

# Lecture #18: Complexity and Orders of Growth

- Certain problems take longer than others to solve, or require more storage space to hold intermediate results.
- We refer to the *time complexity* or *space complexity* of a problem.
- But what does it mean to say that a certain *program* has a particular complexity?
- What does it mean for an *algorithm*?
- What does it mean for a *problem*?

# A Direct Approach

- Well, if you want to know how fast something is, you can time it, which Python happens to make easy:

```
>>> def fib(n):
...     if n <= 1: return n
...     else: return fib(n-2) + fib(n-1)
...
>>> import timeit
>>> timeit.repeat('fib(10)', 'from __main__ import fib', number=5)
[0.0004911422729492188, 0.0004868507385253906, 0.0004870891571044922]
>>> timeit.repeat('fib(20)', 'from __main__ import fib', number=5)
[0.06009697914123535, 0.06010794639587402, 0.06009793281555176]
```

- `timeit.repeat(Stmt, Setup, number=N)` says

Execute **Setup** (a string containing Python code), then execute **Stmt** (a string) **N** times. Repeat this process 3 times and report the time required for each repetition.

## A Direct Approach, Continued

- `timeit.repeat` alone gives a bit too much information: smallest value is probably all that's meaningful; can't trust more than about two significant digits; and would be more useful to get an average time per iteration.
- Fortunately, we can always write programs to support writing programs!

```
>>> def desc_time(expr, setup="", number=1000):  
...     time = 1e6 * min(timeit.repeat(expr, setup, number=number)) / number  
...     return "{} loops, best of 3: {:.2g} usec per loop"\  
...         .format(number, int(time))  
>>> print(desc_time('fib(10)', 'from __main__ import fib'))  
10000 loops, best of 3: 97 usec per loop"""
```

- You can also get this effect from the command line:

```
...# python3 -m timeit --setup='from fib import fib' 'fib(10)'  
10000 loops, best of 3: 97 usec per loop
```

- This command automatically chooses a number of executions of `fib` to give a total time that is large enough for an accurate average, repeats 3 times, and reports the best time.

# Strengths and Problems with Direct Approach

- **Good:** Gives actual times; answers question completely for given input and machine.
- **Bad:** Results apply only to tested inputs.
- **Bad:** Results apply only to particular programs and platforms.
- **Bad:** Cannot tell us anything about complexity of algorithm or of problem.

## But Can't We Extrapolate?

- Why not try a succession of times, and use that to figure out timing in general?

```
...# for t in 5 10 15 20 25 30; do
>     echo -n "$t: "
>     python3 -m timeit --setup='from fib import fib' "fib($t)"
> done
5: 100000 loops, best of 3: 8.16 usec per loop
10: 10000 loops, best of 3: 96.8 usec per loop
15: 1000 loops, best of 3: 1.08 msec per loop
20: 100 loops, best of 3: 12 msec per loop
25: 10 loops, best of 3: 133 msec per loop
30: 10 loops, best of 3: 1.47 sec per loop
```

- This looks to be exponential in  $t$  with exponent of  $\approx 1.6$ .
- **But...** what if the program special-cases some inputs?
- ...and this still only works for a particular program and machine.

## Worst Case, Average Case

- To avoid the problem of getting results only for particular inputs, we usually ask a more general question, such as:
  - What is the *worst case* time to compute  $f(X)$  as a function of the size of  $X$ , or
  - what is the *average case* time to compute  $f(X)$  over all values of  $X$  (weighted by likelihood).
- Average case is hard, so we'll let other courses deal with it.
- But now we seem to have a harder problem than before: how do we get worst-case times? Doesn't that require testing all cases?
- And when we do, aren't we still sensitive to machine model, compiler, etc.?

# Operation Counts and Scaling

- Instead of getting precise answers in units of physical time, we therefore settle for a proxy measure that will remain meaningful over changes in architecture or compiler.
- Choose some operation(s) of interest and count how many times they occur.
- Examples:
  - How many times does `fib` get called recursively during computation of `fib(N)`?
  - How many addition operations get performed by `fib(N)`?
- You can no longer get precise times, but if the operations are well-chosen, results are *proportional* to actual time for different values of  $N$ .
- Thus, we look at how computation time *scales* in the worst case.
- Can compare programs/algorithms on the basis of which scale better.

