

CS 331, Fall 2024

Lecture 4 (9/9)

- Today:
- Fibonacci
 - Word RAM model
 - Largest jump
 - Largest subsequence sum

Fibonacci (Part III, Section 1)

Classic interview question / "gotcha"

Input: $n \in \mathbb{N}$

Output: F_n , n th Fibonacci number

Recursive definition:

$$F_0 = 1, F_1 = 2, F_2 = 3, F_3 = 5, F_4 = 8$$

$$\dots F_n = F_{n-1} + F_{n-2}$$

Observation: $F_n = \exp(\Theta(n))$

Aside In fact,

$F_n \approx \varphi^n$, where

$\varphi \approx 1.618$ is "golden ratio"

First try:

FibNaive(n):

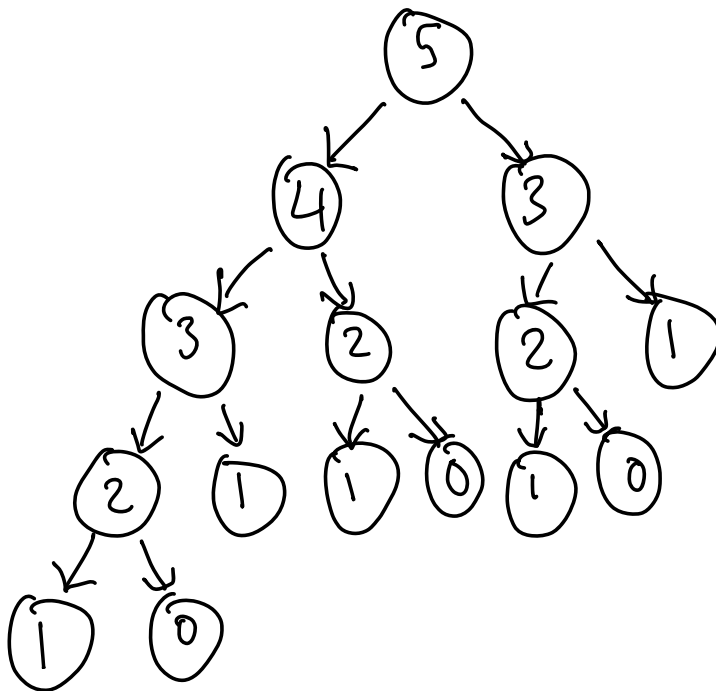
If $n=0$: Return 1

If $n=1$: Return 2

Return FibNaive($n-1$) + FibNaive($n-2$)

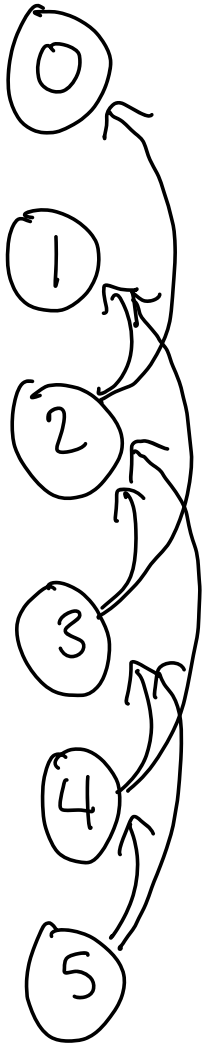
~~X~~ Warning: this will take exponential time!

e.g. FibNaive(5):



depth = n
branching
factor ≈ 2

Idea: do things bottom-up to avoid recomputation



Intuition: induction is typically proven from the base case.

Fib(n):

$L \leftarrow \text{Array.init}(n+1)$ // $L[i] = F_{i+1}$

$L[1] \leftarrow 1$

$L[2] \leftarrow 2$

For $3 \leq i \leq n+1$: $L[i] \leftarrow L[i-1] + L[i-2]$

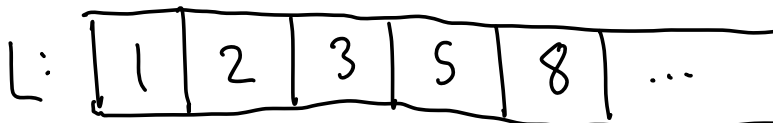
Return $L[n+1]$

Key takeaways:

1) order matters!

