Computational Structures in Data Science

Efficiency
& Run Time Analysis

UC Berkeley

Introductions

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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 Data Structures!
- 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
- *Every* computation 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

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

There is **no use** in fast code if it is wrong!

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 (clock) time!*

Runtime: input size & efficiency

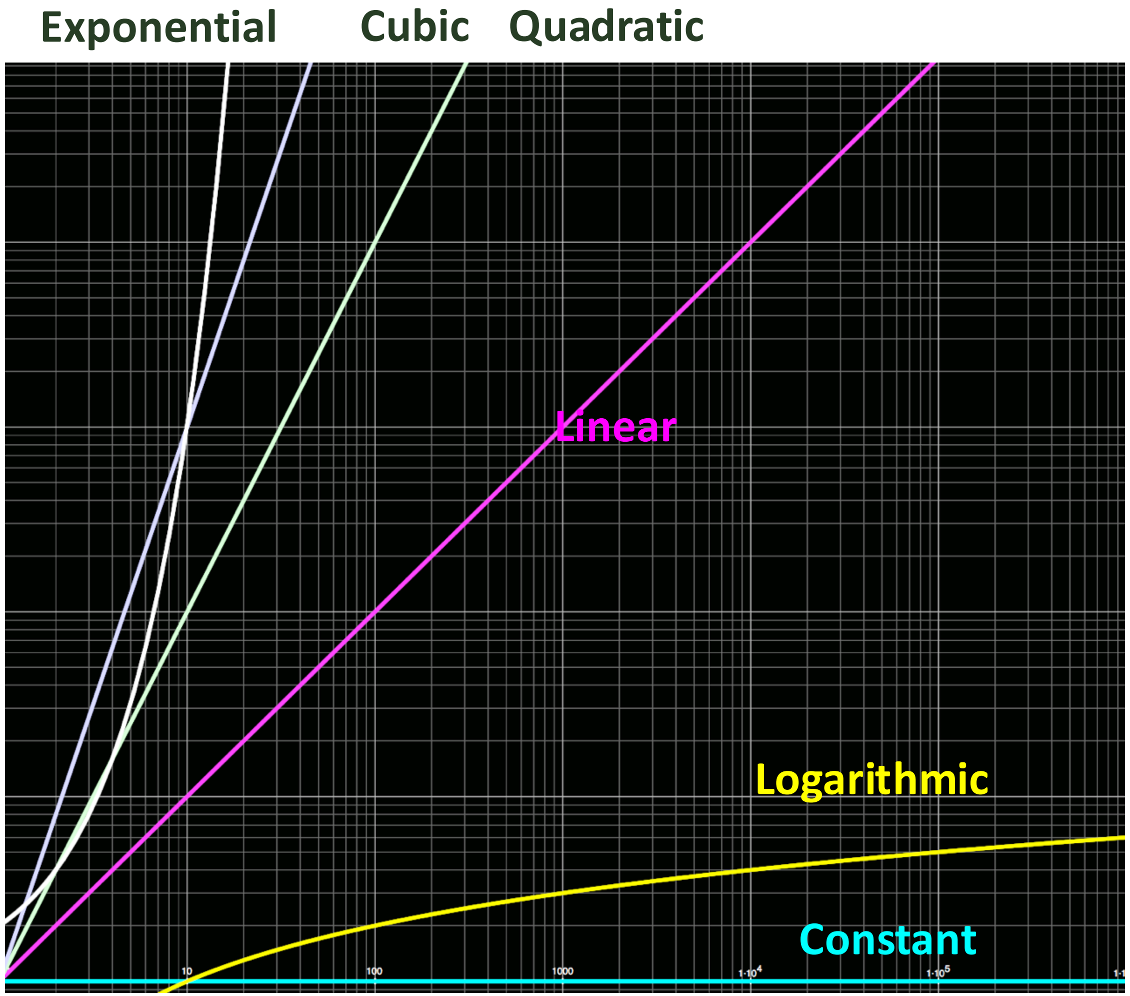
- Definition:
  - **Input size**: the # of things in the input.
  - e.g. length of a list, the number of iterations in a loop.
  - Running time as a function of input size
  - Measures **efficiency**
- Important!
  - In C88C <u>we won't care </u>about the efficiency of your solutions!
  - Efficiency matters in the next courses

