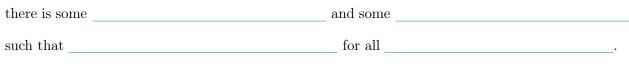
**15-122:** Principles of Imperative Computation

Recitation 03: Function Family Reunion Thursday January 26<sup>th</sup>

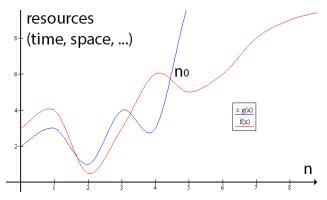
# **Big-O definition**

The 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:







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). For example,  $n^2$  eventually outpaces  $3n \log(n) + 5n$ , so  $3n \log(n) + 5n \in O(n^2)$ . 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  $2f(n) \in O(g(n))$ . In general, for any constants  $k_1, k_2, k_1f(n) + k_2 \in O(g(n))$ .

# **Checkpoint 0**

Using the formal definition of big-O, prove that  $n^3 + 9n^2 - 7n + 2 \in O(n^3)$ .



#### 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(3n + 2) where n is the length of the input array, but O(3n + 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 array of length n, is 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  $n^3 + 9n^2 - 7n + 2 \in O(n^3)$  highlights that  $n^3 + 9n^2 - 7n + 2$  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

 $O(1) \subset O(\log n) \subset O(n) \subset O(n\log n) \subset O(n^2) \subset O(2^n) \subset O(n!)$ 

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.

 $O(3n^{2.5}+2n^2)$  can be written more simply as \_\_\_\_\_

 $O(\log_{10} n + \log_2(7n))$  can be written more simply as \_\_\_\_\_

One interesting consequence of this second result is that  $O(\log_i n) = O(\log_j n)$  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,  $O(\log_2 n)$  instead of the simpler  $O(\log n)$ .

### **Checkpoint 2**

Give the complexity class of the following functions:

$$\begin{split} f(n) &= 16n^2 + 5n + 2 \in \_\_\_\\ g(n,m) &= n^{1.5} \times 16m \in \_\_\_\\ h(x,y) &= \max(x,y) + x^2 \in \_\_\_\\ \end{split}$$

# **Checkpoint 3**

Determine the big-O complexity of the following function.

```
1 int big0_1(int k) {
    int[] A = alloc_array(int, k); // allocating an k-length array takes 0(k) time
2
    for (int i = 0; i < k; i++) {</pre>
3
       for (int j = 1; j < k; j \neq 2) {
4
         A[i] += j;
\mathbf{5}
       }
6
    }
\overline{7}
    int p = 0;
8
    while (p < 10) {
9
       f(A, k); //assume f takes O(k) time
10
       p++;
11
    }
12
    return A[k-1];
13
14 }
```

Always write your complexity in terms of the input variables!

• Line 2 takes time in $O($	)
• The loop on lines 3–7 runs	times
– The loop on lines 4–6 runs	times
* Each run of line 5 takes time in $O($	)
Therefore the loop on lines 4–6 takes time in $O($	)
Therefore the loop on lines 3–7 takes time in $O($	)
• Line 8 takes time in $O($	)
• The loop on lines 9–12 runs	times
- Each run of line 10 takes time in $O($	)
- Each run of line 11 takes time in $O($	)
Therefore the loop on lines 9–12 takes time in $O($	)
• Line 13 takes time in $O($	)
Thus, the function $big0_1$ takes time in $O($ gether	) to run alto-

# **Checkpoint 4**

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)
_2 //@requires \length(L) == m && m > 0;
3 {
                  //
  int[] A = alloc_array(int, n);
4
\mathbf{5}
                  // _____
  for (int i = 0; i < n; i++) {</pre>
6
   for (int j = i; j < n; j++) {</pre>
                  // _____
\overline{7}
   A[i] = i * j;
                  //
8
                  // _____
   }
9
                  //
  }
10
  int c = m;
                  //
11
12
                  //
 while (c > 0) {
13
  L[c] += 122;
                  // _____
14
   c /= 4;
                  //
15
  }
                  // _____
16
                  // _____
  return L[m/2];
17
18 }
                  // _____
 The big-O class of this function is
```