(top-down vs. bottom-up)

2) save your work



"memos"

Dynamic programming:

Smarter and more flexible recursion

(up to now, focus is "divide-and-conquer")

Applications:

- Coding interviews (seriously.)
- Reinforcement learning (founder: Bellman)
- Game theory / economics

Basic idea: 1) define subproblems you want to solve / "memoize"

2) define order to solve them

It can be hard to understand at first.

Payoffs enormous: exponential \Rightarrow near-linear time?

Next 4 lectures: many examples as a field guide

Word RAM model (Part I, Section 7)

Quiz: how fast is fib?

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... // base cases
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For  $3 \leq i \leq n+1$ :  $L[i] \leftarrow L[i-1] + L[i-2]$ 
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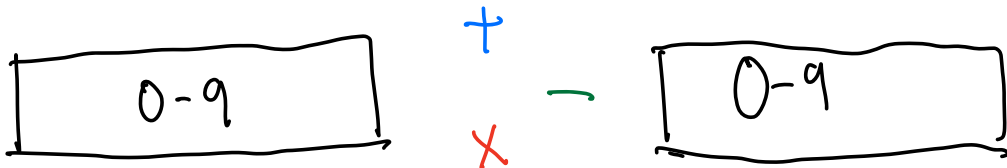
```
Return  $L[n+1]$ 
```

$O(n)$? No!

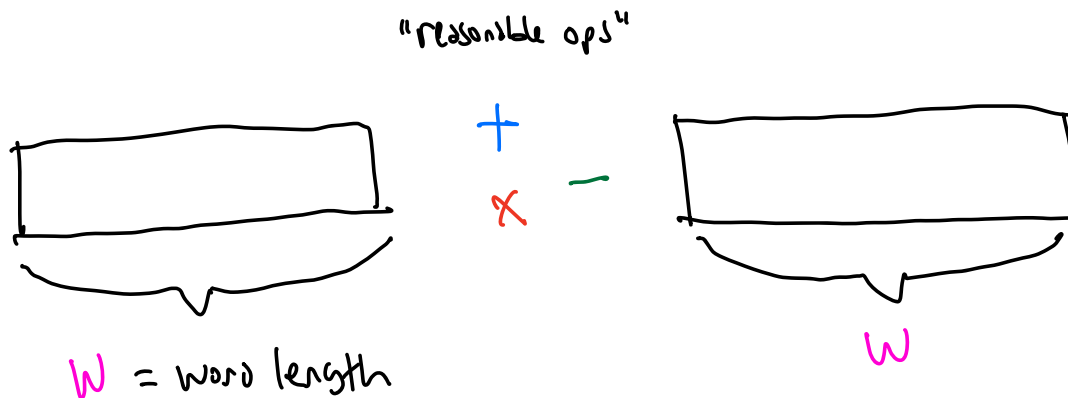
Remember, $L[i] = \exp(\Theta(n))$ is a $\Theta(n)$ -digit number!

$O(n^2) = n \text{ steps} \times \underbrace{O(n)}_{\text{add } n\text{-digit numbers}} \text{ time per step}$

Bit complexity model: bit/digit ops take $O(1)$ time.



Word RAM model:



Assume: takes $O(1)$ time.

Think: $W = 64$, maybe few 100's tops.

It's reasonable to assume

$$\log(n) \leq W.$$

Will do hence forth
unless stated otherwise

Unreasonable to assume

$$n \leq W.$$

keep an eye out!

Examples

- Incrementing a for loop counter $i \in \mathbb{N}$ is $\log(n)$ digits, $O(1)$ time.
- Comparing two numbers in sorting if both $\leq 2^W$, $O(1)$ time.

