UC Berkeley EECS
Lecturer
Michael Ball

Computational Structures in Data Science

Lecture #19: Efficiency

Announcements

- Midterm Grades:
  - likely out tomorrow
  - regrades will open towards the end of the week
  - Then one week to submit a regrade request
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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

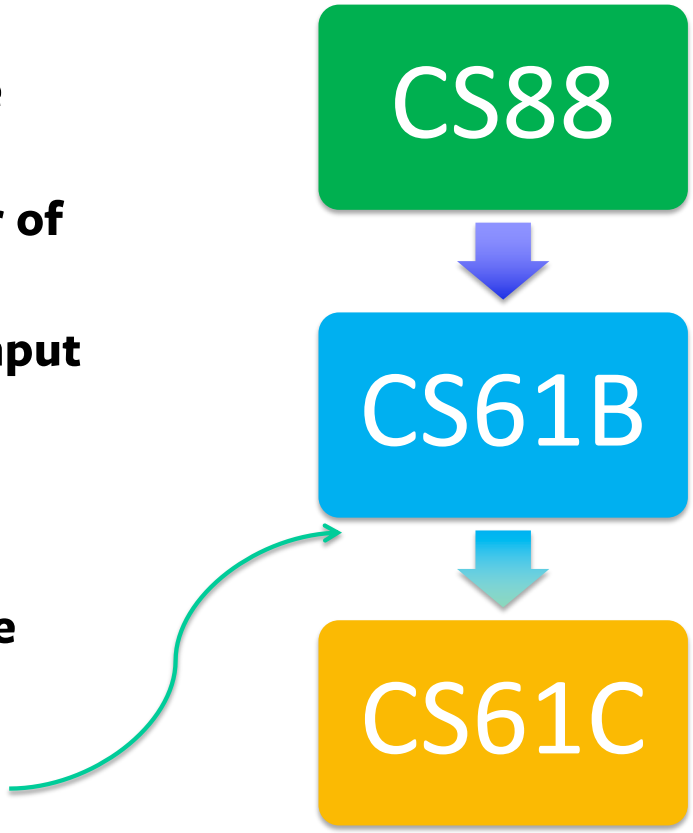
Runtime analysis problem & solution

- Time w/stopwatch, but...
  - Different computers may have different runtimes. ☹
  - Same computer may have different runtime on the same 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**

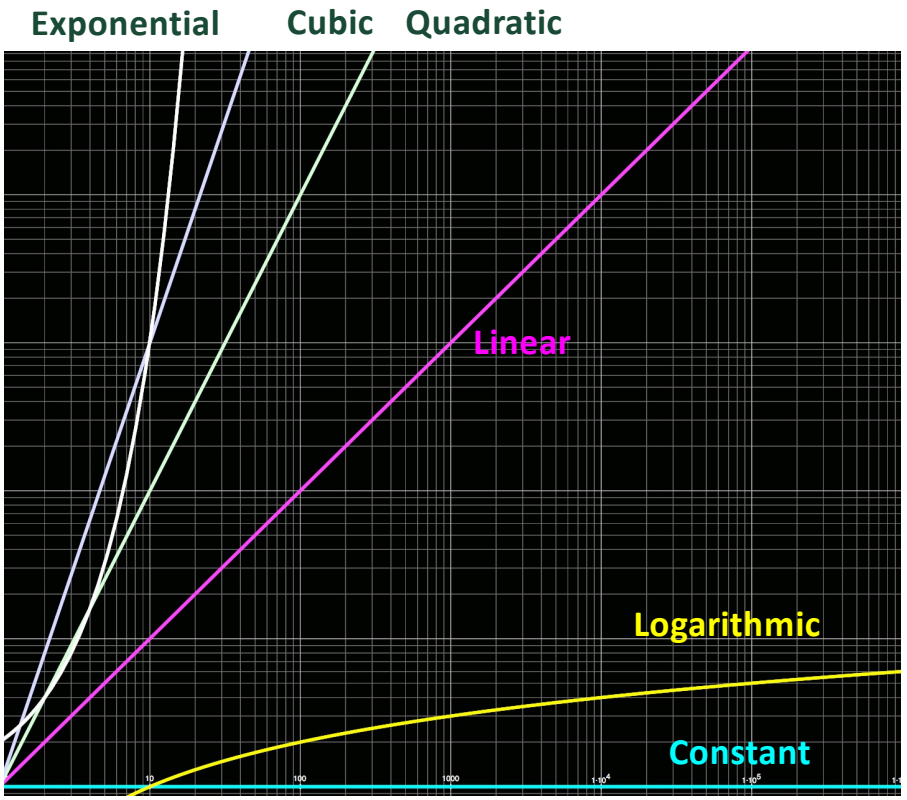


Runtime analysis : worst or average case?

- **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 ever 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**

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

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**

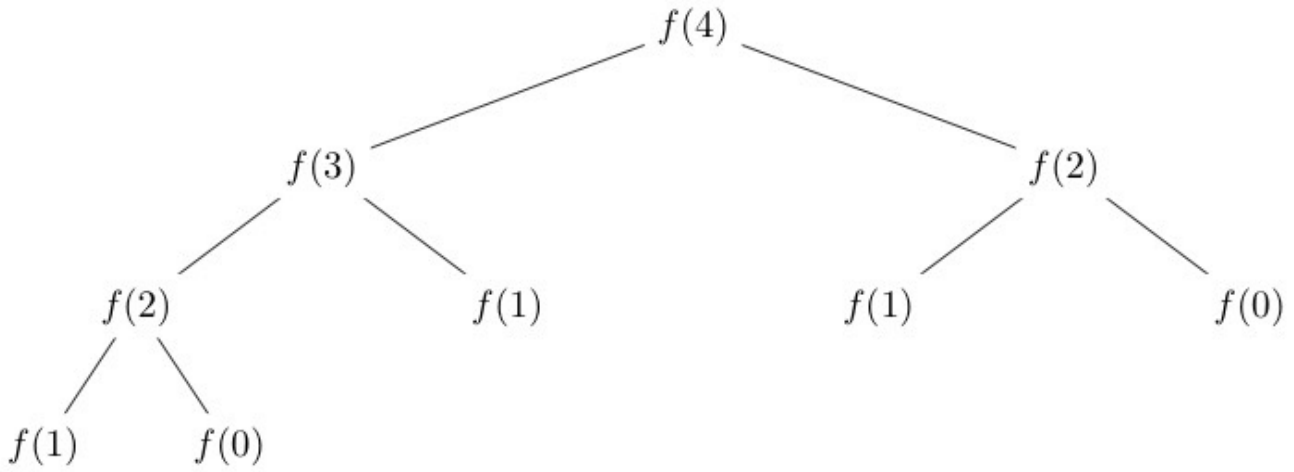
Comparing Fibonacci

```
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!