## Example: Search

- Here's a simple search function:

```
def find_first(L, p):  
    """The index of the first item in list L that satisfies  
    predicate function P, or -1 if none does."""  
    for i, x in enumerate(L): # Yields (0, L[0]), (1, L[1]), ...  
        if p(x): return i  
    return -1
```

- It is reasonable to count calls to `p` as a measure.
- Sometimes, this will return immediately (if `p(L[0])`).
- Can't say much about the average case without knowing more.
- Worst case is that no item satisfies `p`,
- ...in which case, # calls to `p` == `len(L)`.



## Example: Intersection

- Now let's look at two lists:

```
def find_common(L0, L1):  
    """Returns True iff L0 and L1 have an item in common."""  
    for x in L0:  
        for y in L1:  
            if x == y: return True  
    return False
```

- When will this program take longest? \_\_\_\_\_
- If we count comparisons (`==`), how long will the worst case take?  
\_\_\_\_\_
- Or, if  $N = \text{len}(L0) = \text{len}(L1)$ , then \_\_\_\_.

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- When will this program take longest? When there are no common items.
- If we count comparisons (`==`), how long will the worst case take?  
 $\text{len}(L0) \cdot \text{len}(L1)$
- Or, if  $N = \text{len}(L0) = \text{len}(L1)$ , then  $N^2$ .

## Example: Duplicates

- This function looks for repeated items in a sequence:

```
def are_duplicates(L):  
    for i, x in enumerate(L):  
        for j, y in enumerate(L, i+1): # Starts at i+1  
            if x == y: return True  
    return False
```

- Again, this returns **False** in the worst case.
- Formula is more complicated, though. If  $N$  is `len(L)`, then it executes the `==` operation

$$\sum_{1 \leq k < N} N - k = (N - 1) + (N - 2) + \dots + 0 = \underline{\hspace{2cm}} \text{ times.}$$

- This formula is already getting a bit complicated.
- But it **scales** at the same rate as for `find_common` when both arguments have the same length, i.e.:
  - Doubling the size of the input quadruples the time.

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$$\sum_{1 \leq k < N} N - k = (N - 1) + (N - 2) + \dots + 0 = \underline{N(N - 1)/2} \text{ times.}$$

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# Expressing Approximation

- We are looking for measures of program performance that give us a sense of how computation time scales with size of input.
- Sometimes, results for “small” values are not indicative.
  - E.g., suppose we have a prime-number tester that contains a look-up table of the primes up to 1,000,000,000 (about 50 million primes).
  - Tests for numbers up to 1 billion will be faster than for larger numbers.
- In general, we are interested in ignoring finite sets of special cases that a given program can compute quickly.
- So we tend to ask about *asymptotic* behavior of programs: as size of input goes to infinity.
- Finally, precise worst-case functions can be very complicated, and the precision is generally not terribly important anyway.
- These considerations motivate the use of *order notation* to characterize functions that approximate execution time or space.

# The Notation

- Suppose that  $f$  is a function of one parameter returning real numbers.
- We use the notation  $O(f)$  to mean “the set of all one-parameter functions whose absolute values are eventually bounded above by some multiple of  $f$ ’s absolute value.” Formally:

$$O(f) = \{g \mid \text{there exist } p, M \text{ such that if } x > M, |g(x)| \leq p|f(x)|\}$$

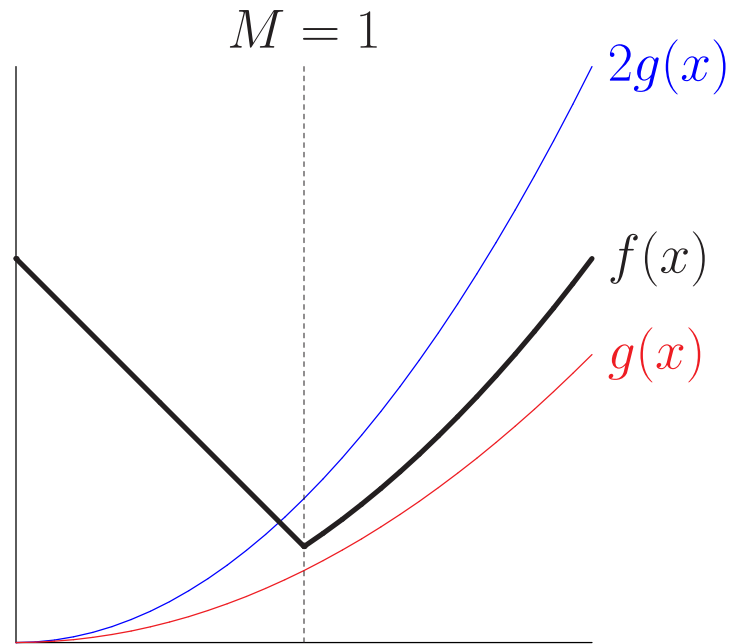
- Similarly, we have “the set of all one-parameter functions whose absolute values are eventually bounded below by some multiple of  $f$ ’s absolute value:”

