Computational Structures in Data Science

UC Berkeley EECS
Lecturer
Michael Ball

UC Berkeley EECS
Adj. Ass. Prof.
Dr. Gerald Friedland

Lecture #18: Efficiency

Computing In The News

- Supreme Court rules in Google's favor in copyright dispute with Oracle over Android software
- https://www.cnbc.com/2021/04/05/supreme-court-rules-in-googles-favor-in-copyright-dispute-with-oracle-over-android-software.html

Announcements

- http://bit.ly/eecs-reporting-form
  - Dept Reporting for culture issues, feedback, etc.
  - Anonymous if desired.
- Ants Proj out soon!

Learning Objectives

- Runtime Analysis:
  - How long will my program take to run?
  - Why can't we just use a clock?
  - How can we simplify understanding computation in an algorithm
- Enjoy this stuff? Take 61B!
- Find it challenging? Don't worry! It's a different way of thinking.

Efficiency is all about trade-offs

- Running Code: Takes Time, Requires Memory
  - More efficient code takes less time or uses less memory
- Any computation we do, requires both time and "space" on our computer.
- Writing efficient code is not obvious
  - Sometimes it is even convoluted!
- But!
- We need a framework before we can optimize code
- Today, we're going to focus on the time component.

Is this code fast?

- Most code doesn't *really* need to be fast! Computers, even your phones are already amazingly fast!
- Sometimes…it does matter!
  - Lots of data
  - Small hardware
  - Complex processes
- Slow code takes up battery power

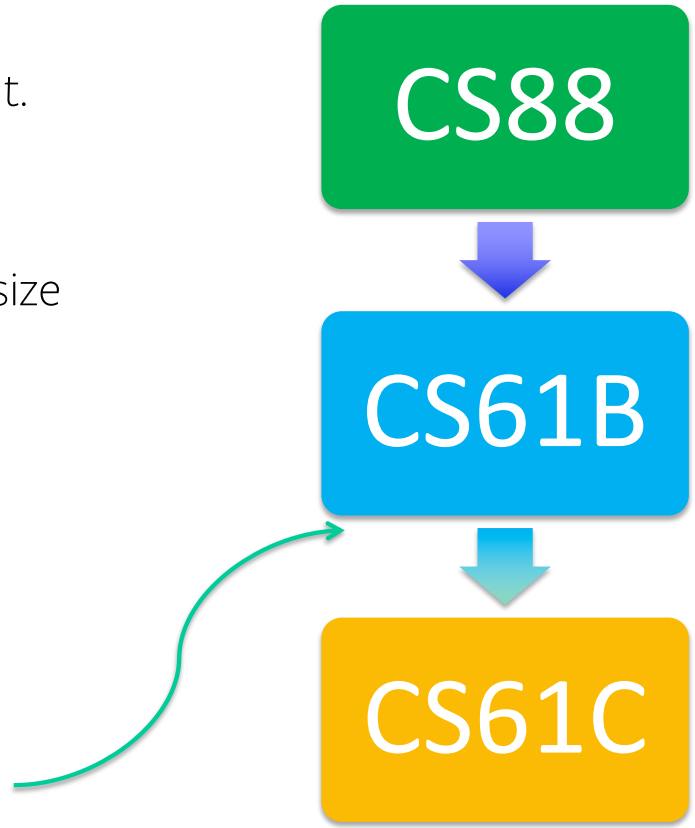
Runtime analysis problem & solution

- Time w/stopwatch, but…
  - Different computers may have different runtimes. ☹
  - Same computer may have different runtime on the <u>same</u> input. ☹
  - Need to implement the algorithm first to run it. ☹

- *Solution*: Count the number of "steps" involved, not time!
  - Each operation = 1 step
    - » 1 + 2 is one step
    - » lst[5] is one step
  - *When we say "runtime", we'll mean # of steps, not time!*

Runtime: input size & efficiency

- Definition:
  - Input size: the # of things in the input.
  - e.g. length of a list, the number of iterations in a loop.
  - Running time as a function of input size
  - Measures efficiency
- Important!
  - In CS88 we won't care about the efficiency of your solutions!
  - ...in CS61B we will

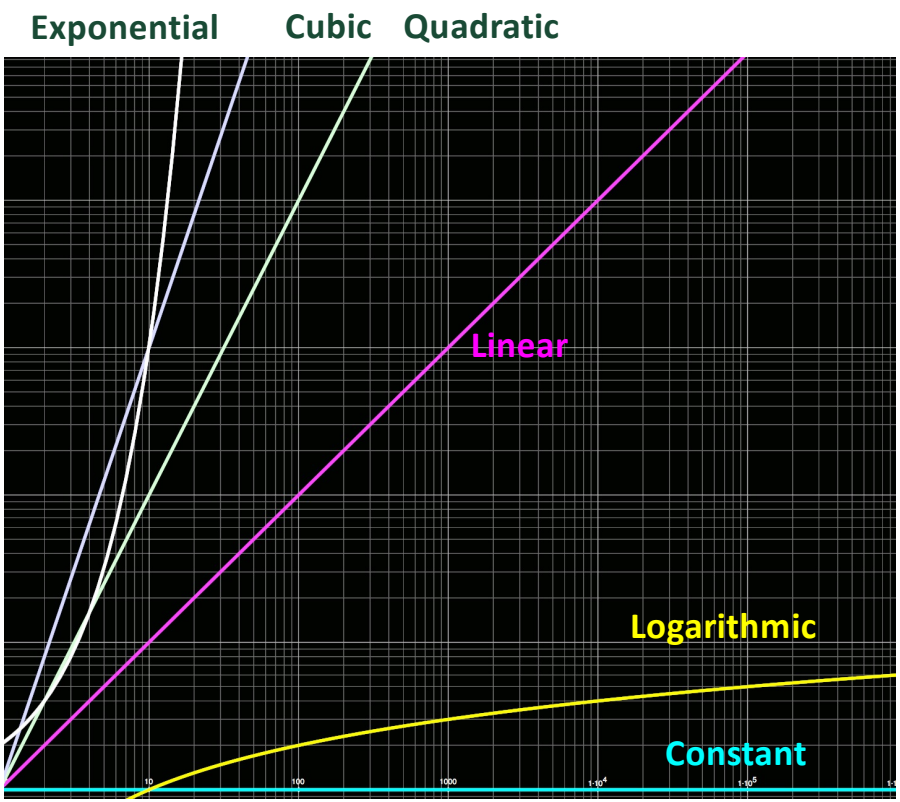


Runtime analysis : worst or average case?

