## Big-O intuition



To the left of $n_{0}$, the functions can do anything. To its right, $c g(n)$ is always greater than or equal to $f(n)$.

Intuitively, $O(g(n))$ is the set of all functions that $g(n)$ can outpace in the long run (with the help of a constant scaling factor $c$ ). For example, $n^{2}$ eventually outpaces $3 n \log (n)+5 n$, so $3 n \log (n)+5 n \in$ $O\left(n^{2}\right)$. Because we only care about long run behavior, we generally can discard constants and can consider only the most significant term in a function.
There are actually infinitely many functions that are in $O(g(n))$ : If $f(n) \in O(g(n))$, then $\frac{1}{2} f(n) \in$ $O(g(n))$ and $\frac{1}{4} f(n) \in O(g(n))$ and $2 f(n) \in O(g(n))$. In general, for any constants $k_{1}, k_{2}, k_{1} f(n)+$ $k_{2} \in O(g(n))$.

## Big-O definition

The formal definition of big-O has a lot of mathematical symbols in it, and so can be very confusing at first. Let's familiarize ourselves with the formal definition and get an intuition behind what it's saying.
$O(g(n))$ is a set of functions, where $f(n) \in O(g(n))$ if and only if:
there is some $\qquad$ and some $\qquad$
such that $\qquad$ for all $\qquad$ .
This definition amounts to putting an asymptotic upper bound on $f(n)$.

## Checkpoint 0

Using the formal definition of big-O, prove that $n^{3}+9 n^{2}-7 n+2 \in O\left(n^{3}\right)$.
$c=$ $\qquad$ , $n_{0}=$ $\qquad$
To show: $\qquad$ (expand $c$ and $n_{0}$ )
A. $n \geq$ $\qquad$ by assumption
B. $\qquad$ by $\qquad$
C. $\qquad$ by $\qquad$
D. $\qquad$ by $\qquad$
E. $\qquad$ by $\qquad$
F. $\qquad$ by

## Simplest, tightest bounds

Something that will come up often with big-O is the idea of a simple and tight bound on the runtime of a function.
It's technically correct to say that linear search is in $O(3 n+2)$ where $n$ is the length of the input array, but $O(3 n+2)$ consists of the exact same functions as $O(n)$, which is simpler.
It's also technically correct to say that binary search, which takes around $\log n$ steps on an $n$-element array, is in $O(n!)$, since $n!>\log n$ for all $n>0$ but it's not very useful. If we ask for a tight bound, we want the closest bound you can give. For binary search, $O(\log n)$ is a tight bound because no function that grows more slowly than $\log n$ provides a correct upper bound for binary search.

## Unless we specify otherwise, we want the simplest, tightest bound!

## Complexity Classes

Big-O sets in simplest and tightest form are used to summarize the complexity of a given function - for example $n^{3}+9 n^{2}-7 n+2 \in O\left(n^{3}\right)$ highlights that $n^{3}+9 n^{2}-7 n+2$ is a cubic function. As such, big-O sets in simplest and tightest form are called complexity classes.
When working with functions with a single argument, say $n$, the most common complexity classes we will encounter in this course are

$$
O(1) \subset O(\log n) \subset O(n) \subset O(n \log n) \subset O\left(n^{2}\right) \subset O\left(2^{n}\right) \subset O(n!)
$$

Every function in the big-O set on the left of the subset symbol $(\subset)$ is also a function in the big-O set on the right (but not necessarily vice versa) - for example $O(\log n) \subset O(n)$ says that every function in $O(\log n)$ is also in $O(n)$.

We use big-O sets in simplest and tightest form also to classify functions with multiple arguments.

## Checkpoint 1

For each of the following big-O sets, give an equivalent big-O set in simplest and tightest form. $O\left(3 n^{2.5}+2 n^{2}\right)$ can be written more simply as $\qquad$
One interesting consequence of this second result is that $O\left(\log _{i} n\right)=O\left(\log _{j} n\right)$ for all $i$ and $j$ (as long as they're both greater than 1 ), because of the change of base formula:

$$
\log _{i} n=\frac{\log _{j} n}{\log _{j} i}
$$

But $\frac{1}{\log _{j} i}$ is just a constant! So, it doesn't matter what base we use for logarithms in big-O notation. When we ask for the simplest, tightest bound in big- $O$, we'll usually take points off if you write, for instance, $O\left(\log _{2} n\right)$ instead of the simpler $O(\log n)$.
$O\left(\log _{10} n+\log _{2}(7 n)\right)$ can be written more simply as $\qquad$

## Checkpoint 2

Give the complexity class of the following functions:
$f(n)=16 n^{2}+5 n+2 \in$ $\qquad$
$g(n, m)=n^{1.5} \times 16 m \in$ $\qquad$
$h(x, y)=\max (x, y)+x^{2} \in$

## Determining Big-O

Determine the big-O complexity of the following function.

```
int bigO_1(int k)
//@requires k >= 0;
{
    int[] A = alloc_array(int, k); // allocating an k-length array takes O(k) time
    for (int i = 0; i < k; i++) {
        for (int j = 1; j < k; j*=2) {
            A[i] += j;
        }
    }
    int p = 0;
    while (p < 10) {
        f(A, k); //assume f takes O(k) time
        p++;
    }
    return A[k-1];
}
```

Always write your complexity in terms of the input variables!

- Line 4 takes time in $O$ ( $\quad$ )
- The loop on lines 5-9 runs $\qquad$ times
- The loop on lines 6-8 runs $\qquad$ times
* Each run of line 7 takes time in $O$ ( )

Therefore the loop on lines 6-8 takes time in $O$ ( )

Therefore the loop on lines 5-9 takes time in $O$ ( $\qquad$

- Line 10 takes time in $O$ ( $\qquad$
- The loop on lines 11-14 runs $\qquad$ times
- Each run of line 12 takes time in $O$ ( $\qquad$
- Each run of line 13 takes time in $O$ ( $\quad$ )

Therefore the loop on lines 11-14 takes time in $O$ ( $\qquad$

- Line 15 takes time in $O$ ( $\qquad$

Thus, the function big0_1 takes time in $O($ $\qquad$ ) to run altogether

## Checkpoint 3

Determine the big-O class of the following function. You may use the lines on the right for scratch work.

```
int big0_2(int[] L, int m, int n)
//@requires \length(L) == m && m > 0 && n >= 0;
{
    int[] A = alloc_array(int, n); //
    for (int i = 0; i < n; i++) { //
        for (int j = i; j < n; j++) { //
            A[i] = i * j; //
        }
    }
    int c = m-1;
    while (c > 0) {
        L[c] += 122;
        //
        c /= 4;
    }
    return L[m/2];
}
```

The big-O class of this function is $\qquad$ .

