Computational Structures in Data Science

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Lecture #18: Efficiency

Solutions for the Wandering Mind

Can you write a quine that mutates on self-replication?

Yes!

Give an example.

A *Fibonacci-quine* outputs a modification of the source by the following rules:

1) The initial source should contain 2.

2) When run, output the source, but *only* the specific number (here 2) changed to the next number of the Fibonacci sequence. For example, 3. Same goes for the output, and the output of the output, etc.

```
s='s=%r;print(s%%(s,round(%s*(1+5**.5)/2)))';
print(s%(s,round(2*(1+5**.5)/2)))
```

Why?

- **Runtime Analysis:**
  - How long will my program take to run?
  - Why can't we just use a clock?
- **Data Structures**
  - OOP helps us organize our *programs*
  - Data Structures help us organize our data!
  - You already know lists and dictionaries!
  - We'll see two new ones today
- **Enjoy this stuff? Take 61B!**
- **Find it challenging? Don't worry! It's a different way of thinking.**

Efficiency

How long is this code going to take to run?

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
- We can't just use a clock
  - Every computer is different? What's the benchmark?

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**
  - ***If we say "running time", we'll mean # of steps, not time!***

Runtime: input size & efficiency

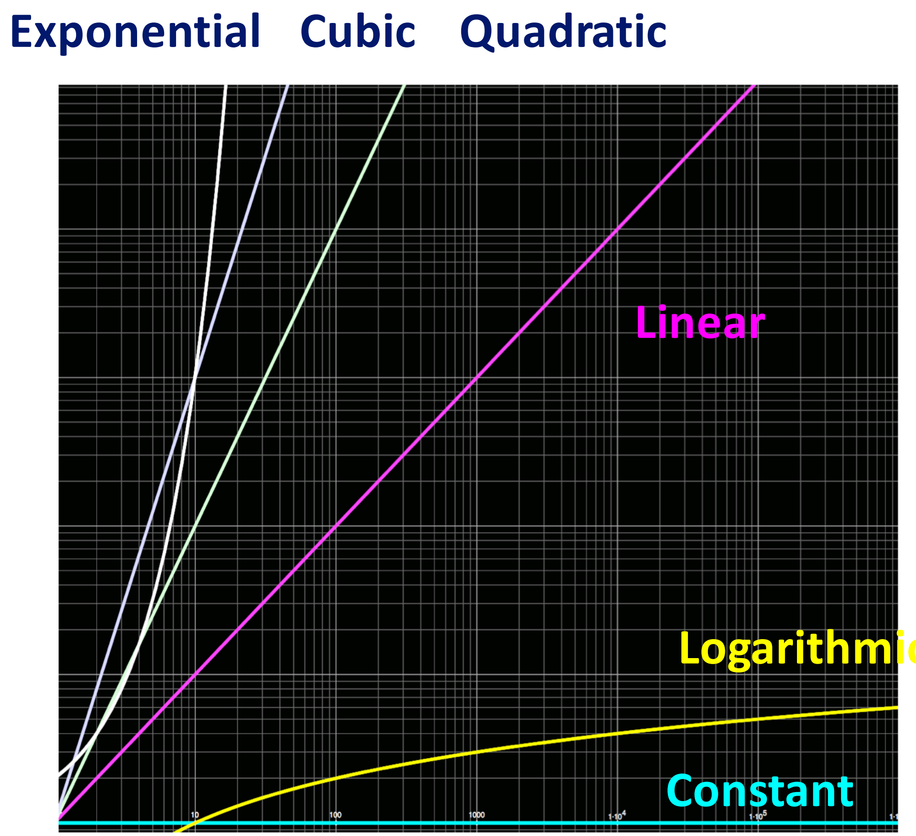
- **Definition**
  - **Input size:** the # of things in the input.
  - E.g., # of things in a list
  - Running time as a function of input size
  - Measures **efficiency**
- **Important!**
  - In CS88 we won't care about the efficiency of your solutions!
  - …in CS61B we will

