Announcements

- Midterm Grades:
  - Out today
  - ~1 week to submit regrade requests
- Today:
  - Understanding the Efficiency of code
  - Why do we care? How do we measure how fast code is?

UC Berkeley EECS
Lecturer
Michael Ball

Efficiency
& Run Time Analysis

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

Beware!

"Premature Optimization is the root of all evil"

- Donald Knuth, Stanford CS Professor,

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

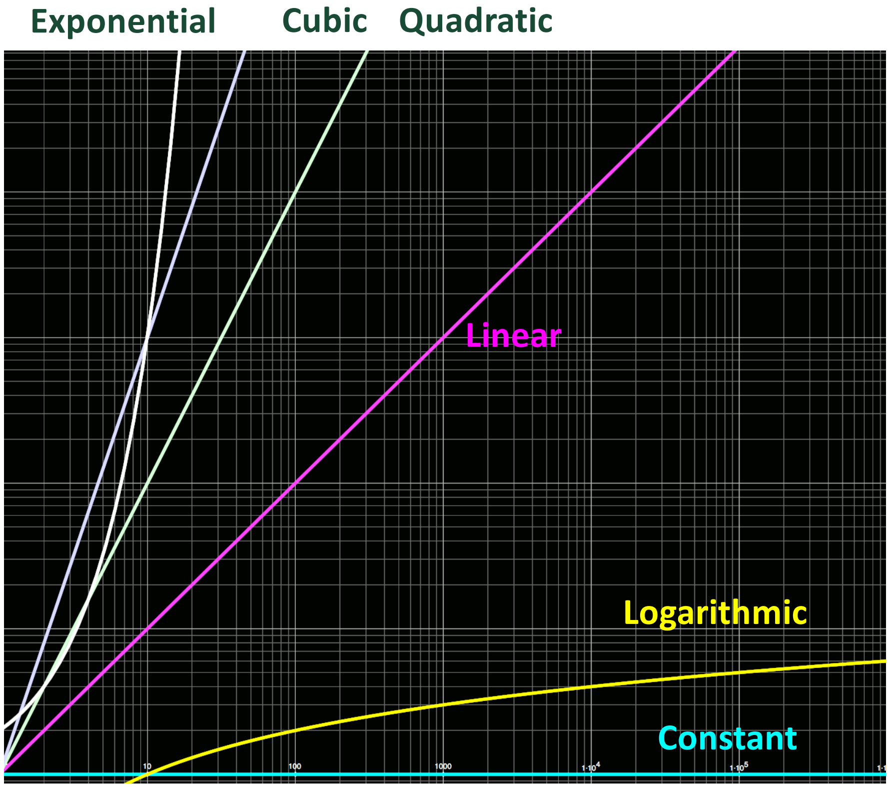
- Definition:
  - **Input size**: the # of things in the input.
  - e.g. length of a list, the number of iterations in a loop.
  - Running time as a function of input size
  - Measures **efficiency**
- Important!
  - In CS88 we won't care about the efficiency of your solutions!
  - …in CS61B we will

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**

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
  - <u>Sorted</u> 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

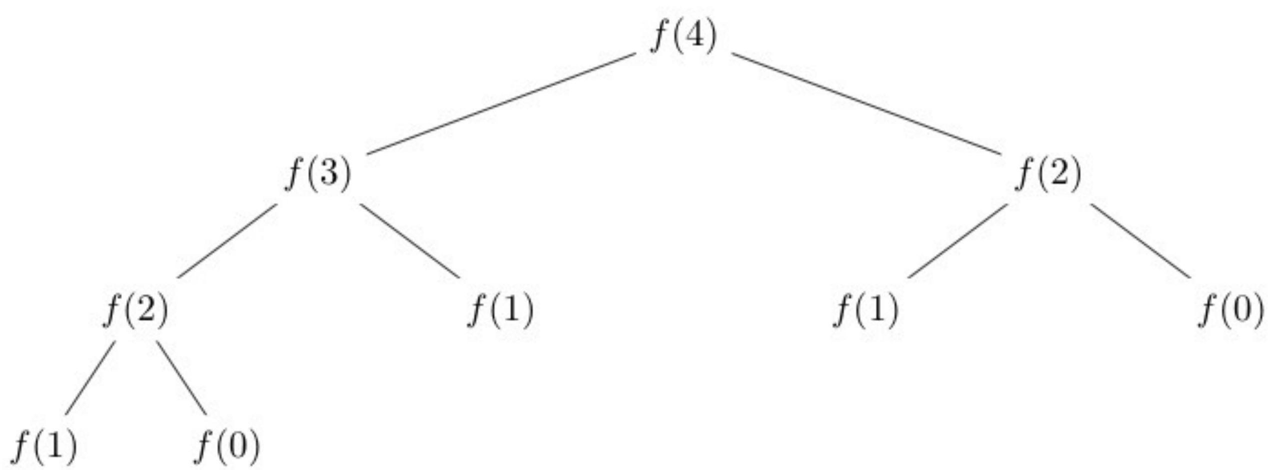
Comparing Fibonacci

```
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) ⟶



Why?

- Notice there was all this duplication in the tree?
- What is the exact order of growth?
  - It's exponential.
  - phi to the N (φ^n), where phi is the golden ratio.

N	Operations
1	1
2	3
3	5
4	9
7	41
8	67
20	21891

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Computational Structures in Data Science

Improving Efficiency

Learning Objectives

- Learn how to cache the results to save time.
- "memoization" is a specific version to avoid repeated calculations

Example

- Use a dictionary to cache results.
- This is called *memoization*

```
fib_results = {}
def memo_fib(n): # Look up values in our dictionary.
    global fib_results
    if n in fib_results:
        print(f'found {n} -> {fib_results[n]}')
        return fib_results[n]
    if n < 2:
        fib_results[n] = n
        return n
    result = memo_fib(n - 1) + memo_fib(n - 2)
    fib_results[n] = result
    return result
```

A Better Approach

- Python's functools module has a `cache` function
- https://docs.python.org/3/library/functools.html#module-functools
- Uses a technique called decorators that we don't cover.

```
from functools import cache

@cache
def cache_fib(n): # Recursive
    if n < 2:
        return n
    return cache_fib(n - 1) + cache_fib(n - 2)
```

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!