- Could use avg case
  - Average running time over a vast # of inputs
- Instead: use worst case
  - Consider running time as input grows
- Why?
  - Nice to know most time we'd <u>ever</u> spend
  - Worst case happens often
  - Avg is often ~ worst
- Often called "Big O" for "order"
  - O(1), O(n) …

Runtime analysis: Final abstraction

- Instead of an exact number of operations we'll use abstraction
  - Want order of growth, or dominant term
- In CS88 we'll consider
  - Constant
  - Logarithmic
  - Linear
  - Quadratic
  - Exponential
- E.g. $10\ n^2 + 4 \log n + n$
  - ...is quadratic



Graph of order of growth curves on log-log plot

Example: Finding a student (by ID)

- Input
  - Unsorted list of students L
  - Find student S
- Output
  - True if S is in L, else False
- Pseudocode Algorithm
  - Go through one by one, checking for match.
  - If match, true
  - If exhausted L and didn't find S, false

- Worst-case running time as function of the size of L?
  1. Constant
  2. Logarithmic
  3. Linear
  4. Quadratic
  5. Exponential

Example: Finding a student (by ID)

- Input
  - Sorted list of students L
  - Find student S
- Output : same
- Pseudocode Algorithm
  - Start in middle
  - If match, report true
  - If exhausted, throw away half of L and check again in the middle of remaining part of L
  - If nobody left, report false

- Worst-case running time as function of the size of L?
  1. Constant
  2. Logarithmic
  3. Linear
  4. Quadratic
  5. Exponential

Computational Patterns

- If the number of steps to solve a problem is always the same → Constant time: O(1)
- If the number of steps increases similarly for each larger input → Linear Time: O(n)
  - Most commonly: `for each item`
- If the number of steps increases by some a factor of the input → Quadradic Time: $O(n^2)$
  - Most commonly: Nested for Loops
- Two harder cases:
  - Logarithmic Time: O(log n)
    - »We can double our input with only one more level of work
    - »Dividing data in "half" (or thirds, etc)
  - Exponential Time: $O(2^n)$
    - »For each bigger input we have 2x the amount of work!
    - »Certain forms of Tree Recursion

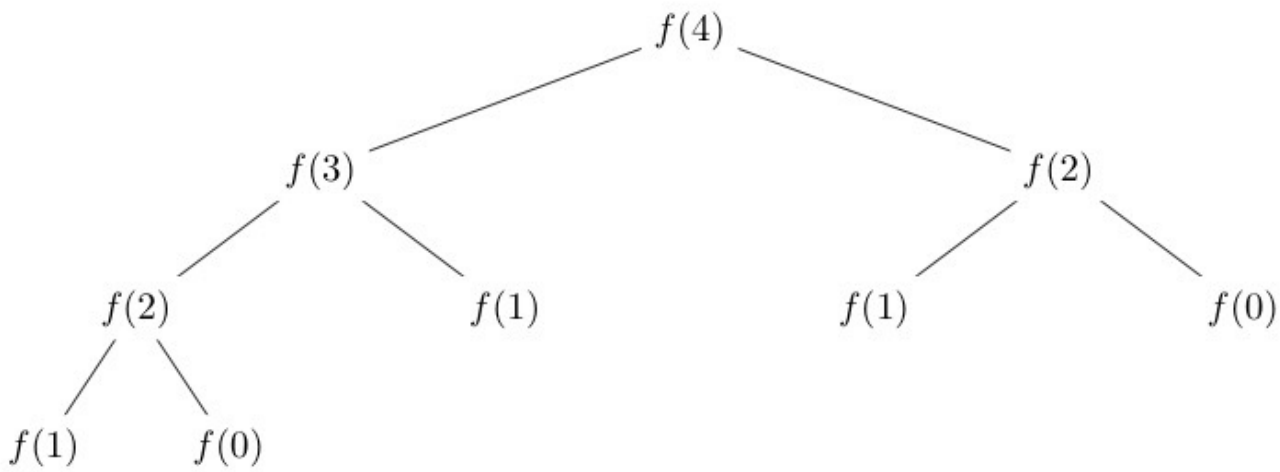
Comparing Fibonacci

```
def iter_fib(n):
    x, y = 0, 1
    for _ in range(n):
        x, y = y, x+y
    return x


def fib(n): # Recursive
    if n < 2:
        return n
    return fib(n - 1) + fib(n - 2)
```

Tree Recursion

- Fib(4) → 9 Calls
- Fib(5) → 16 Calls
- Fib(6) → 26 Calls
- Fib(7) → 43 Calls
- Fib(20) →



What next?

- Understanding *algorithmic complexity* helps us know whether something is possible to solve.
- Gives us a formal reason for understanding why a program might be slow
- This is only the beginning:
  - We've only talked about time complexity, but there is *space complexity.*
  - In other words: How much memory does my program require?
  - Often you can trade time for space and vice-versa
  - Tools like "caching" and "memorization" do this.

- If you think this is cool take CS61B!