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
  - The "average" can be similar to the 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 C88Cx we'll consider
  - Constant `O(1)`
  - Logarithmic `O(log n)`
  - Linear `O(n)`
  - Quadratic `O(n²)`
  - Exponential `O(2ⁿ)`
- e.g. **`10n²`** `+ 4log(n) + n`
  - ...is **quadratic**



Graph of order of growth curves on log-log plot

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Practicing Analyzing Efficiency

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Example: Finding a student (by ID)

- Input
  - <u>Unsorted</u> 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)**
  - e.g. getting a result does not depend on the size of the input
  - `lst[n]` is one step no matter how many items are in the list.
- 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

Computational Patterns

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

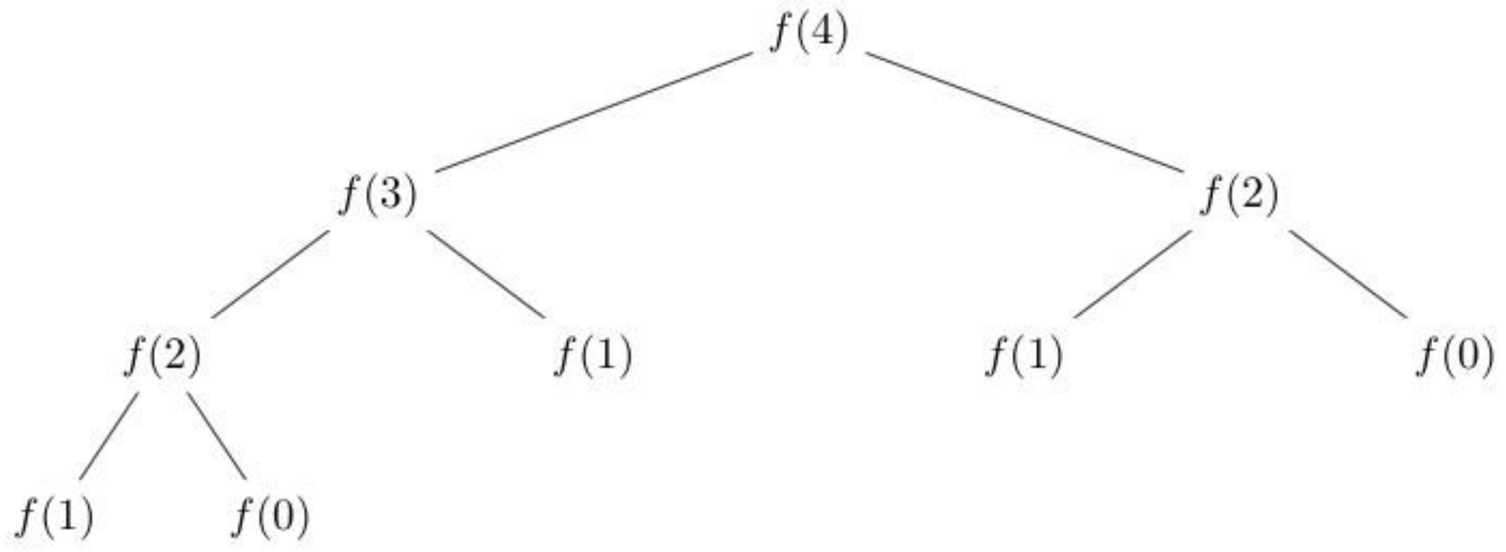
Comparing Fibonacci

```
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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Improving Efficiency

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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
- Uses a technique called decorators that we don't cover.
  - Decorators are really just a "shortcut" for higher order functions.
  - e.g. `cache_fib = cache(fib)` is a similar approach to the function below, but less commonly used.

```
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.

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Thank you!

See you next week ☺

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