Bonus algo: $\text{Fib}(n)$ in $O(n \log n)$ time
(see Part II, Section 5.3)

Largest jump (Part III, Section 2.1)

Input: L is a list of n elements in \mathbb{R}

Output: (i, j) with $1 \leq i \leq j \leq n$

Maximizing $L[j] - L[i]$

Example

	Day						
	1	2	3	4	5	6	7
GME Stocks	8	12	4	9	17	1	13

How to maximize profit?

Buy ↓ Sell →	1	2	3	4	5	6	7
1	0	4	-4	1	9	-7	5
2		0	-8	-3	5	-11	1
3			0	5	13	-3	9
4				0	8	-8	4
5					0	-16	-4
6						0	12
7							0
Best:	0	4	0	5	13	0	12

Time: $O(n^2)$ (for each i, j , compute $L(j) - L(i)$)

How to improve?

Idea: What do we need to know for $Best(j)$?

$$Best(j) = \max_{i \in (j)} L(j) - L(i) = L(j) - \min_{i \in (j)} L(i)$$

maintain

Faster algo, take 1:

① Pass over list, maintain running min.

e.g.

8	12	4	9	17	1	13
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MinUpTo 8 8 4 4 4 1 1

$$\text{MinUpTo}[j] = \min_{i \in [j]} L[i]$$

② Compute all $\text{Best}[j] = L[j] - \text{MinUpTo}[j]$

Both steps $O(n)$ time. Why?

$$\text{MinUpTo}[j] = \min \left(\underbrace{\text{MinUpTo}[j-1]}_{\text{memoized}}, L[j] \right)$$

Faster algo, take 2:

All subproblems: (i, j) , $n + \binom{n}{2} = \Theta(n^2)$ of them.

Special subproblems: (i^*, j) where $i^* = \text{MinUpTo}(j)$

$$\text{Best}(j) = L[j] - L(i^*).$$

only $O(n)$ of them.

Are Special subproblems harder?

Not with memoization!

$$\text{Best}(j) = \max \left(0, \text{Best}(j-1) + \underbrace{L[j] - L[j-1]}_{\text{difference in sell price}} \right)$$

buy on day j $i^* = j$ buy on day $< j$, keep i^* the same

No need for MinUpTo . $O(1)$ time per $\text{Best}(j)$
= $O(n)$ total.

- General strategy:
- 1) Design any correct algo.
 - 2) Repeated structure? *Memoize!*
 - 3) Go back to step 1). *Simplify.*
(the hardest step)

Largest subsequence sum (Part IV, Section 2.2)

Input: L is a list of n elements in \mathbb{R}

Output: (i, j) with $1 \leq i \leq j \leq n$

maximizing $L[i] + L[i+1] + \dots + L[j-1] + L[j]$
Subsequence sum

Example

25	-60	7	-13	30
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First try:

	End →	1	2	3	4	5
Start ↓						
1		25	-35	-28	-41	-11
2			-60	-53	-66	-36
3				7	-6	24
4					-13	17
5						30

Naive: $\underbrace{O(n^2)}_{\# \text{ subproblems}} \times \underbrace{O(n)}_{\text{time / subproblem}} = O(n^3)$

Better: $O(n^2) \times \underbrace{O(1)}_{\text{proceed row by row, left-to-right.}}$ = $O(n^2)$

$$\sum_{k=i}^j L(k) = \underbrace{\sum_{k=i}^{j-1} L(k)}_{\text{memoized}} + L(j)$$

Time to simplify.

Can we define $O(n)$ special subproblems?

$Best(j)$ = largest subsequence sum ending on j

Recursive formula:

$$Best(j) = \max \left(L(j), Best(j-1) + L(j) \right)$$

don't include $L(j-1)$

include $L(j-1)$.
may as well continue
in best possible way

Again, $O(1)$ per subproblem using *memoization*

\Rightarrow LSS in $O(n)$ time. ☺

(Kadane, at a CMU seminar)