

Lecture #22: 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*?

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A Direct Approach

- Well, if you want to know how fast something is, you can time it.
- Python happens to make this 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('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.

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A Direct Approach, Continued

- You can also use this 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.

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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.

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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 ≈ 1.6 .
- **But...** what if the program special-cases some inputs?
- ...and this still only works for a particular program and machine.

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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.?

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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.

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Asymptotic Results

- 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.
- So in general, we tend to ask about *asymptotic* behavior of programs: as size of input goes to infinity.

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Expressing Approximation

- So, we are looking for measures of program performance that give us a sense of how computation time scales with size of input.
- And we are further interested in ignoring finite sets of special cases that a given program can compute quickly.
- 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 express approximations of execution time or space.

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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:"

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

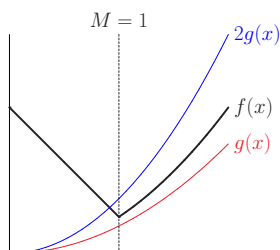
- And finally those bounded both above and below:

$$\Theta(f) = \Omega(f) \cap O(f)$$

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Illustration

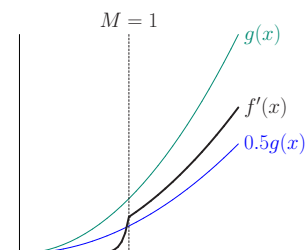


- Here, $f \in O(g)$ ($p = 2$, see blue line), even though $f(x) > g(x)$. Likewise, $f \in \Omega(g)$ ($p = 1$, see red line), and therefore $f \in \Theta(g)$.
- That is, $f(x)$ is eventually (for $x > M = 1$) no more than proportional to $g(x)$ and no less than proportional to $g(x)$.

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Illustration, contd.



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

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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 one above means "the set of all functions $g(x)$ 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.