Runtime analysis : worst or avg 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"**
  - We use "Omega" denote runtime

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
  - <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

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**

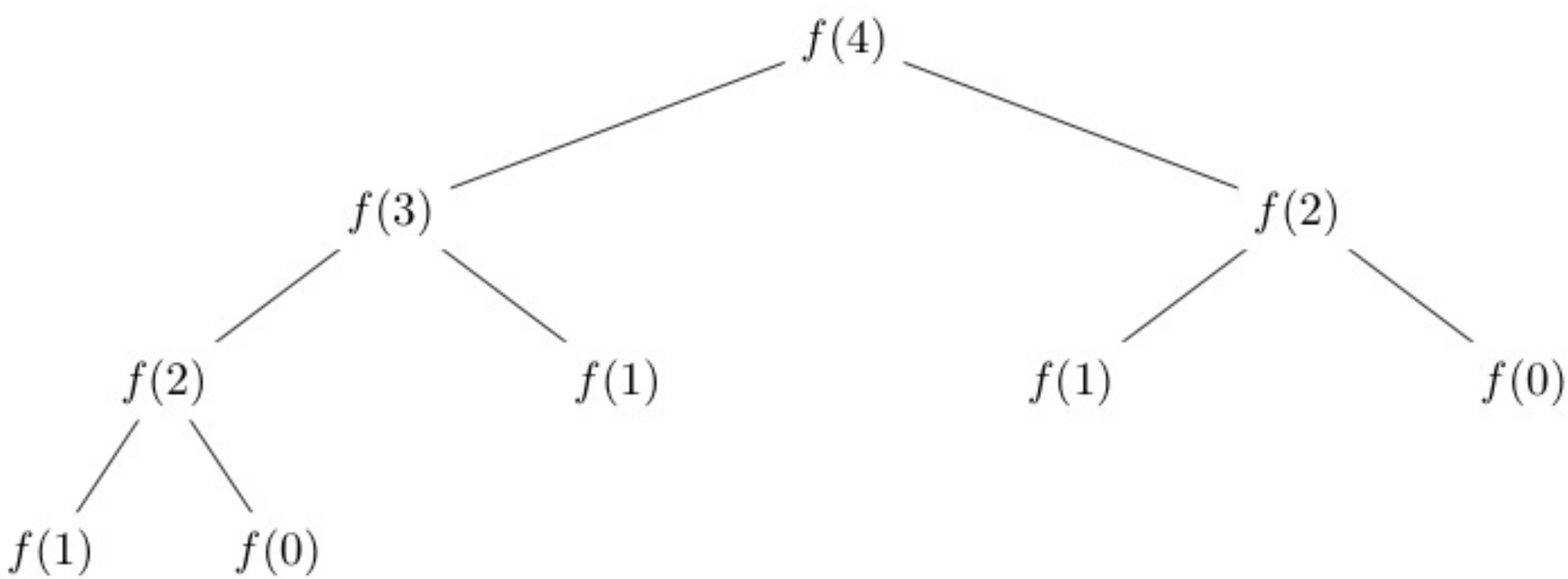
Comparing Fibonacci

```
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 times you can trade time for space and vice-versa**
  – **Tools like "caching" and "memorization" do this.**

- **If you think this is cool take CS61B!**

Thoughts for the Wandering Mind

Consider the following simple Python code:

```
x = input("Enter a number between 0 and 1:")
for i in range(10):
        x=-x**2+4*x
print x
```

Plot the function implemented by the code.

- Could you predict using sampling (e.g., interpolate from the results of inputs 0, 0.25, 0.5, 0.75, 1)?
- Could you predict using calculus (e.g., using the derivative of $f(x)=-x^2+4x$)?
- Could a neural network learn the function, given enough (input, output) tuples as training data?