$$\Omega(f) = \{g \mid \text{there exist } q > 0, M \text{ such that if } x > M, q|f(x)| \leq |g(x)|\}$$

- And finally those bounded both above and below:

$$\begin{aligned}\Theta(f) &= \Omega(f) \cap O(f) \\ &= \{g \mid \exists q > 0, p, \text{ and } M \text{ such that if } x > M, q|f(x)| \leq |g(x)| \leq p|f(x)|\}\end{aligned}$$

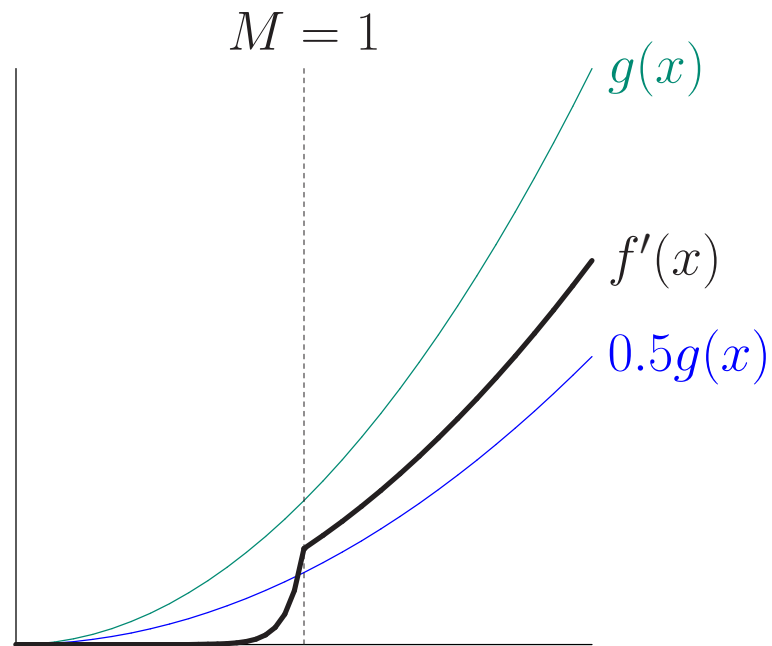
# Illustration



- Here,  $f \in O(g)$  ( $p = 2$ , see blue line), even though  $f(x) > g(x)$ . Likewise,  $f \in \Omega(g)$  ( $p = 1$ , see red line), and therefore  $f \in \Theta(g)$ .
- That is,  $f(x)$  is eventually (for  $x > M = 1$ ) no more than proportional to  $g(x)$  and no less than proportional to  $g(x)$ .



## Illustration, contd.



- Here,  $f' \in \Omega(g)$  ( $p = 0.5$ ), even though  $g(x) > f'(x)$  everywhere.

# Uses of the Notation

- You may have seen  $O(\cdot)$  notation in math, where we say things like

$$f(x) \in f(0) + f'(0)x + \frac{f''(0)}{2}x^2 + O(f'''(0)x^3)$$

- Adding or multiplying sets of functions produces sets of functions. The expression to the right of  $\in$  above means “the set of all functions  $g$  such that

$$g(x) = f(0) + f'(0)x + \frac{f''(0)}{2}x^2 + h(x)$$

where  $h(x) \in O(f'''(0)x^3)$ .”

- I prefer  $\in$  to the traditional  $=$ , since the latter makes no formal sense.
- (Technically, we should say  $h \in O(\lambda x : f'''(0)x^3)$  and so forth, but I don't think that clarifies anything!)