Here we introduce the "little-oh" and "big-oh" notation invented by number theorists a hundred years ago and now commonplace in mathematical analysis and computer science.

### **DEFINITION** Little-oh

A function f is **of smaller order than** g as  $x \to \infty$  if  $\lim_{x \to \infty} \frac{f(x)}{g(x)} = 0$ . We indicate this by writing f = o(g) ("f is little-oh of g").

Notice that saying f = o(g) as  $x \to \infty$  is another way to say that f grows slower than g as  $x \to \infty$ .

## **EXAMPLE 4** Using Little-oh Notation

- (a)  $\ln x = o(x)$  as  $x \to \infty$  because  $\lim_{x \to \infty} \frac{\ln x}{x} = 0$
- **(b)**  $x^2 = o(x^3 + 1)$  as  $x \to \infty$  because  $\lim_{x \to \infty} \frac{x^2}{x^3 + 1} = 0$

### **DEFINITION** Big-oh

Let f(x) and g(x) be positive for x sufficiently large. Then f is **of at most the order of** g as  $x \to \infty$  if there is a positive integer M for which

$$\frac{f(x)}{g(x)} \le M,$$

for x sufficiently large. We indicate this by writing f = O(g) ("f is big-oh of g").

# **EXAMPLE 5** Using Big-oh Notation

- (a)  $x + \sin x = O(x)$  as  $x \to \infty$  because  $\frac{x + \sin x}{x} \le 2$  for x sufficiently large.
- **(b)**  $e^x + x^2 = O(e^x)$  as  $x \to \infty$  because  $\frac{e^x + x^2}{e^x} \to 1$  as  $x \to \infty$ .
- (c)  $x = O(e^x)$  as  $x \to \infty$  because  $\frac{x}{e^x} \to 0$  as  $x \to \infty$ .

If you look at the definitions again, you will see that f = o(g) implies f = O(g) for functions that are positive for x sufficiently large. Also, if f and g grow at the same rate, then f = O(g) and g = O(f) (Exercise 11).

# **Sequential vs. Binary Search**

Computer scientists often measure the efficiency of an algorithm by counting the number of steps a computer must take to execute the algorithm. There can be significant differences

in how efficiently algorithms perform, even if they are designed to accomplish the same task. These differences are often described in big-oh notation. Here is an example.

Webster's Third New International Dictionary lists about 26,000 words that begin with the letter a. One way to look up a word, or to learn if it is not there, is to read through the list one word at a time until you either find the word or determine that it is not there. This method, called sequential search, makes no particular use of the words' alphabetical arrangement. You are sure to get an answer, but it might take 26,000 steps.

Another way to find the word or to learn it is not there is to go straight to the middle of the list (give or take a few words). If you do not find the word, then go to the middle of the half that contains it and forget about the half that does not. (You know which half contains it because you know the list is ordered alphabetically.) This method eliminates roughly 13,000 words in a single step. If you do not find the word on the second try, then jump to the middle of the half that contains it. Continue this way until you have either found the word or divided the list in half so many times there are no words left. How many times do you have to divide the list to find the word or learn that it is not there? At most 15, because

$$(26,000/2^{15}) < 1.$$

That certainly beats a possible 26,000 steps.

For a list of length n, a sequential search algorithm takes on the order of n steps to find a word or determine that it is not in the list. A binary search, as the second algorithm is called, takes on the order of  $\log_2 n$  steps. The reason is that if  $2^{m-1} < n \le 2^m$ , then  $m-1 < \log_2 n \le m$ , and the number of bisections required to narrow the list to one word will be at most  $m = \lceil \log_2 n \rceil$ , the integer ceiling for  $\log_2 n$ .

Big-oh notation provides a compact way to say all this. The number of steps in a sequential search of an ordered list is O(n); the number of steps in a binary search is  $O(\log_2 n)$ . In our example, there is a big difference between the two (26,000 vs. 15), and the difference can only increase with n because n grows faster than  $\log_2 n$  as  $n \to \infty$  (as in Example 1d).